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Increasing the initiation of antiretroviral therapy through optimal placement of diagnostic technologies for pediatric HIV in Zimbabwe: A modeling analysis

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ABSTRACT

Objectives: Point-of-care (POC) devices for infant HIV testing provide timely result-return and increase antiretroviral (ART) initiation. We aimed to optimally locate POC devices to increase 30-day ART initiation in Matabeleland South, Zimbabwe.

Methods: We developed an optimization model to identify the locations for limited POC devices at health facilities, maximizing the number of infants who receive HIV test results and initiate ART within 30 days of testing. We compared location-optimization model results to non-model-based decision heuristics, which are more practical and less data-intensive. Heuristics assign POC devices based on demand, test positivity, laboratory result-return probability, and POC machine functionality.

Results: With the current placement of 11 existing POC machines, 37% of all tested infants with HIV were projected to receive results and 35% were projected to initiate ART within 30 days of testing. With optimal placement of existing machines, 46% were projected to receive results and 44% to initiate ART within 30 days, retaining three machines in current locations, moving eight to new facilities. Relocation based on the highest POC device functionality would be the best-performing heuristic decision (44% receiving results and 42% initiating ART withing 30 days); although, it still would not perform as well as the optimization-based approach.

Conclusion: Optimal and *ad hoc* heuristic relocation of limited POC machines would increase timely result-return and ART initiation, without further, often costly, interventions. Location optimization can enhance decision-making regarding the placement of medical technologies for HIV care.

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Introduction

Over 1.7 million children were living with HIV in 2021, with 88% of them in sub-Saharan Africa [1,2]. In 2021, there were 4800 new HIV infections among children aged 0-14 years in Zimbabwe, with most likely acquired through vertical transmission either during pregnancy, at the time of delivery, or during breastfeeding [3,4]. Infant testing is recommended for infants exposed to HIV during pregnancy, with prompt antiretroviral (ART) initiation thereafter [4]. However, as of 2020, only 76% of infants recommended for testing accessed testing within 2 months of birth in sub-Saharan Africa [5,6]. Early diagnosis and ART initiation are critical for reducing mortality risk among children born with HIV [7,8]. Moreover, the result-return time for infant testing varies widely, often up to 2 months, and 20-50% of patients never receive the results [9]. Gaps in the care processes necessary for testing infants and children exposed to HIV have led to only 54% of children living with HIV initiating ART, a percentage far lower than in adults [2].

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The prolonged turnaround times for diagnostic platforms, such as laboratory-based nucleic acid tests, coupled with the limited availability of ART formulations suitable for children, pose barriers to prompt and effective HIV diagnosis and treatment in the region. For laboratory-based testing, samples collected in health facilities are batched, transported, and processed in central laboratories, and results are electronically received by health facilities. Budget constraints (impacting labor and transportation of samples), shipping times, and the limited number of central laboratories lead to delays in turnaround times [10,11]. Newly available technologies, such as novel point-of-care (POC) nucleic acid tests that return the results on the same day and allow quicker ART initiation than laboratory assays, may address these gaps and reduce infant mortality [9,12]. However, because it is costly to buy these devices for every health facility, the number of available devices remains limited, especially in resource-limited settings.

Optimizing the placement of POC devices across geographical locations and the allocation of samples between POC and laboratory-based tests will maximize the number of infants treated and their survival, both in the short- and long-term [13]. Because POC devices are portable instruments, requiring limited infrastructure and training, and given that they can be reliably used by clinicians and lay health workers [14,15], it is possible to relocate them when needed to optimize same-day diagnosis and rapid ART initiation for the greatest number of infants. Location-optimization models use mathematical methods to rigorously determine the most efficient location of limited resources, maximizing the outcome of interest (*e.g.*, ART initiation) while considering constraints (*e.g.*, limited POC machines) [16]. Assignment based on heuristics is another approach to allocating diagnostic technologies based on simple decision rules or guidelines rather than complex models or algorithms. This approach can be effective in settings where the use of more sophisticated models may not be feasible or practical. We used both location-optimization methods and decision heuristics to analyze the placement of current and additional POC machines in Matabeleland South, Zimbabwe, with the goal of maximizing the number of infants who initiate ART within 30 days of HIV testing. Matabeleland South is the province in Zimbabwe with the highest HIV prevalence among adults aged 15 years and older: 17.6% in 2019 [17].

