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eLMIS Pharmaceutical Forecasting, Approval and Receipt in Relation to Stock-Outs and Availability in Kigoma, Tanzania

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Abstract
This study examined the associations between eLMIS-recorded pharmaceuticals forecasting, approval and receipt in relation to stock-outs and availability in Kigoma, Tanzania. A retrospective quantitative case study used 1,725 medicine-level observations from three purposively selected public healthcare facilities across reporting cycles spanning from July 2025 to July 2026. Five mixed-effects regression models examined forecasting-to-approval, approval-to-receipt, and the associations of previous-period receipts with availability, stock-out occurrence and positive stock-out duration. Overall medicine availability was 92.56%; however, availability varied across pharmaceuticals and facility types, whereas some products had availability below 80%. Also, product-specific gaps occurred between forecasted, approved and received quantities. Forecast quantity was positively associated with approved quantity ($\beta = 0.787$, $p < 0.001$), while previous-period approved quantity was positively associated with following receipts ($\beta = 0.391$, $p < 0.001$). Previous-period receipt quantity was negatively and significantly associated with lower odds of stock-out occurrence ($\beta = -0.217$, $p < 0.001$). The study was limited to three purposively selected public healthcare facilities and retrospective records covering approximately one year. Health facilities should track differences between forecasted, approved and received quantities to identify medicine supply gaps and address stock-outs. The study distinguishes the relationships associated with successive supply chain stages and demonstrates why forecast and approval quantities alone may not adequately indicate medicine availability. Pharmaceutical availability requires alignment between information-based planning, supply decisions, and operational fulfilment by the MSD.

Introduction
Access to medicines is a fundamental goal of effective healthcare systems, ensuring that medicines are available at the point of care when and where they are needed (World Health Organisation, 2023). Adequate medicine availability supports continuity of care, reduces treatment interruptions, and contributes to effective healthcare delivery (Atif et al., 2021; World Health Organisation, 2023). Yet, equitable medicine availability remains a critical global challenge (Bilal et al., 2025). Evidence from

eight sub-Saharan African countries shows low availability of essential medicines, with availability of women's priority medicines ranging from 22% to 40% and children's medicines ranging from 28% to 57% (Droti et al., 2019). Medicine shortages can increase healthcare costs, interrupt treatment, and compromise patient safety (Bilal et al., 2025). Medicine shortages may delay treatment, push patients to seek medicines from alternative sources and contribute to serious complications, including prolonged hospital stays and death (Elias & Mushi, 2024).

Maintaining medicine availability requires accurate forecasting of medicine requirements to ensure health facilities receive appropriate quantities to meet patient needs (World Health Organisation, 2023). Accurate medicine forecasting depends on reliable logistics data to estimate medicine requirements and inform supply chain decisions (Niyomugaba et al., 2026). Information technologies support this process by facilitating the collection, processing, and use of logistics data for supply chain decision-making (Bilal et al., 2024). Better forecasting tools and end-to-end data visibility support more informed supply decisions. In many African countries, electronic Logistics Management Information Systems (eLMIS) have been introduced to collect, organise, analyse, and report logistics data on health products at all levels of the health-system (Choudrie et al., 2017; Niyomugaba et al., 2026). These functions are intended to support evidence-based supply chain decisions and improve medicine supply management. Ali et al. (2026) found that e-LMIS-based information visibility, stock management, and demand forecasting have a positive and significant effect on drug distribution performance.

In Tanzania, eLMIS was introduced as part of broader reforms to public healthcare supply chain management to improve logistics data for supply chain decision-making (Mkumbwa et al., 2023; Mwencha et al., 2017). Its implementation has been associated with improvements in logistics data use, inventory management, supply chain performance, and medicine availability (Milulu et al., 2024). Through the eLMIS supply chain process, forecasted medicine requirements are reviewed and approved before orders are placed and medicines are received at health facilities(Ministry of Health, 2024). At the forecasting stage, eLMIS estimate the quantities of medicines required by health facilities. The forecasted quantities are then reviewed and may be adjusted during the approval process before orders are finalised. Following approval and ordering, health facilities receive medicines from the Medical Stores Department (MSD). These stages link eLMIS forecasting with the planning, authorisation, and physical supply of pharmaceuticals to health facilities.

Despite these initiatives, the availability of pharmaceuticals in Tanzanian public health facilities remains below the national target. According to the National Audit Office of Tanzania (2026), the availability of essential medicines in public health facilities was 62% in 2024/25, below the national target of 79%. Mayunga et al. (2025) indicated that facilities experience a median of three stock-out episodes and 94 stock-out days during the preceding three months. Similarly, Elias & Mushi (2024) reported an average availability of 74.8% for medicines and medical supplies in selected public health facilities in Tanzania. In 2020/21, 26 referral hospitals and three specialised hospitals also issued National Health Insurance Fund (NHIF) referral forms worth approximately TZS 6.96 billion because the required medicines were unavailable (National Audit Office of Tanzania, 2022). Medicine availability remains a challenge, with average availability declining between 2018/19 and 2020/21 across hospitals, health centres, and dispensaries, with availability of 64.3% in council hospitals, 68.0% in health centres, and 54.8% in dispensaries (Ruhago et al., 2023).

