Supply Chain Integration and Inventory Control as Drivers of Medical Supply Chain Performance in Tanzania: Moderation by Information Technology

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Abstract
Reliable medical supply chains are critical to Tanzania's progress toward universal health coverage, yet public facilities continue to experience stockouts, delays, and waste. Grounded in the Resource-Based View, this study examines how Supply Chain Integration and Inventory Control shape Medical Supply Chain Performance and whether Information Technology conditions those effects. An explanatory cross-sectional survey was conducted among healthcare workers in public health centres and dispensaries in Songwe Region (n = 289), using validated Likert scales and estimating a variance-based structural equation model. Results show that Supply Chain Integration and Inventory Control are associated with higher Medical Supply Chain Performance, while Information Technology exerts the strongest direct influence. Information Technology also amplifies the payoff from Supply Chain Integration but attenuates the benefit of traditional inventory routines when they are not IT-aligned. Theoretically, the findings extend the Resource-Based View by identifying Information Technology as a platform resource that complements integration (co-specialization) and sets boundary conditions for inventory capabilities. Managers and policymakers should strategically embed Information Technology across supply chain functions by strengthening system interoperability, institutionalizing Information Technology-driven inventory governance (parameter tuning, FEFO enforcement, removal of duplicative paper processes), and investing in user capability and data stewardship to secure durable performance gains in the medical supply chain.

Keywords: *Medical supply chain performance; supply chain integration; inventory control; information technology.*

INTRODUCTION

Persistent challenges in accessing essential medical supplies continue to undermine healthcare delivery in Tanzania, with recurrent stockouts, delays, and wastage documented across public facilities (Mwakasala & Makoye, 2024; Silabi et al., 2023). Ensuring reliable, affordable, and high-quality medical products is central to Sustainable Development Goal 3 (SDG 3) on good Health and well-being, making the performance of national supply systems a public health priority (Sweileh, 2021).

The Medical Stores Department (MSD) manages nationwide procurement, warehousing and distribution in Tanzania. Despite reforms, most notably the Electronic Logistics Management Information System (e-LMIS**)**, persistent problems such as stockouts, delivery delays, weak demand forecasting, and commodity expiry remain, with particularly poor performance reported in regions like Songwe (CAG, 2023; Milulu et al., 2024). These operational shortfalls erode service readiness and public confidence (Kesale et al., 2022).

Two operational capabilities are particularly salient for Medical Supply Chain Performance (MSCP). Supply Chain Integration (SCI**)** is the coordinated alignment of planning and execution through information sharing, collaboration, and systems linkage that supports more accurate forecasting and timelier replenishment (Alzoubi et al., 2022; Fernández, 2022). Inventory Control (INC), disciplined ordering, monitoring, and expiry management, reduces wastage and stabilises service continuity (Guo et al., 2024; Hezam et al., 2023). When weakly deployed, gaps in SCI and INC translate directly into avoidable stockouts and higher carrying costs.

Information Technology (IT) can enhance these capabilities by improving real-time visibility, interoperability, and automation across health system tiers (Yu et al., 2021; Mollel et al., 2024). Yet IT tools yield performance gains only when they are reliable and embedded in day-to-day routines; uneven connectivity, parameter mis-tuning, or parallel paper processes can dilute their benefits (Milulu et al., 2024).

Guiding this study, the Resource-Based View (RBV) explains performance differences by positing that firms possess and deploy valuable, rare, inimitable, and non-substitutable capabilities (Barney, 1991). Within this lens, SCI and INC are operational capabilities whose value depends on complementarity and fit with other resources, notably IT infrastructure and data quality (Afrifa et al., 2021; Wetering & Versendaal, 2020). We therefore conceptualize IT as a platform capability that can condition the returns to SCI and INC: when IT systems are reliable and well-governed, they should amplify the performance contribution of integration; when misaligned, they can substitute for or blunt the payoff to local inventory routines, a boundary condition that extends RBV's treatment of co-specialized assets (Giustiziero et al., 2023).

Despite ongoing digitization, few empirical studies in Tanzania test, within an RBV framework, whether IT moderates both the SCI→MSCP and INC→MSCP relationships. This study addresses that gap by modelling SCI and INC as core operational capabilities and theorizing IT as a moderator that conditions their effects on MSCP. We then empirically test this moderation model using facility-level survey evidence from the public sector and derive actionable recommendations for MSD-managed supply chains.