Methods

Analytic overview

We built a location-optimization model to assign the currently available POC machines to health facilities in Matabeleland South to maximize 30-day infant ART initiation. The location-optimization model requires detailed district-level data and computational expertise to implement; in the absence of access to optimization tools, decisions about device location are made without mathematical models. For settings where optimization tools are unavailable, we investigated four potential non-model-based decision-making heuristics based on readily available data and compared them with the results of our location-optimization model. We also analyzed two additional scenarios: the additional number of POC machines needed to achieve a goal of 50% ART initiation within 30 days of infant testing, and the impact of a potential increase in demand (defined as the number of infants seeking testing) resulting from the new assignment of a POC machine to a health facility.

Model structure

Our optimization approach is an integer programming-based model which identifies the optimal placement of the existing POC machines to maximize the number of children initiating ART within 30 days of infant testing. Although other optimization software tools are available, we chose to develop our optimization model in Python (version 3.8.6) [18] to allow it to be specific for this policy question and to improve flexibility, transparency, and ease of replication. The objective function of our optimization model maximizes the total number of infants who initiate ART within 30 days of testing through either POC or laboratory testing. We imposed a constraint to ensure that each machine is assigned to only one health facility. Children presenting to health facilities not assigned a POC device undergo a conventional laboratory-based testing. We define POC machine functionality as the proportion of weekdays on which samples can be processed, reflecting the combined impact of availability of electricity, consumables (reagents and test cartridges), machine maintenance, trained staff, and other resources.

Data inputs

We used regional data obtained from 122 health facilities in Matabeleland South, Zimbabwe. We modeled the full cohort of 4724 HIV-exposed infants, with and without HIV, who were tested in the health facilities between January 2019 and January 2020. At the time of analysis, there were 11 available POC machines processing infant testing samples, located at 10 health care facilities in Matabeleland South.

Table 1 presents input data parameters, including the number of infants undergoing infant testing in each facility (demand), the test positivity proportion among those infants, and the probabilities of result-return within 30 days for POC and conventional laboratory-based testing.

There are four key steps in the cascade of care that affect the translation of a positive test result into a successful ART initiation: result-return probability, time to result-return, probability of ART initiation after result-return, and time from result-return to ART initiation. There are high-quality data to inform the first two parameters and very limited data to inform the second two. We have therefore incorporated these steps into the model by focusing on the probability of and time to result-return, which differ markedly for POC and laboratory assays. We held the probability of ART initiation after result-return constant at an assumed value of 95% [17] and assumed that ART initiation would occur on the day of result-return. In the limited situations in which data on all four steps were available, we ensured that the overall probability and time from test collection to ART initiation in the available data were reflected in the product of result-return and ART initiation and in the sum of time to result-return and time to ART initiation. In the base case, we assumed that the demand did not significantly increase with the introduction of a POC device. However, we conducted a scenario analysis reflecting potentially increased demand for health facilities when a POC machine was introduced.

Input parameters are derived from both published literature and routine program data, including from the Organization for Public Health Interventions and Development's/United States Agency for International Development/United States President's Emergency Plan for Relief-supported Target, Accelerate and Sustain Quality Care for HIV Epidemic Control program, and the Ministry of Health and Child Care of Zimbabwe.

Model outcomes

The outcomes of the optimization model include the optimal location assignments of each POC machine, proportion of positive test results returned to infants/caregivers within 30 days, and proportion of infants with HIV initiating ART within 30 days of a positive HIV test (number of children who initiate ART divided by

Table 1
Input data parameters.

Parameter		Base case estimate	Sensitivity range	Source
Univariate analysis				
Demand (number of infants who present for testing)		Health-facility-specific, by month 0 to 65 (Refer to Section S6 for full dataset)	20% ±	Routine data by the National AIDS and TB Program in Zimbabwe, 2019
Test positivity (%)		District-specific (1.0, 4.3, 3.3, 2.5, 2.8, 1.7, 2.0)[a]	20% ±	Routine data by the National AIDS and TB Program in Zimbabwe, 2019
Test results received by caregiver within 30 days (%)	POC infant diagnosis testing	98.3	95-100	[19,20]
	Conventional early infant laboratory testing	District-specific (27, 37, 37, 43, 35, 15, 30)[a]	20% ±	Routine data by the National AIDS and TB Program in Zimbabwe, 2019
Antiretroviral therapy initiation within 30 days among children with HIV who receive their positive test results (%)		95	90-100	Assumption
Functionality of POC machines (proportion of weekdays when devices are working, %)		District-specific (70, 80, 35, 35, 90, 35, 98)[a]	30% ±	Estimate based on site observations over 2019
Scenario analysis				
Number of POC machines		11	11-40	Routine data by the National AIDS and TB Program in Zimbabwe, 2019
Increased demand when POC machine is introduced (%)		N/A	5-30	Assumption