These findings raise questions about whether technology-supported forecasting translates into medicine availability at the facility-level. Improvements in logistics data management and forecasting do not necessarily guarantee medicine availability. Forecasted requirements pass through supply chain processes before medicines reach health facilities. The effectiveness of this process therefore

depends not only on the accuracy of forecasts but also on how forecasted requirements are translated into approved orders and later fulfilled through medicine delivery. eLMIS supports the forecasting stage by generating estimates of medicine requirements based on available logistics and consumption data. However, the quantities initially forecast through eLMIS may be revised or altered during the review and approval process. Similarly, the quantity received by a facility may differ from the approved quantity. Discrepancies between forecasted requirements, approved orders, and quantities actually received may weaken the contribution of eLMIS-supported forecasting to medicine availability at the facility-level. Each stage of the medicine supply pathway serves a distinct function in translating facility-level requirements into medicine availability. Building on these perspectives, this study argues that the contribution of eLMIS-supported forecasting to medicine availability cannot be understood by examining forecasting alone. Rather, this contribution must be considered in relation to the processes through which forecasted requirements are reviewed, approved, and fulfilled. Although previous studies have examined digital logistics systems, pharmaceutical forecasting and medicine availability, less is known about how forecasted, approved and received quantities are associated with stock-out occurrence, stock-out duration and medicine availability at the facility-level. In particular, the extent to which the different stages of the medicine supply pathway are associated with these distinct outcomes remains insufficiently understood in Tanzania's public healthcare supply chain. This study addressed this gap by analysing retrospective medicine-level records from three public healthcare facilities in Kigoma Region, examining forecasted, approved and received quantities in relation to stock-out occurrence, stock-out duration and medicine availability. Specifically, the study addresses the following research questions

RQ1: How are eLMIS-forecasted quantities associated with approved quantities?
RQ2: How are previously approved quantities associated with quantities subsequently received?
RQ3: How are previous-period received quantities associated with subsequent stock-out occurrence?
RQ4: How are previous-period received quantities associated with subsequent stock-out duration?
RQ5: How are previous-period received quantities associated with subsequent medicine availability?

Tanzania pharmaceuticals supply flow

Figure 1 illustrates Tanzania's bottom-up quantification process, through which facility-level medicine requirements are consolidated and reviewed before approval and transfer to the Medical Stores Department (MSD) for supply planning and distribution. The figure shows how forecasted requirements progress through approval and supply stages before medicines reach health facilities.

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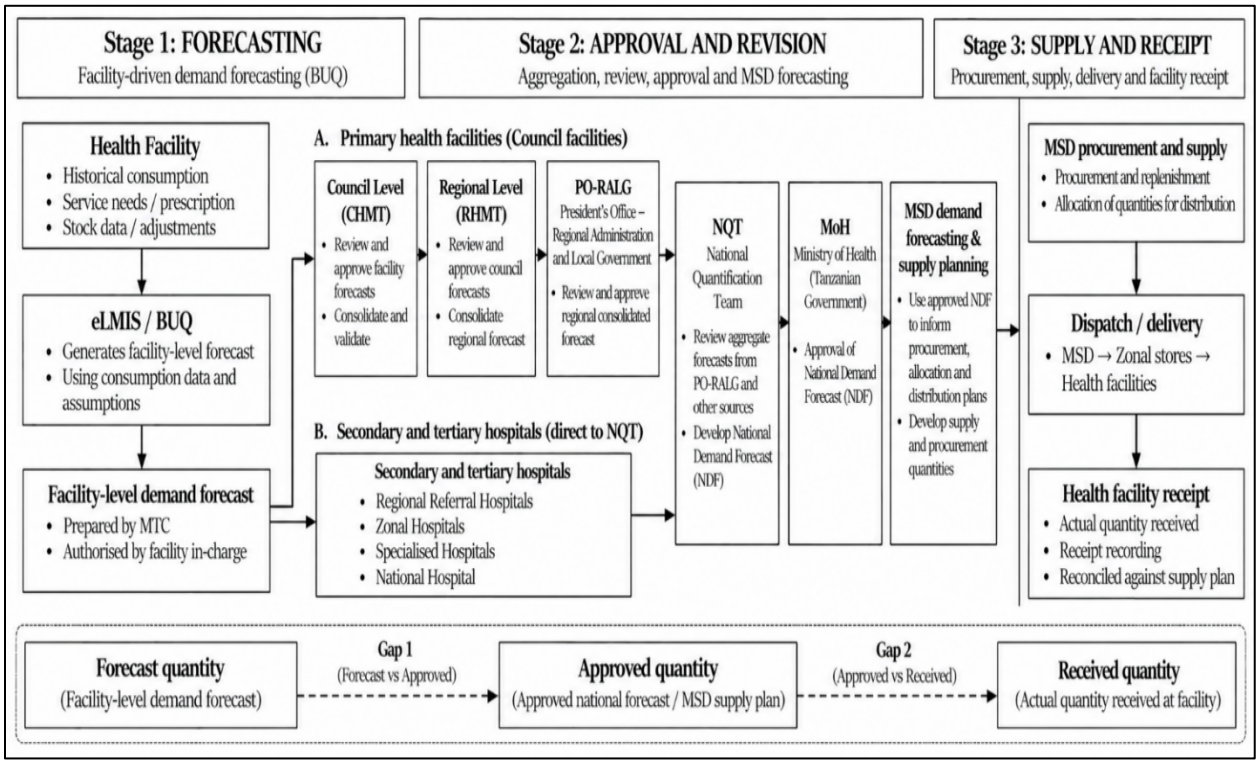