LITERATURE REVIEW

Theoretical Background

Resource-Based View (RBV)

The Resource-Based View (RBV) attributes performance differences to the possession and deployment of valuable, rare, inimitable, and non-substitutable resources and capabilities (Barney, 1991). In supply chain contexts, operational capabilities such as effective inventory systems, integrated information flows, and skilled personnel are frequently advanced as strategic assets that underpin superior outcomes (Giustiziero et al., 2023; Wetering & Versendaal, 2020). Within this lens, two capabilities are salient for Medical Supply Chain Performance (MSCP): Supply Chain Integration (SCI), the coordinated alignment of planning and execution through information sharing, collaboration, and systems linkage, and Inventory Control (INC), disciplined ordering, monitoring, and expiry management.

RBV further emphasises complementarity among co-specialized assets; consequently, we expect the realized value of SCI and INC to depend on their fit with IT infrastructure and data quality. Information Technology (IT) is a platform capability that can condition the returns to SCI and INC by enhancing real-time visibility, interoperability, and automation (Yu et al., 2021). The literature supports RBV as a coherent lens for modelling

SCI and INC as performance-enhancing capabilities. Still, it offers limited evidence on whether an IT platform capability systematically strengthens these effects in Tanzania's public sector. This study addresses that gap by theorizing and testing IT's conditioning role.

Empirical Literature and Hypotheses Development

Supply Chain Integration and Medical Supply Chain Performance

Empirical studies associate integration with gains in forecasting accuracy, reduced lead-time variability, and higher availability (Alzoubi et al., 2022; Fernández, 2022). In Tanzania, coordination with the Medical Stores Department and structured information sharing are particularly salient given dispersed facilities and variable demand patterns (Wiedenmayer et al., 2021). While this body of work indicates that SCI enhances visibility and delivery reliability, the magnitude of SCI's contribution under varying levels of IT maturity remains under-documented for Tanzania. Accordingly, we hypothesise a positive SCI→MSCP relationship and evaluate whether IT conditions affect it.

H1: Supply Chain Integration (SCI) positively influences Medical Supply Chain Performance (MSCP).

Inventory Control and Medical Supply Chain Performance

Evidence indicates that robust inventory control reduces expiries, stabilizes service continuity, and lowers costs through disciplined replenishment and FEFO-based stock rotation (Guo et al., 2024; Hezam et al., 2023). Persistent replenishment discipline and expiry management weaknesses have been reported despite IT investments, underscoring the need to align facility routines with system parameters. The literature, therefore, implies a positive association between INC and MSCP. Yet, it remains unclear in Tanzania whether IT platforms consistently augment local inventory routines or, under misalignment, attenuate their marginal returns. We test a positive INC→MSCP relationship and examine IT's conditioning role.

H2: Inventory Control (INC) positively influences Medical Supply Chain Performance (MSCP).

Moderating Role of Information Technology

From an RBV perspective, IT is a platform capability that complements operational routines by improving data timeliness and accuracy and supporting automation (Yu et al., 2021; Mollel et al., 2024). Where connectivity is stable and parameters are well-governed, IT should amplify the performance contribution of integration; conversely, misconfigured systems or duplicative paper processes may blunt the marginal benefits of local inventory routines. Existing studies generally support IT's role in strengthening visibility and process control. Yet, little evidence quantifies the sign and size of IT's moderating effect on the SCI→MSCP and INC→MSCP relationships in Tanzania. We therefore model IT as a moderator of both links and empirically estimate the conditional effects.

H3: IT positively moderates the relationship between SCI and MSCP.
H4: IT positively moderates the relationship between INC and MSCP.

Conceptual Framework
Figure 1 summarizes the RBV-based framework: SCI and INC are operational capabilities that drive MSCP, and IT is a platform capability that conditions both effects by enabling visibility, interoperability, and automation. The model specifies direct effects (H1, H2) and moderated paths (H3, H4).