[a] (Beitbridge, Bulilima, Gwanda, Insiza, Mangwe, Matobo, Umzingwane) POC, point-of-care; TB, tuberculosis

number of children who test positive). The technical details are fully documented in the Supplement, Section 1.

Ad hoc *heuristic decisions*

We compared location-optimization model results to non-model-based decision heuristics that assign POC devices based on four conditions: (i) High demand: this heuristic assigns POC devices to health facilities with the highest demand (number of infants tested). (ii) High test positivity proportion: this heuristic assigns POC machines to districts where HIV positivity proportions are the highest. Within each district, POC devices are assigned to health facilities with the highest demand. (iii) Low laboratory result-return probability: this heuristic assigns POC machines to districts with the lowest proportion of results from conventional laboratories returned within 30 days. We allocate the existing 11 machines as follows: districts with a 30-day result-return proportion of 15% (one district) receive three POC machines, districts with a result-return proportion of 16-30% (two districts) receive two POC machines, and the remaining districts (four districts) receive one. Within each district, POC devices are assigned to health facilities with the highest demand. (iv) High functionality: this heuristic assigns POC devices to districts based on POC device functionality. Districts with POC machines able to be used on more than 50% of weekdays receive two POC devices, otherwise, they receive one. Within each district, the POC devices are assigned to health facilities with the highest demand.

Uncertainty analysis

To investigate uncertainty, we conducted univariate sensitivity analyses on all key model input parameters, including probability of results returned within 30 days after conventional laboratory testing and POC testing, proportion of infants initiating ART after receipt of positive HIV test results, POC device functionality, and demand. The ranges for variation in each parameter are reported in Table 1.

We also conducted scenario analyses to investigate the potential changes in POC implementation. First, introducing a POC machine to a facility that previously relied on laboratory-based testing may impact demand for testing. We evaluated a scenario in which demand increased in facilities where a POC machine was located (by 5%, 10%, 20%, and 30%; Supplement, Section 5). For the sake of comparison, we modeled a similar increase in demand for all facilities with POC machines, regardless of whether the POC machine was newly located there or retained there (unchanged from the current location). Second, because POC device functionality is an important driver of ART initiation, we evaluated scenarios of current (mean: 63%), low (mean: 44%), and high (mean: 75%) functionality of POC machines. District-specific functionalities are given in Table 1. In addition, to inform how additional resources could increase timely ART initiation, we analyzed the impact of adding new POC machines. We followed our optimization-based approach to assign the number of new POC machines needed to achieve 50% overall 30-day ART initiation.

Results

Optimization analysis

In the baseline scenario with the current placement of the existing 11 POC machines, of the infants testing HIV-positive, 37% were projected to receive their results and 35% to initiate ART within 30 days. With model-optimized locations, the projected 30-day result-return would increase to 46% and the 30-day ART initiation would increase to 44%. The model-optimized location assignment would retain three machines in their current locations and would move eight machines to new facilities (Figure 1).

Heuristic analysis

Table 2 and Figure S1 present the locations of POC machines as well as the estimated performance of the model-optimized relocation and each heuristic approach. Of the four heuristic approaches, relocation based on high test positivity proportions would demonstrate the lowest proportions of 30-day result-return (38.3%) and ART initiation (36.4%), with only a slight improvement compared with the current location (37.2% and 35.3%). Relocation based on the highest POC device functionality would be the best-performing heuristic decision (43.9% and 41.7%); although, it still would not perform as well as the optimization-based approach (46.3% and 44.0%).