Figure 1: Tanzania forecast-to-receipt realisation flow
Source: (Authors adapted from MOH-2024)

Literature review

Organisational Information Processing Theory (OIPT) suggests that organisational performance depends on the alignment between information-processing requirements and the capacity to process information under uncertainty (Galbraith, 1974; Premkumar et al., 2005). This perspective suggests that information must be translated into coordinated decisions for the organisation to realise its outcomes. In Tanzania, eLMIS forecasting provides an information basis for estimating requirements, but its usefulness depends on how forecasts inform approval and supply decisions. Forecasts based on historical consumption may underestimate requirements when previous stock-outs suppress recorded consumption (Leung et al., 2016). Premkumar et al. (2005) suggest that coordination across interdependent decision-making stages matters when uncertainty requires interpreting and acting on information. In this theoretical context, the study argues that forecasted requirements inform the approval process, through which forecast quantities are translated into authorised quantities. However, adjustments do not always improve forecast accuracy, as their effectiveness depends on the information and judgement used (Fildes et al., 2009; Fildes & Goodwin, 2021). The literature presents mixed evidence on whether improved forecasting translates into medicine availability. Bilal et al. (2025) suggest that better forecasting and forecast adjustments can improve demand estimation and support availability. Fildes et al. (2009; Fildes & Goodwin, 2021) suggested that forecast adjustments do not consistently improve forecast accuracy, as judgemental overrides can introduce bias and reduce accuracy. Moreover, studies report gaps between approved orders and quantities delivered, with limited supplier fulfilment and distribution constraints interrupting the supply process (Bam et al., 2017; Kuwawenaruwa et al., 2020; Mwencha et al., 2017; Vledder et al., 2019). The literature further

indicates low order fulfilment by the Medical Stores Department (Githendu et al., 2020; Wiedenmayer et al., 2019).

In contrast to the OIPT perspective, the literature suggests that adequate information processing at the forecasting stage does not necessarily guarantee performance at subsequent supply chain stages, as accurate forecasts may not translate into medicine availability when approved orders are not fully fulfilled or delivered on time. In practice, forecasts should reflect actual facility requirements, while approval decisions account for operational needs such as available resources and government priorities. Appropriate approval should improve the alignment between requested and authorised quantities. Timely receipt of sufficient quantities can reduce stock-out risk and support medicine availability. Accordingly, this study hypothesised that

H1: Forecasted quantities are positively associated with approved quantities.
H2: Approved quantities are positively associated with received quantities.
H3: Previous-period received quantities are positively associated with medicine availability.
H4: Previous-period received quantities are negatively associated with stock-out occurrence.
H5: Previous-period received quantities are negatively associated with stock-out duration

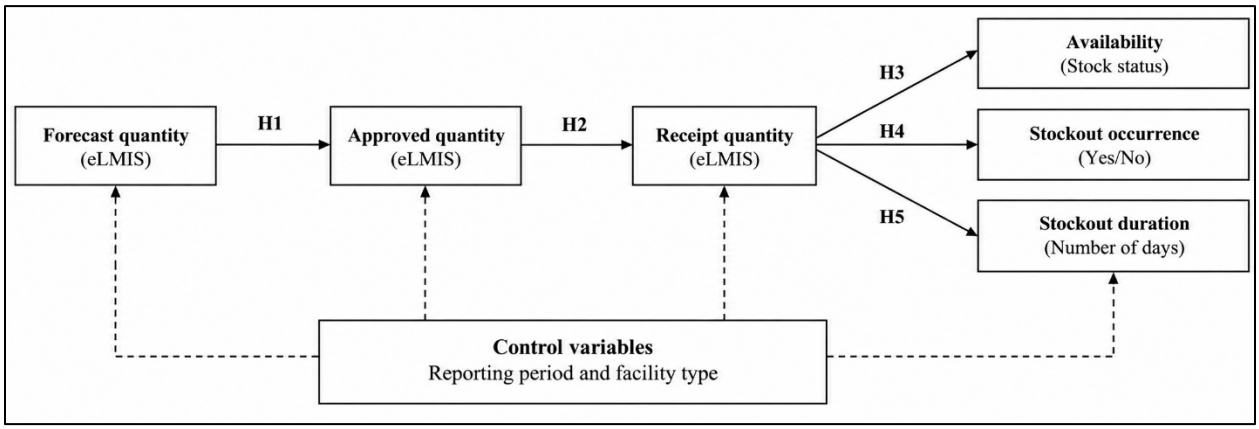


Figure 2: Conceptual model

Figure 2 illustrates the hypothesised relationships between medicine forecasting, approval, receipt, and availability outcomes. H1–H5 represent the relationships tested, while reporting period and facility type are included as control variables.