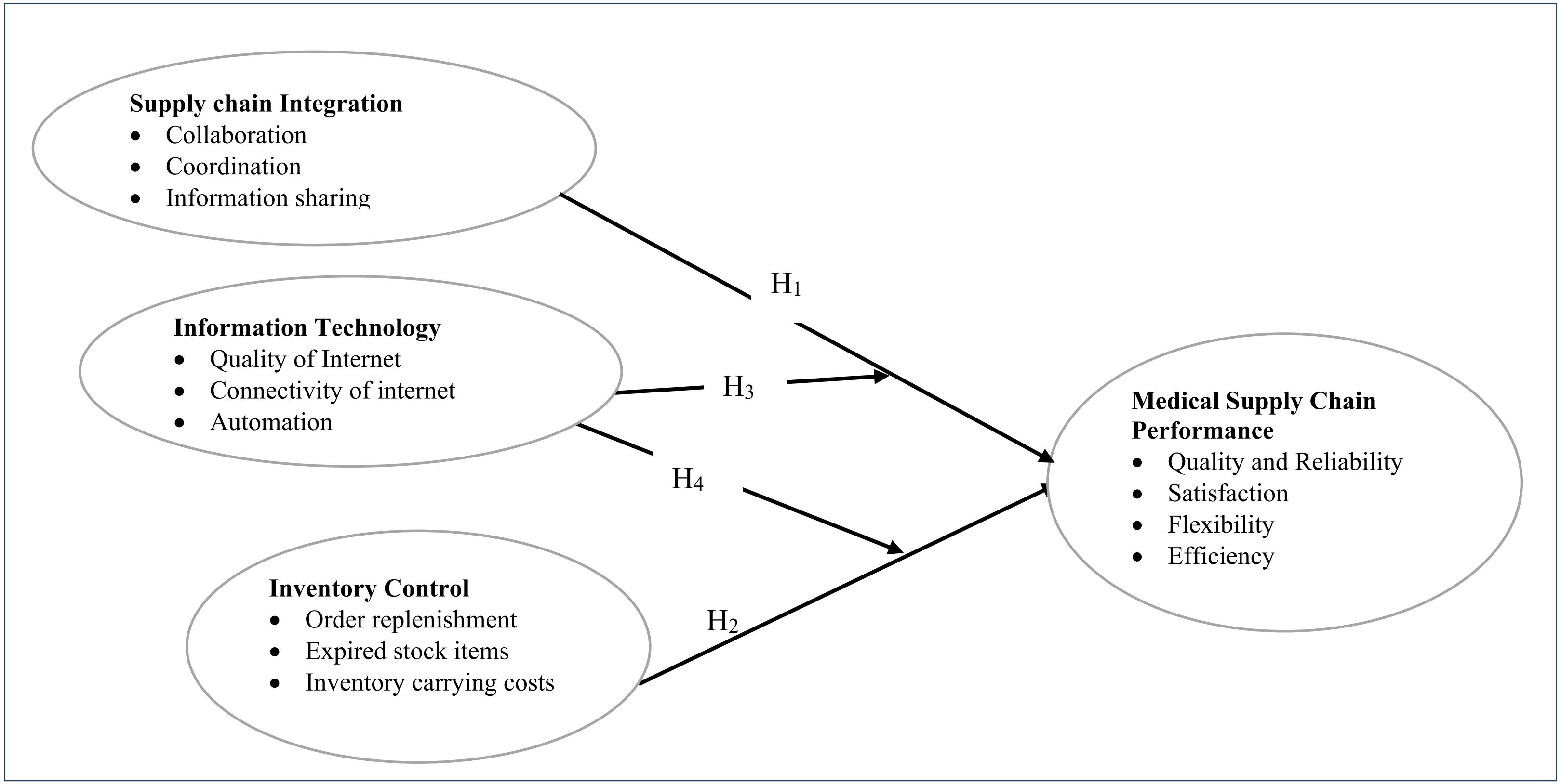

Figure 1: *Conceptual framework (RBV): IT moderates the effects of SCI and INC on MSCP.*
Source: Researcher (2025)

METHODS

Research philosophy, design, and approach

This study adopts a positivist, deductive design to test theory-driven hypotheses on Medical Supply Chain Performance (MSCP), using an explanatory cross-sectional survey to collect quantitative data at a single point in time from geographically dispersed facilities. The study Hypothesis estimates with variance-based structural equation modelling (PLS-SEM), a technique well suited to prediction-oriented research, reflective latent constructs, and moderation analysis (Creswell, 2018; Bentouhami et al., 2021; Mukherji & Albon, 2022; Firdaus et al., 2021; Hair et al., 2022; Sarstedt et al., 2021).