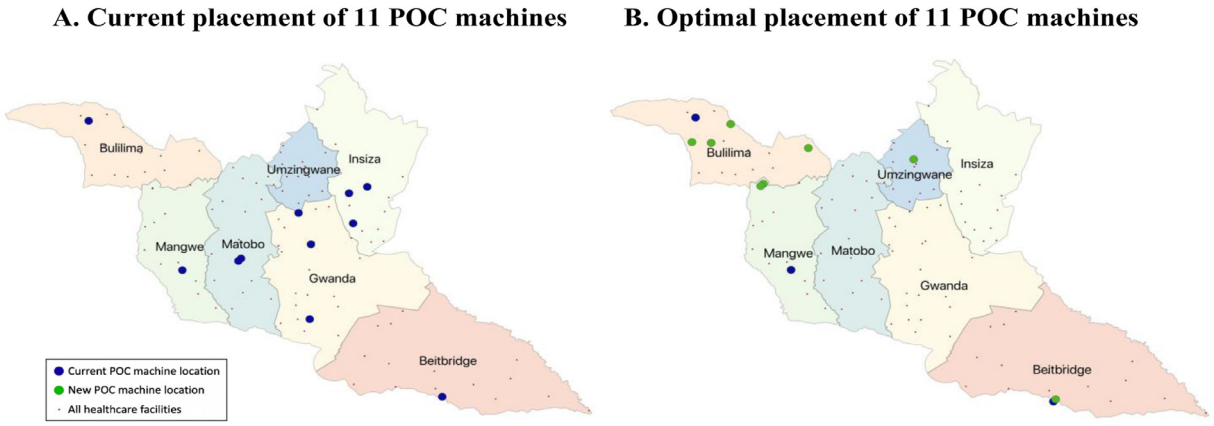

Figure 1. Current and optimal placement of 11 point-of-care machines in Matabeleland South, Zimbabwe. This figure shows the map of the districts within the province of Matabeleland South. Panel A shows the current locations of the 11 existing POC machines, and Panel B shows their locations as suggested by the location-optimization model in the base case analysis. Blue dots indicate machines that remain in their current locations after location optimization, and green dots indicate machines that would be moved to a different location after optimization. Under optimal placement, three POC machines would remain in place, and eight would move to new health facilities. POC, point-of-care.

Table 2
Locations of POC machines under different relocation strategies

District	Health facilities[a]	Current allocation[b]	Model-optimized allocation	Heuristic relocation decisions			
				Demand	Test positivity	Result-return	POC functionality
A	A1						
	A7						
B	B3						
	B5						
	B6						
	B7						
	B14						
C	C1						
	C4						
	C8						
	C10						
	C11						
	C15						
D	D3						
	D8						
	D15						
E	E2						
	E11						
	E13						
F	F9						
	F13						
	F17						
G	G3						
	G8						
Outcomes	**30-day result-return**	37.2%	46.3%	41.5%	38.3%	42.1%	43.9%
	30-day antiretroviral therapy initiation	35.3%	44.0%	39.4%	36.4%	40.0%	41.7%

POC, point-of-care.
Gray: current location of a POC machine; green: new location for a POC machine. In model-optimized and heuristic decisions, if a current location is maintained, it is shown as gray.
[a]Health facility names are coded. [b]F9 has two POC devices in the current allocation.

Sensitivity analyses

Table 3 demonstrates the sensitivity of the outcome (proportion of tested infants with HIV who initiate ART within 30 days of positive test) to changes in model parameters. In all conditions tested, the model-optimized location would achieve higher 30-day ART initiation than the current allocation, shown in the table as positive values for "improvement". The largest improvements in 30-day ART initiation would be seen with the highest evaluated estimates for (i) demand, (ii) POC machine functionality, and (iii) proportion of ART initiation after a positive test. If the functionality of POC machines were at the upper limit of the evaluated range, the improvement in 30-day ART initiation for the optimized locations compared with the current locations would be 9.5%, which is higher than the base case (8.7%). These sensitivity analyses show that the model-optimized placement of machines would be consistent across wide-ranging variation in the five examined model parameters.

The model-optimized locations assigned for POC machines would remain the same in the sensitivity analyses, except with variation in the functionality of POC machines, as presented in Figure S2. In addition, sensitivity analyses on result-return probabilities, ART initiation probability, POC device functionality, and demand are presented in Tables S1 and S2. Table S1 shows the heuristic results under the base case assumptions and with univariate sensitivity analyses on key model input parameters.