Methodology

Research design

This study adopted a retrospective observational quantitative design using repeated pharmaceutical observations across reporting periods in three purposively selected public healthcare facilities in Kigoma Region, Tanzania. The case-study approach provided a contextual examination of the pharmaceutical supply pathway from forecasting and approval-to-receipt and subsequent medicine availability and stock-out outcomes. Understanding this relationship requires examining forecasted, approved, and received quantities alongside observed pharmaceutical availability and stock-out outcomes. The quantitative approach enables statistical assessment of the relationships between quantities at the three stages and stock-out occurrence, stock-out duration, and availability.

Study Setting and Selection of Facilities

The study was conducted in three public healthcare facilities in Kigoma Region, Tanzania. The facilities were selected purposively based on their willingness to participate, the availability of eLMIS data, and the need to include different levels of healthcare provision. Facility selection also considered geographical location, with preference given to facilities situated far from town centres, where pharmaceutical supply chain operating conditions may differ from those in more central locations. However, the selected hospital was located within a town centre, reflecting the predominantly urban location of hospitals compared with lower-level healthcare facilities.

Data Retrieval and Cleaning

Data were obtained from the electronic Logistics Management Information System (eLMIS) through personnel responsible for medicine ordering and logistics management. The records covered medicine forecasting, quantity approval, receipt, stock-out occurrence, stock-out duration, and availability across the selected public healthcare facilities from July 2025 to July 2026. The dispensary dataset contained six reporting cycles. The hospital and health-centre datasets initially covered six cycles each; however, the November–December 2025 cycle was incomplete for the hospital, and the January–February 2026 cycle was incomplete for the health centre. These incomplete cycles were excluded, leaving five reporting cycles for each of the hospital and health-centre datasets and six for the dispensary dataset. The final analytical dataset comprised 1,725 observations of these, 829 from the hospital, 413 from the health centre, and 483 from the dispensary. These observations covered 347 distinct item codes, with repeated observations reflecting the recording of medicines across facilities and reporting periods. The analysis was restricted to product records available within the retained reporting cycles.

Variable Operationalisation and Measurement

Table 1 summarises the variables used in the regression analysis, their operational definitions, and their roles in the models.

Table 1: Variable operationalisation

Variable	Operational definition	Role
ELMIS forecast quantity	Quantity forecast for the reporting period	Predictor
Approved quantity	Quantity authorised for supply during the reporting period	Outcome (Model 1)
Approved quantity (lagged)	Approved quantity from the preceding period	Predictor (Model 2)
Quantity received	Quantity recorded as received during the reporting period	Outcome (Model 2)
Quantity received (lagged)	Quantity received in the preceding period	Predictor (Models 3–5)
Availability	Recorded medicine availability measure	Outcome (Model 3)
Stock-out occurrence	Binary indicator: 1 = stock-out recorded; 0 = no stock-out	Outcome (Model 4)
Stock-out duration	Recorded number of days a medicine was unavailable	Outcome (Model 5)
Reporting period	Categorical reporting period indicator	Control
Facility type	Hospital, health centre, and dispensary	Control
Panel ID	Identifier used to account for repeated observations through a random-intercept	Random effect

Because reporting periods varied in length and the number of cycles differed across facility levels, medicine availability in our study was calculated using the actual number of days covered by each reporting period. It was defined as the proportion of days during which the healthcare product was available at the facility and was calculated as follows:

$$\textbf{Availabilityy}_{\textbf{it}} = \left(1 - \frac{\textbf{Stockout days}_{\textbf{it}}}{\textbf{Reporting period days}_{\textbf{t}}}\right) \times 100 \quad (1)$$

The calculation therefore used the actual reporting period duration rather than a fixed 60-day denominator. To reflect the sequence of the ordering and supply process, the forecasted and approved quantities from the previous reporting cycle were linked to the quantities received in the next cycle using lagged variables. Stock-out occurrence was defined as whether a medicine was unavailable for at least one day during the reporting period.

$$\textbf{StockoutOccurrence}_{\textbf{it}} = \begin{matrix} \textbf{1, if Stockout Days}_{\boldsymbol{it}} > \textbf{0} \\ \textbf{0, if Stockout Days}_{\boldsymbol{it}} = \textbf{0} \end{matrix} \quad (2)$$

Stock-out duration was measured as the number of days a medicine was reported to be unavailable at the facility during the reporting period. Observations with 30 or more stock-out days were excluded from the stock-out occurrence and duration models. This decision was informed by field consultations, in which prolonged non-availability was interpreted as medicines that were not routinely used at the corresponding facility service level. A sensitivity analysis was conducted to assess whether excluding these observations influences the estimated association.

$$\textbf{Analysis Eligible}_{\textbf{it}} = \begin{matrix} \textbf{1, if } \textbf{0} \leq \textbf{Stockout Days}_{\textbf{it}} < \textbf{30} \\ \textbf{0, if Stockout Days}_{\textbf{it}} \geq \textbf{30} \end{matrix} \quad (3)$$

Lagged Variables and Temporal Ordering

Lagged variables were used to reflect the sequence of pharmaceutical supply chain activities across successive reporting periods. Approved quantities from the preceding period were used to examine their association with quantities received in the following period, while quantities received in the preceding period were used to examine their association with subsequent healthcare product availability, stock-out occurrence, and stock-out duration. This approach recognises that approval, delivery, and medicine availability occur at different stages of the supply process and that their relationships may extend across reporting periods. Lagging the explanatory variables establishes temporal ordering (Bellemare et al., 2017; Reed, 2015). Of the 1,725 observations, 1,161 were verified as consecutive-period transitions.