Population, sampling techniques, and sample size.

The empirical setting was the Songwe Region in Tanzania. The target population comprised healthcare workers who ordered, received, stored, or dispensed medicines and medical supplies at public health centres and dispensaries supplied by the Medical Stores Department (MSD). The study excludes staff from MSD personnel because the unit of analysis was the service-delivery facility and the focus was on facility-level practices and outcomes (Wiedenmayer et al., 2021).

Using a multistage probability strategy to balance geographical coverage with fieldwork feasibility. Councils in Songwe (Mbozi, Ileje, Momba, Tunduma, and Songwe) served as strata to ensure representation across administrative areas. Within each stratum, facilities were selected as clusters from District Medical Office lists, and eligible staff within sampled facilities were then chosen by simple random sampling, an approach consistent with best practice in survey sampling for dispersed populations (Bhandari, 2021; Lohr, 2021; Rahman et al., 2022). The a priori sample size was calculated using Yamane's (1967) formula at 95% confidence and a 5% margin of error, yielding (n=289). It exceeds common PLS-SEM heuristics—such as the 10-times rule based on the maximum number of structural paths entering an endogenous construct—and provides adequate power to detect both direct and interaction (moderation) effects (Hair et al., 2019; Hair et al., 2022).

Measures and instrument development

Data were collected via a structured questionnaire with five-point Likert scales (1 = strongly disagree to 5 = strongly agree). Instrument adaptation followed a staged protocol that mapped constructs to local workflows, sourced items from validated scales, and relied on expert review by supply-chain and public-health specialists to establish content validity. Items were forward–back translated by bilingual reviewers to ensure conceptual equivalence, cognitively pre-tested in two non-sampled facilities to check comprehension and cultural fit, and then piloted with approximately 20 respondents to assess clarity, item–total correlations, and preliminary reliability; wording was refined and ambiguous items revised or earmarked for removal (Podsakoff et al., 2003; Hair et al., 2022).

Supply Chain Integration (SCI) uses coordination, information sharing, collaboration, and systems alignment (Alzoubi et al., 2022; Fernández, 2022; Birhanu et al., 2022). Inventory Control (INC) covered replenishment discipline, expiry management using first-expiry-first-out (FEFO), and inventory carrying-cost consciousness (Guo et al., 2024; Hezam et al., 2023). Information Technology (IT), specified as the moderator, captured internet quality and uptime, connectivity, and interoperability with e-LMIS/ERP/EDI/API links, and process automation such as e-ordering, auto-replenishment, and barcode/RFID dashboards (El-Baz & Ruel, 2021; Kauppi & Luzzini, 2022; Spieske & Birkel, 2021; Yu et al., 2021). MSCP reflected quality and reliability, user satisfaction, flexibility, and efficiency (e.g., on-time-in-full, stockout days, and order-cycle time) when contextualized for the Tanzanian public sector (Wiedenmayer et al., 2021; CAG, 2023; George & Elrashid, 2023; Silabi et al., 2023).

Data collection, bias mitigation, and ethics

Surveys were administered in person or via supervised self-administration, during routine working hours after obtaining council and facility permissions. Participation was voluntary and anonymous; a written informed consent was required before completion. Ethical approval was granted by the relevant research ethics committee at the Open University of Tanzania, where I obtained a permit for data collection, and government research permits were obtained from the competent authorities in the offices of the regional administrative secretaries in Songwe and Mbeya regions. Facility-level approvals were secured from in-charges before fieldwork commenced (Creswell, 2018).

Data preparation and analysis

Data preparation followed a pre-specified pipeline. Coding verification and range checks were undertaken, followed by missing-data diagnostics. When item-level missingness was at or below five percent and plausibly Missing At Random, values were imputed using expectation–maximization or mean imputation as appropriate; when missingness exceeded five percent or appeared Not Missing At Random, cases were handled by list-wise deletion with sensitivity analyses to assess robustness (Hair et al., 2022). Potential outliers were screened using leverage, and Mahalanobis distance with conservative cut-offs, and distributional properties (skewness, kurtosis) and bivariate correlations were inspected (Hair et al., 2019). Before structural estimation, predictors were mean-centred, and product terms were created for the moderation effects SCI × IT and INC × IT (Hair et al., 2022; Sarstedt et al., 2021).