Table 3
One-way sensitivity analyses for optimization location decisions: Proportion of tested infants with HIV who initiate ART within 30 days of a positive test

	Parameters	% ART initiation within 30 days		
		Current allocation	Model-optimized allocation[a]	Improvement[b]
	Base case value	35.3	44.0	8.7
Upper limit	POC result-return probability	35.5	44.3	8.8
	Lab result-return probability	40.3	48.9	8.6
	ART initiation probability	37.2	46.3	9.1
	Functionality of POC machines	38.2	47.7	9.5
	Demand	42.4	52.8	10.4
Lower limit	POC result-return probability	35.0	43.3	8.3
	Lab result-return probability	30.3	39.0	8.7
	ART initiation probability	33.5	41.7	8.2
	Functionality of POC machines	33.9	38.2	4.3
	Demand	28.3	35.2	6.9

ART, antiretroviral therapy; POC, point-of-care.
[a] The model-optimized locations assigned for POC machines remained the same in the presented sensitivity analyses, except with variation in functionality of POC machines, as presented in Figure S2.
[b] Improvement = Difference between model-optimized and current allocations, Ranges for variations in input parameters are shown in Table 1.

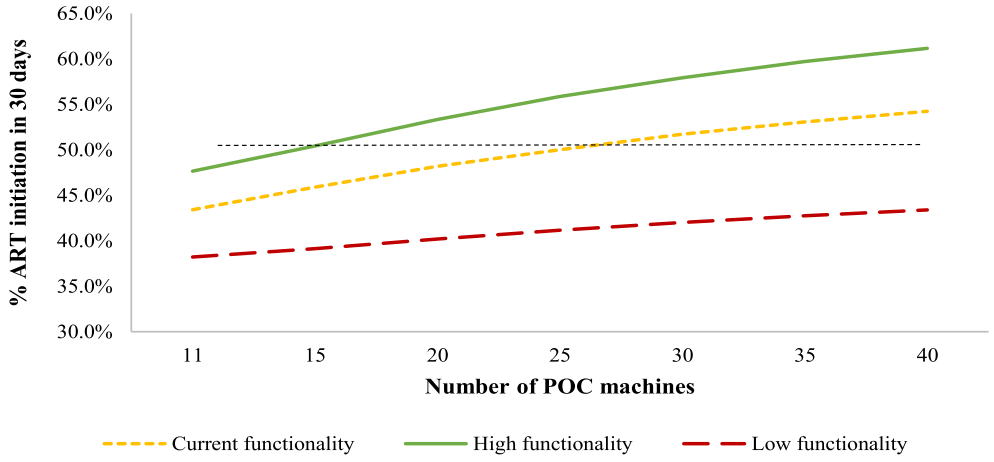

Figure 2. Percentage of ART initiation among infants who tested positive for HIV due to the total number of POC machines across different functionality rates. Figure 2 shows results of multi-way sensitivity analyses varying both number of available POC machines (base case value: 11) and functionality of each machine (defined as proportion of weekdays on which each machine is functioning; functionality rates are district-specific and values and ranges are reported in Table 1). The horizontal axis shows the number of available machines. Current functionality is shown in the yellow small dashed line; high functionality is shown in the green solid line; and low functionality is shown in the red large dashed line. The vertical axis indicates the projected proportion of all tested infants with HIV who initiate ART within 30 days of testing. The black dotted line indicates a threshold of 50% ART initiation, for comparison.
ART, antiretroviral therapy; POC, point-of-care.

Among the heuristic decisions, allocation based on POC functionality would be the closest to the optimal allocation in every scenario sensitivity analysis (Table S1).

Scenario analyses

Increased demand

When we simulated a 5% relative increase in demand for all sites with a POC machine, the model-projected difference in 30-day ART initiation between the current (36%) and model-optimized (45%) relocation would be 9%. The projected differences in ART initiation between the two allocations remained similar (around 9-12%) when the demand increased by 10%, 20%, or 30%. The results of the sensitivity analysis are depicted in Figure S3.