Regression Model Specification

To account for repeated observations within pharmaceutical-level panels, the regression models included a panel-level random-intercept, while reporting period and facility type were included as control variables. Facility type was retained to account for observed differences between the three selected facilities. The facility type coefficients represent conditional differences among the sampled facilities rather than independently identified effects of healthcare level.

Model 1:

$$\log(1 + AQ_{it}) = \beta_0 + \beta_1 \log(1 + FQ_{it}) + \gamma_t + \delta_j + u_i + \varepsilon_{it} \quad (4)$$

Model 2:

$$\log(1 + QR_{it}) = \beta_0 + \beta_1 \log(1 + AQ_{i,t-1}) + \gamma_t + \delta_j + u_i + \varepsilon_{it} \quad (5)$$

Model :3

$$AV_{it} = \beta_0 + \beta_1 \log(1 + QR_{i,t-1}) + \gamma_t + \delta_j + u_p + \varepsilon_{it} \quad (6)$$

Model:4

$$logit(P(SO_{it} = 1)) = \beta_0 + \beta_1 \log(1 + QR_{i,t-1}) + \gamma_t + \delta_j + u_i \quad (7)$$

Model:5

$$\log(1 + SD_{it}) = \beta_0 + \beta_1 \log(1 + QR_{i,t-1}) + \gamma_t + \delta_j + u_i + \varepsilon_{it} \quad (8)$$

Where;

AQ_{it}= Approved quantity for medicine observation (i) in reporting period (t)
FQ_{it}=eLMIS forecast quantity for medicine observation (i) in reporting period (t)
QR=Quantity received for medicine observation (i) in reporting period (t)
$QR_{i,t-1}$ =Quantity received in the preceding reporting period
$AQ_{i,t-1}$=Approved quantity in the preceding reporting period
AV_{it}=Recorded medicine availability measure
SO_{it}=Stockout occurrence (1 = stockout; 0 = no stockout)
SD_{it}=Stockout duration in days
log=Natural logarithm transformation applied to the specified quantity or duration variable
γ_t=represents reporting-period effects,
δ_j= represents facility-type effects,
u_p=is the panel-level random intercept,
ε_{it}=is the residual error.
i= facility type.
p= panel identifier used to group repeated observations

Estimation Procedure

The five models were estimated in R using linear mixed-effects regression for continuous outcomes and logistic mixed-effects regression for stock-out occurrence. Models were estimated using maximum likelihood, and statistical significance was assessed using the model-specific coefficient tests.

Model Diagnostics

Model convergence and singularity were assessed across all five mixed-effects models. None was identified as singular, and the refitted logistic model converged without reported errors. Multicollinearity was within acceptable limits. Sensitivity analyses examined extreme quantity observations, exclusion of observations with stock-out durations of 30 days or longer, and restriction of selected lagged-predictor models to verified consecutive-period transitions. Extreme-value checks indicated limited coefficient changes in Models 1, 2, 4, and 5. Restricting Model 4 to consecutive-period transitions reduced the lagged-receipt coefficient from −0.217 to -0.128, but the association remained statistically significant (p=0.012). For Model 5, excluding observations with 60-day stock-out durations changed the coefficient from -0.0160 (p=0.104) to -0.0125 (p=0.119), preserving the negative direction and statistical non-significance. Additional DHARMa diagnostics were conducted for Model 5 because stock-out duration is a positive, potentially skewed outcome that may be affected by unusually long durations and reporting period limits. The uniformity test detected no significant deviation from the expected residual distribution (D=0.0484, p=0.1142), and the outlier test identified no significant excess of outliers (3/610, p=0.1244). The model was non-singular, with a panel-level random-intercept standard deviation of 0.2197 and a residual standard deviation of 0.3568. However, the dispersion test was significant (1.1759, p=0.002), indicating residual variability. Based on the study settings and data, the models were retained for analysis because their convergence and sensitivity results supported the stability of the findings.

Table 2: Model diagnostics

Diagnostic	Statistic	Result
Multicollinearity		
VIF: Forecast quantity	VIF	2.924
VIF: Approved quantity	VIF	2.669
VIF: Received quantity	VIF	1.393
Model convergence		
Model 1 convergence	Maximum absolute gradient	0.0000080
Model 2 convergence	Maximum absolute gradient	0.0000052
Model 3 convergence	Maximum absolute gradient	0.0000091
Model 4 convergence	Maximum absolute gradient	0.0001288
Model 5 convergence	Maximum absolute gradient	0.0000077
Model 5 sensitivity convergence	Maximum absolute gradient	0.0000002
Model 5 DHARMa diagnostics		
Residual uniformity	KS statistic (D)	0.048443
Residual uniformity	p-value	0.1142
Residual dispersion	Dispersion statistic	1.1759
Residual dispersion	p-value	0.002
Outlier test	Number of outliers	3/610
Outlier test	p-value	0.1244

Results

As shown in Figure 3, medicine availability was highest at dispensaries (95.4%), followed by health centres (94.2%), and lowest at hospitals (90.0%).