Descriptive statistics (means and standard deviations) and correlations were computed in SPSS v27. PLS-SEM estimation was performed in SmartPLS v4.1 with all constructs specified as reflective. Measurement quality was assessed against standard thresholds, retaining indicators with loadings of at least 0.708, accepting composite reliability between 0.70 and 0.95, and confirming convergent validity where average variance extracted was at least 0.50; discriminant validity was evaluated using the heterotrait–monotrait ratio with targets below 0.85–0.90 (Hair et al., 2019; Hair et al., 2022; Sarstedt et al., 2021). Inner and outer model collinearity was examined using variance inflation factors, with acceptable values ranging from 3 to 5 (Hair et al., 2019). To address common-method bias, Harman's single-factor test was applied with a criterion of less than 50% variance explained, and full-collinearity VIFs were inspected with a threshold of 3.3 or lower (Podsakoff et al., 2003; Kock, 2015). Structural paths were tested using non-parametric bootstrapping with at least 5,000 resamples, adopting significance thresholds of ($t \geq 1.96$) and ($p \leq .05$) (Hair et al., 2022). Moderation was estimated using the two-stage approach, and conditional effects were probed with simple-slope analyses at low (−1 SD), mean, and high (+1 SD) levels of IT following recommended procedures for variance-based SEM (Hair et al., 2019; Hair et al., 2022; Sarstedt et al., 2021).

MSCP was modelled as a reflective latent construct. For hypothesis testing, analyses relied on SmartPLS latent variable scores weighted by outer loadings, whereas unweighted item means were reported solely for descriptive summaries and were not used for inferential testing (Hair et al., 2019; Hair et al., 2022).

Results

This section reports the SmartPLS v4.1 results in the recommended order: measurement model assessment followed by structural model assessment.

Measurement model evaluation

Reliability and validity adhered to recommended thresholds (Hair et al., 2019, 2020; Sarstedt et al., 2021): loadings ≥ 0.708, composite reliability

0.70–0.95, AVE ≥ 0.50, HTMT < 0.85–0.90 with confidence intervals excluding 1, and inner/outer VIF < 3–5.

Table 1
Reliability and convergent validity

Construct	Cronbach's α	Composite (ρA)	Composite (ρC)	AVE
INC_	0.862	0.876	0.917	0.787
IT_	0.807	0.850	0.885	0.722
MSCP_	0.866	0.889	0.907	0.711
SCI_	0.895	0.918	0.926	0.758

Source: Survey data (2024)

Table 2
Discriminant validity (HTMT)

	INC_	IT_	MSCP_	SCI_	IT_×SCI_	IT_×INC_
INC_	—					
IT_	0.522	—				
MSCP_	0.704	0.845	—			
SCI_	0.388	0.372	0.547	—		
IT_×SCI_	0.082	0.344	0.234	0.121	—	
IT_×INC_	0.056	0.430	0.298	0.073	0.564	—

Source: Survey data (2024)

Structural model evaluation

Model paths were evaluated via bootstrapping (≥5,000 resamples) with significance at $t \geq 1.96$ and $p \leq .05$. Explanatory power used $R^2 \approx 0.25/0.50/0.75$ for weak/moderate/substantial; effect sizes used $f^2 = .02/.15/.35$; predictive relevance required $Q^2 > 0$ (blindfolding) and PLS predict for out-of-sample performance. Robustness checks (optional) included multi-group analysis and controls (facility level, region, ownership, and budget). IT functioned analytically as a moderator interacting with SCI and INC to amplify their effects on MSCP.