Functionality and incremental benefit of allocating additional POC machines

When district-specific functionality (shown in Table 1) was varied by ±30% from base case estimates with the current number of machines held constant, the projected 30-day ART initiation ranged from 34 to 38% under the current allocation and from 38 to 48% under the optimal allocation (Table 3). If additional POC machines were available, the number of POC machines required to achieve 50% ART initiation within 30 days of testing varied with functionality (Figure 2). When district-specific functionality was varied to the upper limits (mean: 75%), 15 total (+4) POC machines would be required. When varying functionality to the lower limits (mean: 44%), more than 100 POC machines would be needed to achieve the same outcome. With the current functionality (mean: 63%), the 50% 30-day ART initiation target could be achieved with 25 machines.

Discussion

Feasible and affordable interventions are essential to increase timely ART initiation in infants. In this modeling analysis, we showed that the relocation of POC machines in Matabeleland South, Zimbabwe could improve the outcomes in the early HIV treatment of infants. Our study has several key findings.

First, the relocation of currently available POC machines can increase the number of caregivers/infants receiving results and infants initiating ART within a month of testing. A limited number of POC machines can be located more effectively, and optimal machine locations can be updated as new data become available. Im-

portantly, even with optimal allocation, specific targets, such as 50% 30-day ART initiation, could not be met with the number of POC machines currently available in this province. This modeling framework can identify where additional resources are needed, such as adding new machines or improving the functionality of existing ones. Given the structural similarities of infant testing networks across many parts of sub-Saharan Africa, our methodology provides insights into more effective POC device placement plans that may be relevant in other settings [21,22].

Second, the functionality of POC machines (proportion of weekdays on which samples are able to be processed) is an important determinant of the impact of POC infant testing machines. Increasing the current functionality of POC machines would increase the number of caretakers who receive HIV test results and infants who initiate ART. Machine functionality will also affect the benefit gained by adding new POC machines: a 30-day ART initiation proportion of 50% could be achieved with only four additional machines with high functionality (75%) compared with 14 additional machines required with current functionality (63%). Other important factors in the scale-up of POC diagnostics are the maintenance of current POC technologies, supply chain management of testing commodities, and staff trainings to minimize sample rejection [23]. The impact of machine functionality in our analysis underscores the need to appropriately plan for the resources required to establish (training, mentorship, power sources) and maintain (machine maintenance, test cartridges, and reagents) POC platforms for infant testing to fully realize the clinical and cost-effectiveness offered by POC infant testing technology [9,24]. If the POC machine is not functioning when a patient arrives at the health facility, we assumed that the patient would return for testing at a later time or at another health facility. This assumption is reasonable given the uncertainties involved in tracking and transferring person-level samples to the appropriate laboratory.

Third, our analysis underscores the value of heuristic models as decision aides for locating POC machines based on up-to-date data in the absence of formal location-optimization modeling [25]. The heuristic models considered in our analysis were based on readily available data and provided valuable insights into the relocation of POC machines. Our analysis highlights the importance of using any of the heuristic models as decision-making tools in situations where formal location-optimization modeling may not be available or feasible. Depending on the available data, one of the heuristic-informed allocations could be preferred to random assignment. Assigning machines to health care facilities with high functionality of POC machines and the highest demand for testing will result in a substantial improvement in result-return and ART initiation [13]. Intuitively, this makes sense for two reasons: (i) reaching more patients will improve the average patient outcomes, and (ii) considering the costs of the device, the cost per test will drop if more patients use the technology [26].

The 90-90-90 target aims to have 90% of people living with HIV know their status, 90% of people who know their HIV-positive status accessing ART, and 90% of people on ART achieving suppressed viral loads [5]. This target does not specify the time from initial testing at which these steps should be achieved. Although we project 30-day rather than “ever” ART initiation and thus cannot compare our results directly to UNAIDS targets, our analysis demonstrates that even with 40 machines operating with improved functionality, Matabeleland South would only achieve a 60% 30-day ART initiation rate (as illustrated in Figure 2). This indicates that significant investments would be necessary to reach a 90% 30-day ART initiation target.