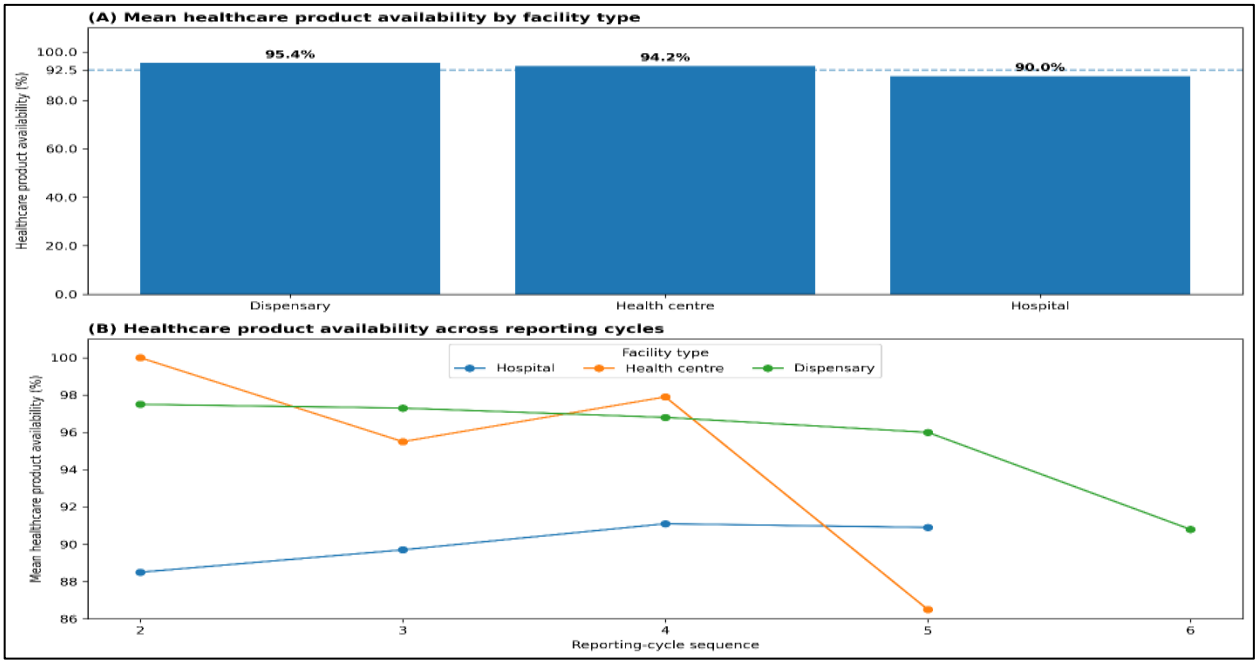


Figure 3: Pharmaceuticals Availability

The mean availability across the three facility types was 92.56%, although some differences were evident between facility levels. Hospital medicine availability increased from 88.5% in Cycle 2 to 91.0% in Cycle 4, remaining relatively stable at 90.9% in Cycle 5. Health centres showed greater variation, with availability falling from 100.0% in Cycle 2 to 95.5% in Cycle 3, rising to 97.9% in Cycle 4, and then dropping to 86.5% in Cycle 5. At dispensaries, availability remained relatively stable at 97–98% across Cycles 2–4, before declining to 96.0% in Cycle 5 and 90.8% in Cycle 6.

Pharmaceuticals Stock-out

As shown in Figure 4, hospitals had the highest stock-out occurrence, with stock-outs recorded in 55.7% of observations, compared with 21.1% for dispensaries and 6.85% for health centres. However, the mean duration of positive stock-outs was shortest in hospitals (11.0 days), compared with 12.0 days in health centres and 13.2 days in dispensaries. Although hospitals experienced stock-outs more frequently, dispensaries had longer average stock-out durations when stock-outs occurred.