Table 3
Predictive relevance (Q^2)

Endogenous Construct	Q^2
MSCP_	0.33

Table 4
Inner model collinearity (VIF)

Path	VIF
INC_ → MSCP_	1.337
IT_ → MSCP_	1.555
SCI_ → MSCP_	1.269
IT_×SCI_ → MSCP_	1.577
IT_×INC_ → MSCP_	1.613

Source: Survey data (2024)

Table 5
Effect sizes (f^2)

Path	**f^2**
INC_ → MSCP_	0.182
IT_ → MSCP_	1.783
SCI_ → MSCP_	0.181
IT_×SCI_ → MSCP_	0.068
IT_×INC_ → MSCP_	0.123

Source: Survey data (2024)

Table 6. Explained variance (R^2)

Endogenous Construct	**R^2**
MSCP_	0.818

Overall, diagnostics indicate reliable and valid measures, acceptable collinearity, meaningful direct and moderated effects, with decisive IT contribution and substantial explained and predictive variance for MSCP.

Hypothesis Testing and Path Coefficients
Hypotheses were tested using bootstrapping with 5,000 resamples. Results are summarized in Table 7.

Table 7
Path coefficients and significance (bootstrapping, 5,000 resamples)

Path	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
INC_ → MSCP_	0.211	0.210	0.034	6.141	0.000
IT_ → MSCP_	0.710	0.712	0.032	22.021	0.000
SCI_ → MSCP_	0.204	0.205	0.034	5.951	0.000
IT_×SCI_ → MSCP_	0.151	0.153	0.037	4.114	0.000
IT_×INC_ → MSCP_	-0.195	-0.198	0.038	5.200	0.000

Source: Survey data (2024)

Overall, the diagnostics indicate reliable and valid measures, acceptable collinearity, and substantial explained and predictive variance for MSCP; taken together, the results support significant direct effects of INC, IT, and SCI on MSCP, with IT making a decisive contribution and significantly moderating both the SCI→MSCP and INC→MSCP relationships

Response rate
Of 314 targeted respondents, 289 completed the survey (response rate = 92%), which exceeds common thresholds for high-quality survey research. Following established survey methodology practices, non-response bias was assessed using the extrapolation approach by comparing early vs late respondents on key study constructs and observable characteristics.

Independent-samples t-tests indicated no statistically significant differences between the groups ($p > 0.05$), suggesting that non-response bias is unlikely to threaten the validity of the findings. Consistent with Kuya and Kelei (2022), who categorize response rates above 70% as superb, the response rate achieved in this study is considered methodologically robust.

Based on this assertion, the response rate was deemed impressive. The response rate for this study is shown in Table 7. The results (found that more than 70% of respondents responded to their research, "Buyer-supplier integration's influence on supplier logistics performance" are consistent with the response rate of over 70%.

Table 8:
Respondents' Rate

Type of Respondent	Number of respondents		Per cent
	Expected	Actual	
Workers from Health Centres and Dispensaries in Songwe Region	314	289	92

Discussion of Results

The results portray a coherent pattern: Supply Chain Integration (SCI) and Inventory Control (INC) are both associated with higher Medical Supply Chain Performance (MSCP), and Information Technology (IT) exerts the strongest direct influence while conditioning the returns to these capabilities. Interpreted through the Resource-Based View (RBV), SCI and INC function as internal, performance-enhancing capabilities. Depending on alignment, IT can operate as a complementary resource that amplifies or attenuates productivity. The positive SCI effect aligns with evidence that coordinated planning, information sharing, and systems alignment reduce stockouts and improve availability (Alzoubi et al., 2022; Fernández, 2022; Birhanu et al., 2022; George & Elrashid, 2023; Wiedenmayer et al., 2021). The positive INC effect is consistent with studies showing that disciplined replenishment and FEFO-based expiry control stabilize supply and reduce waste (Guo et al., 2024; Hezam et al., 2023). The dominant direct role of IT aligns with research linking connectivity, interoperability, and automation to shorter cycles and more reliable fulfilment (Yu et al., 2021; Spieske & Birkel, 2021).

Beyond confirming RBV expectations, the moderation pattern advances theory in two ways. First, the positive IT×SCI effect indicates co-specialization: when IT quality and interoperability are high, integration routines translate more fully into performance. In RBV terms, IT and SCI are complementary assets, and their joint deployment yields super-additive returns. Second, the negative IT×INC effect marks a boundary condition for

RBV: as IT workflows (e.g., e-ordering, parameterized auto-replenishment) become dominant, the incremental value of legacy, manually governed inventory routines falls, unless those routines are re-engineered to be IT-native**.** It refines RBV by showing that the value of a capability depends on resource orchestration and its fit with the IT stack; capability returns are not uniform but depend on how processes are parameterized, trained, and governed in IT environments (see also Hezam et al., 2023; Milulu et al., 2024). In short, IT is not merely another resource but a platform resource that conditions when and how internal capabilities create value.