Our study had several limitations. First, we lacked data about patient residence locations. Therefore, we assumed that patients in each district would visit health facilities only in the district where they reside. More comprehensive data collection and additional analysis would help inform how infant caregivers select which facility to attend and could facilitate more detailed geospatial modeling that incorporates travel routes and times to facilities across district borders. Although specific quantitative results will differ using data from other districts, our results were robust across a wide range of sensitivity and scenario analyses, suggesting that they may be generalizable to other provinces in Zimbabwe and other countries in sub-Saharan Africa, and the location-optimization approach serves as a model that could be useful in many settings. Second, we assumed that POC device functionality was the same across all facilities in each district, both because individual facility-level functionality data were limited and because functionality is not yet known for facilities currently without POC machines. Third, we did not consider the potential impact of diverting POC machine use for other purposes, namely tuberculosis diagnosis, HIV diagnostic testing for older children and adults, and HIV RNA monitoring for people on ART, which could lead to changes in use and clinical benefits [27].

In addition, we assumed that the probability of 30-day ART initiation after the receipt of a positive result would be the same for children undergoing POC testing as for those undergoing laboratory-based testing. This is a conservative assumption; ART initiation rates after the receipt of a positive result are typically higher for children undergoing POC testing than for those undergoing laboratory-based testing [19,20]. Therefore, using the same 30-day ART initiation across these two groups would limit the clinical improvement of optimally assigned POC machines.

This analysis excludes economic costs and an explicit consideration of distributional equity; both are beyond the scope of this first analysis and are important areas for future research. The full costs of adding or relocating POC devices will include device, cartridge, and reagent purchases; transport and training costs; and the long-term costs of caring for children with HIV, including clinical care, laboratory monitoring, and ART (all of which will increase as more children are diagnosed and treated). In addition, long-term clinical outcomes, such as life-years saved by earlier HIV diagnosis and ART initiation, will impact a full assessment of the value of alternative numbers and locations of POC machines. Equity must remain a priority in the allocation of health care technology; a comprehensive analysis of distributional equity alongside location optimization is ongoing. In Matabeleland South, the current POC machine assignments were originally made by program planners to ensure that there was access to at least one POC machine in each district (within each district, placement was then based on infant testing sample volume). This led to placement almost exclusively at district, mission, or provincial hospitals with the highest patient volume. The heuristic models evaluated in this analysis suggested placement of POC devices at already high-functioning sites (*e.g.*, those with high demand and high POC device functionality), which may not be consistent with equitable program goals. However, these heuristic models can be used by program planners to estimate the likely outcomes of alternative approaches, with the ultimate objective of achieving both geographic equity of access (*i.e.,* ensuring POC access in each district) and optimized effectiveness (*i.e.,* ensuring additional placements serve to maximize the proportion of infants initiating ART within 30 days of a positive test) as countries strive to increase pediatric ART coverage.

This analysis was conducted as a close collaboration between modeling investigators, program planners in Zimbabwe, and the Ministry of Health and Child Care of Zimbabwe, and thus, there is programmatic support for evaluating the optimal placement of POC machines by both the government and donors. This is particularly relevant in the scenario analysis that examines the placement of additional machines. There are likely to be additional challenges when considering moving the existing machines, which are currently located to ensure that at least one POC machine is

available within each district of a given province. Important local considerations to moving existing machines include equity of access and resistance of local health systems stakeholders, communities, and health service users. This analysis is not meant to promote removing resources from specific health facilities. Rather, we hope this quantitative analysis demonstrates the role that location-optimization technologies can play in improving efficiencies of public health program planning and the potential clinical impact of using these technologies to inform the allocation of newly available POC devices.

Conclusion

This study highlights the potential role for optimization-based location of limited POC machines for infant HIV testing and for the use of decision heuristics based on readily available data if modeling methods are not accessible. Relocation of currently available POC machines would result in a substantial increase in 30-day result-return and ART initiation, a potential life-saving intervention for infants with HIV.

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Ethics approval

This work was approved by the Mass General Brigham Institutional Review Board.

Author contributions

All authors contributed substantively to this manuscript in the following ways: study design (MY, KAW, ALC, AKA, CFF, MSJ), data analysis (MY, KAW, AKA), interpretation of results (all authors), drafting the manuscript (MY, AKA, CFF), critical revision of the manuscript (all authors), and final approval of submitted version (all authors).

Role of the funding source

The funders of this study had no role in the study design, data collection, data analysis, data interpretation, or writing of the report. All authors had full access to data and the corresponding author had the final responsibility to submit it for publication.

Declarations of competing interest

The authors have no competing interests to declare.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ijid.2023.05.013.

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