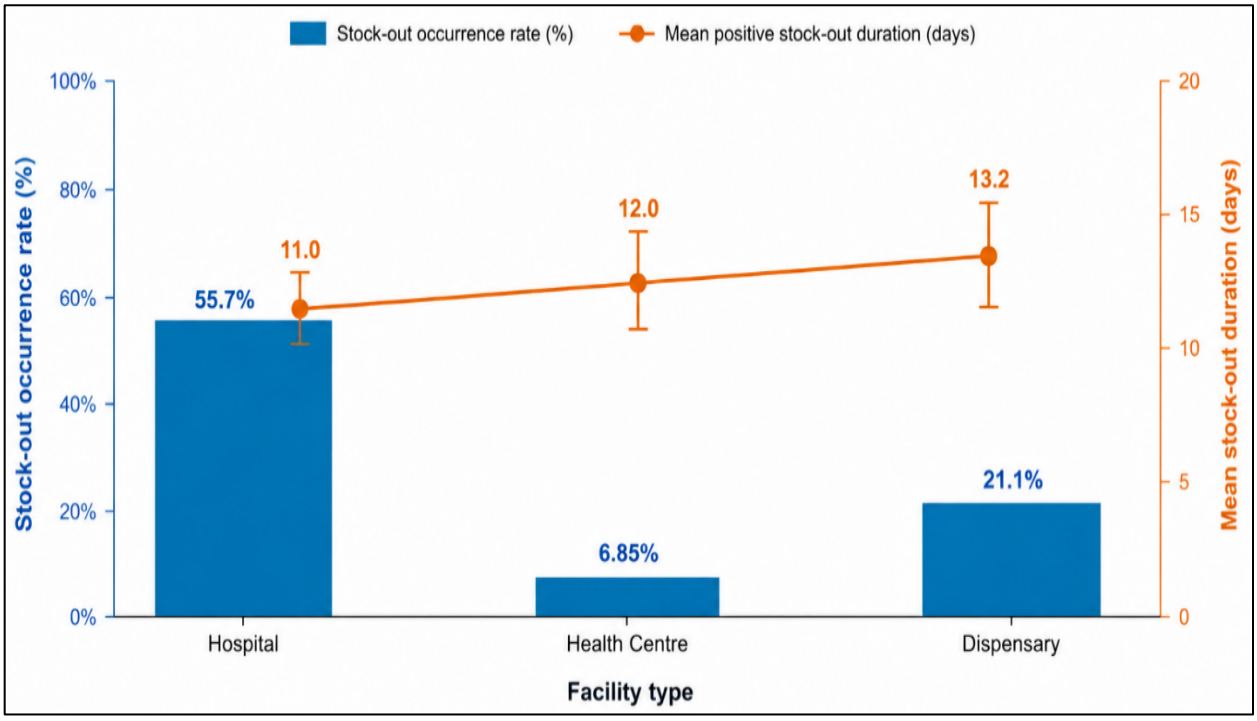


Figure 4: Stock-out occurrence and mean duration of stock-outs

Healthcare product supply Mixed-effects regression

As indicated in Table 3, forecasted quantities were positively associated with approved quantities ($\beta = 0.787$, $p < 0.001$), while previous-period approved quantities were positively associated with subsequent receipts ($\beta = 0.391$, $p < 0.001$). Previous-period receipts were negatively associated with stock-out occurrence ($\beta = -0.217$, $p < 0.001$), indicating lower odds of stock-outs when larger quantities had been received, but their associations with availability ($p = 0.080$) and stock-out duration ($p = 0.109$) were not statistically significant. Among the controls, reporting period and facility type were not significantly associated with approved quantities in Model 1. In Model 2, Period 4 and facility type were significant. Health centres had lower receipts, while hospitals had higher receipts relative to dispensaries. In Model 3, availability was higher in Period 4. In Model 4, stock-out odds were higher

in Period 6 and in hospitals but lower in health centres compared to dispensaries. In Model 5, stock-out duration was shorter in Period 4 and longer in health centres relative to dispensaries. Based on these results, H1, H2 and H4 are supported at the 5% significance level. H3 and H5 are not statistically supported at the 5% significance level

Table 3: Mixed-effects regression results for healthcare product supply outcomes

Predictor	Model 1: Approved quantity	Model 2: Received quantity	Model 3: Availability	Model 4: Stock-out occurrence	Model 5: Stock-out duration
Main predictors					
Forecast quantity	0.787(p < 0.001)	NA	NA	NA	NA
Lagged approved quantity	NA	0.391(p < 0.001)	NA	NA	AN
Lagged received quantity	NA	NA	0.0021(p = 0.080)	-0.217(p < 0.001)	-0.0147(p = 0.109)
Period 3	-0.067	-0.106	-0.0017	-0.124	-0.0605
Period 4	-0.192	0.440*	0.0139*	-0.427*	-0.1332**
Period 5	0.075	0.102	0.0028	-0.422	0.0744
Period 6	-0.056	-0.025	-0.0055	1.536***	−0.0146
Health centre	-0.224	-0.392*	-0.0160	-0.887*	0.6475***
Hospital	-0.044	2.383***	-0.0227	3.357***	-0.0408
Observations	1,725	1,725	1,725	1,725	610
Panel groups	527	527	527	527	298
Model type	Linear mixed	Linear mixed	Linear mixed	Logistic mixed	Linear mixed

Reference: Dispensaries

Sensitivity analysis

Three sensitivity analyses were conducted. First, temporal-alignment sensitivity restricted the analysis to verified consecutive-period observations because some records did not have verified consecutive transitions. Second, extreme-value sensitivity excluded observations above the 99th percentile to assess whether unusually large quantities influenced the results. Third, case-exclusion sensitivity removed observations with 30 or more stockout days to assess whether these cases affected the stockout duration results.

$$Percentage\ change\ = \left(\frac{|\beta_s - \beta_b|}{\beta_b}\right) \times\ 100 \quad (9)$$

The sensitivity analyses presented in Table 4 showed that Models 1 and 2 were robust to extreme values, with coefficient changes below 5%. Temporal-alignment affected Models 3 and 4 more substantially, although Model 4 remained significant (p = 0.0124). Excluding the ≥ 30-duration stock-out cases changed the Model 5 coefficient by 22.1%, but the association remained non-significant (p = 0.1134).