Theoretical implications (RBV)

The findings substantiate SCI and INC as valuable internal capabilities while extending RBV in three respects. First, they demonstrate complementarity between IT and SCI: performance gains from integration are larger when paired with robust IT, consistent with RBV's emphasis on resource bundles rather than isolated assets (Alzoubi et al., 2022; Yu et al., 2021). Second, they identify a boundary condition for INC: without IT alignment (e.g., tuned reorder points/lead times, in-system FEFO), automated routines can substitute for manual controls, reducing the marginal contribution of traditional INC. Third, they highlight resource orchestration as a mechanism: the same capability (INC) can yield different returns depending on how it is governed and embedded in IT-enabled workflows. Collectively, this moves beyond confirmation to specify when RBV capabilities pay off in public-sector health supply chains.

Managerial and policy implications

Beyond managerial actions at the facility level, the findings carry significant implications at the system and policy levels. Sustainable performance improvements in Tanzania's medical supply chain require institutional and regulatory conditions that scale IT- enabled integration across facilities.

First, national financing frameworks should prioritize earmarked investments in last-mile connectivity, power redundancy and system maintenance budgets to ensure baseline IT reliability. As highlighted by CAG (2023), infrastructure instability and inconsistent system usage undermine the effectiveness of automated replenishment and the integrity of audits.

Second, regulatory authorities should formalize national standards for master data governance (item catalogues, units of measure, pack sizes), interoperability protocols between e-LMIS and ERP platforms, and structured parameter governance. Evidence suggests that weak data governance and system fragmentation distort demand signals and compromise inventory accuracy (Wiedenmayer et al., 2021; Hezam et al., 2023).

Third, coordinated donor programs and structured public–private partnerships (PPPs) can accelerate the adoption of Automatic Identification and Data Capture (AIDC), including barcoding and RFID, particularly in resource-constrained facilities. Scaling such technologies has been associated with improved traceability, reduced expiry losses, and enhanced stock visibility (Guo et al., 2024; Hezam et al., 2023).

Fourth, regulatory guidance should institutionalize audit trails, parameter review cycles, and automated exception monitoring to stabilize replenishment systems and reduce opportunistic or ad hoc overrides. Institutional oversight mechanisms have been shown to strengthen accountability and operational transparency in public supply chains (CAG, 2023).

Finally, regional coordination mechanisms, such as collaborative forecasting platforms and pooled procurement arrangements, can mitigate demand volatility and improve supply continuity across facilities. Such inter-organizational integration aligns with emerging evidence on supply chain resilience and predictive performance monitoring (Yu et al., 2021; Spieske & Birkel, 2021).

Embedding standardized KPI monitoring (e.g., OTIF (On Time In Full), stockout days, expiry rates) alongside PLS predict-style predictive performance tracking into routine supervisory systems can further institutionalize data-driven decision-making and sustain reform momentum (Yu et al., 2021; CAG, 2023).

CONCLUSION

The study shows that SCI and INC relate positively to MSCP, while IT is the dominant lever shaping how those capabilities convert into performance. In RBV terms, IT acts as a platform resource that amplifies the value of integration and reconfigures returns to inventory routines unless they are IT-driven, process-aligned. The actionable path, therefore, is to pair reliable IT infrastructure and interoperability with IT-native inventory governance, targeted capability building, and robust data stewardship, so that performance gains are both realized and sustained (Alzoubi et al., 2022; Fernández, 2022; Spieske & Birkel, 2021).

Limitations and future research

The cross-sectional design limits causal inference; phased or longitudinal studies, ideally linked to transactional e-LMIS logs and periodic physical counts, would better identify dynamics and reduce common-method risk (CAG, 2023; Milulu et al., 2024). Process evaluations should probe when IT complements rather than substitutes for local inventory routines, focusing on parameter governance, user training, and workflow redesign. Future work could also examine the cost-effectiveness and equity implications of IT-enabled supply-chain upgrades and deploy multilevel models to capture interactions between facility capabilities and system-level supports.

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