Table 4: Sensitivity analysis

o	Model	Baseline coefficient	Sensitivity coefficient	N	Change (%)	p-value (sensitivity)
Temporal-alignment	2	0.3909	0.3754	1,161	3.96	NA
Temporal-alignment	3	0.00211	0.00129	1,161	38.6	NA
Temporal-alignment	4	-0.2165	-0.1278	1,161	41.0	0.0124
Extreme values	1	0.7866	0.7747	1,706	1.51	NA
Extreme values	2	0.3909	0.3744	1,701	4.23	NA
Extreme values	4	-0.2165	-0.2168	1,707	0.11	NA
Extreme values	5	-0.01470	-0.01505	603	2.42	NA
Case-exclusion	5	-0.01470	-0.01145	591	22.1	0.1134

Discussion

Medicine availability in the study area was relatively high, at 92.56% across the observed facility reporting periods. However, availability varied across studies in Tanzania. Elias & Mushi (2024) reported an average availability of 74.8% for medicines and medical supplies in selected public health facilities, while Mayunga et al. (2025) reported an availability of 94.4% for essential maternal-health medicines. These differences may reflect differences in how medicine availability was defined and measured, the medicines assessed, and the study settings, rather than actual differences in medicine availability across studies. Although overall medicine availability was relatively high, some pharmaceuticals had availability below 80%, while others experienced stock-out periods of up to 20 days. Hospitals experienced stock-outs more frequently but had shorter average stock-out durations, whereas dispensaries experienced stock-outs less often but had longer durations when shortages occurred. It is argued that hospitals face greater patient demand and require a wider range of medicines, increasing the likelihood that individual medicines will run out (Masters et al., 2014). American Society of Health-System Pharmacists (2009) argued that hospitals have the role of managing emergency cases and encouraging faster responses to shortages. Field conjecture reveals that hospital staff borrow medicines from nearby facilities to address immediate needs. By contrast, health workers at dispensaries were observed advising patients to seek medicines from nearby dispensaries or health centres when supplies were unavailable. Such practices may help patients find alternatives but do not necessarily resolve the stock shortage at the affected facility, potentially contributing to longer stock-out durations**.** The findings further reveal both positive and negative patterns in the pharmaceutical supply chain realisation pathway. Forecast quantities were positively associated with approved quantities. However, approval gaps occurred for some medicines, including metronidazole at health centres (17,500 units below forecast) and ciprofloxacin at hospitals (11,597 units below forecast). Similarly, although previous-period approved quantities were positively associated with subsequent receipts, receipt fulfilment was low for several medicines, including examination gloves at hospitals (30.4%). Previous-period receipts were negatively associated with stock-out occurrence, indicating lower stock-out odds with higher receipts. However, receipts were not significantly associated with stock-out duration. The association with availability was positive but not statistically significant.

Conclusion

This study highlights the importance of examining pharmaceutical supply chains as interconnected processes rather than isolated activities. Effective pharmaceutical availability requires alignment between information-based planning, supply decisions, and operational fulfilment. The findings underscore the importance of eLMIS in improving pharmaceutical supply chain visibility and

supporting evidence-based medicine quantification. However, its contribution to medicine availability depends on how recorded forecasts are translated into approved quantities and actual deliveries. Effective use of eLMIS therefore requires coordination between health facilities, approval, and MSD, alongside routine monitoring of fulfilment gaps and stock-outs.

The Ministry of Health and other stakeholders responsible for eLMIS should consider adapting healthcare product lists to each facility's needs and service levels, rather than applying the same standard list across all facilities. The medicine review and approval process should also involve stakeholders to ensure that approved quantities better reflect facility needs. In addition, MSD should continue improving its order fulfilment rate to reduce supply gaps and their effects on medicine availability at health facilities. The Ministry of Health, health facilities and the Medical Stores Department (MSD) should strengthen the link between eLMIS-recorded medicine forecasts, approved quantities, and quantities actually delivered, with routine facility-level monitoring of order fulfilment and stock-out occurrence.

Future studies should address the study's limitation of being conducted in only three healthcare facilities by using longitudinal data from a larger and more geographically diverse sample of facilities to examine how discrepancies between forecasted, approved, and received quantities influence medicine availability, stock-out occurrence, and stock-out duration over time. Further research should investigate the effects of forecasting adjustment factors on forecasting accuracy, including whether adjustments made during the quantification and approval processes improve or reduce forecast accuracy. Studies should also examine the operational and supply chain factors that explain why approved quantities may not be fully delivered or received on time, and how these fulfilment gaps affect the continuity of medicine availability at healthcare facilities.

Declarations

Ethics approval and consent to participate
This study received ethical clearance from the National Institute for Medical Research (NIMR) Lake Zone, Tanzania (Reference No. LZIRB/222/2026). Permission to conduct the study was obtained from Mzumbe University (Reference No. MU/PhD/SOB/MZC/122513195/T.24/25), the President's Office–Regional Administration and Local Government (TAMISEMI; Reference No. AB.307/323/01'R/493), the Ministry of Health (Reference No. PA.104/2620/01/653), and the Medical Stores Department (Reference No. EA.253/309/01C/103). The study was conducted in accordance with applicable ethical guidelines and regulations, including the principles of the Declaration of Helsinki.

Availability of data and materials
All data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Use of AI and AI-assisted technologies
During the preparation of this manuscript, the authors used ChatGPT (OpenAI) for language editing, clarity improvement, and refinement of manuscript text. The authors reviewed and verified all AI-assisted outputs and remain fully responsible for the content, interpretation, and conclusions of the manuscript.

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