



A Simulation-Based Decision Support Framework for Resilient Public Pharmaceutical Chains: A Case Study

Dana Al Khusaibi¹, Dhuwa Al Amri¹, Samira Afsharfard¹, Sana Nabati², Reza Babazadeh²,
Mehdi A. Kamran^{1,*}

¹ Department of Logistics, Tourism, and Services Management, German University of Technology in Oman, P. O. Box 1816, PC 130, Muscat, Oman

² Department of Industrial Engineering, Faculty of Engineering, Urmia University, Urmia, Iran

ARTICLE INFO

Article history:

Received: 10 July 2026

Received in revised form: 20 August 2026

Accepted: 22 August 2026

Available online: 23 August 2026

Keywords:

Public Healthcare Logistics; Pharmaceutical Distribution; Supply Chain Resilience; Simulation Modelling; Risk Analysis; Decision Support; Network Design

ABSTRACT

Public healthcare systems in emerging economies face growing challenges in maintaining resilient pharmaceutical supply chains due to geographic dispersion, seasonal demand variation, and operational disruptions. However, simulation-based decision-support approaches remain limited in government-operated healthcare logistics, particularly in the Middle East and North Africa. Therefore, this study develops and validates a simulation-based model of Oman's public pharmaceutical distribution network to evaluate network performance and resilience under operational disruptions and structural changes. The model represents Oman's 2024 distribution network, comprising two primary distribution centres and 72 public hospitals and health centres. Moreover, network analysis, optimization, and discrete-event simulation with risk analysis are integrated within a unified framework to support strategic network planning and decision-making. The model is validated by comparing simulated total supply cost with actual 2024 operating cost, resulting in an error of only 0.004%. Results show that the existing network provides moderate resilience, with service level declining to 63.6% under the most severe disruption scenario. Furthermore, adding a distribution centre increases transportation cost by 11.3% without improving resilience. Consequently, network expansion alone cannot ensure greater resilience, highlighting the need to consider the interrelationships among network structure, transportation cost, demand, and disruption risk when making strategic logistics decisions. Overall, the proposed framework supports evidence-based decision-making and planning for resilient public pharmaceutical logistics.

1. Introduction

Public healthcare systems worldwide face increasing pressure to maintain resilient pharmaceutical supply chains amid growing demand, geographic dispersion, fiscal constraints, and recurring disruptions. The vulnerability of these supply chains is particularly concerning because global pharmaceutical production and sourcing remain geographically concentrated. China produces an estimated 40% of global active pharmaceutical ingredients, while India procures nearly 70% of its active pharmaceutical ingredients from China [1]. Such concentration can amplify the effects of localized disruptions and contribute to shortages across interconnected markets. These

* Corresponding author.

E-mail address: mehdi.kamran@gutech.edu.om

vulnerabilities became particularly evident during the COVID-19 pandemic, which exposed structural weaknesses in government-operated medical logistics systems, including sudden demand surges, transport route failures, facility shutdowns, and inventory shortages [2]. For example, cardiovascular medicines were reported to be out of stock for more than 90 days in Ethiopian hospitals during the pandemic [3]. Moreover, Pava and Tucker [4] reported baseline global medicine shortages of 17.2%, with disparities reaching 87.6% in low-income countries. These findings demonstrate that pharmaceutical supply chain disruptions can extend beyond temporary operational inefficiencies and directly affect the availability and accessibility of essential medicines.

The consequences of supply chain vulnerabilities extend across operational and economic dimensions, as disruptions can generate cascading effects in which localized failures propagate through interconnected supply networks and result in prolonged consequences [5]. Accordingly, the complexity of distribution and supply chain networks requires the simultaneous consideration of multiple operational and structural factors, including demand uncertainty, transportation disruptions, facility and capacity constraints, inventory availability, and infrastructure limitations [6, 7, 8, 9, 10]. For instance, Zandkarimkhani *et al.*, [6] showed that demand uncertainty can lead to lost sales even under optimized network configurations, while Lücker *et al.*, [8] highlighted the importance of inventory and reserve capacity in mitigating disruption risks. Moreover, supply chain decision-making becomes more challenging when products cannot be stored and therefore require continuous or timely production and distribution [11]. These challenges become particularly consequential in pharmaceutical distribution networks because the availability of medicines is directly linked to clinical care and public health. Consequently, medication shortages and supply disruptions can extend beyond operational and economic losses to increase costs, medication errors, adverse events, and mortality [12]. Therefore, the specific characteristics and consequences of pharmaceutical supply chains underscore the need for approaches capable of simultaneously representing strategic network decisions and the dynamic operational consequences of disruptions, thereby enabling a more comprehensive evaluation of network performance and resilience.

Simulation and digital twin technologies have been extensively applied in commercial and industrial supply chains to analyze resilience, stress-test network configurations, and quantify disruption impacts [13, 14]. However, their application to publicly funded pharmaceutical distribution systems remains limited, particularly in the West Asia and North Africa (WANA) region. Existing healthcare supply chain studies predominantly focus on private hospital logistics or commercial pharmaceutical networks, while population-scale, state-operated systems are rarely modelled using validated simulation frameworks [15]. This gap is especially critical in countries where ministries of health centrally manage procurement, warehousing, and nationwide distribution.

The Sultanate of Oman provides an illustrative case. The Ministry of Health (MOH) operates a centrally managed pharmaceutical distribution network supplying public hospitals and health centers across northern and central Oman. This network must serve geographically dispersed facilities, manage fluctuating demand patterns—including seasonal migration effects such as the annual Khareef movement—and respond to infrastructure constraints and transport disruptions. Despite the strategic importance of this network, planning decisions are largely based on historical practices and manual risk assessments, with limited use of simulation-based decision support tools.

To address this gap, this study develops and validates a data-driven digital twin of Oman's public pharmaceutical distribution network using AnyLogistix (ALX). The model integrates Greenfield Analysis (GFA), Network Optimization (NO), and discrete-event simulation with embedded risk analysis into a unified modelling framework. The digital twin is calibrated using real operational and financial data from the 2024 calendar year and represents the two primary distribution centers

located in Muscat and Nizwa supplying 72 public hospitals and health centers. Model validation is performed by benchmarking simulated total logistics cost against actual MOH expenditure, achieving a deviation of less than 0.005%, thereby ensuring strong empirical consistency between the simulated and real systems.

Using this validated baseline configuration, four structured simulation experiments are conducted to evaluate network resilience and cost–service trade-offs. The first experiment establishes baseline system performance under three realistic disruption scenarios: temporary facility shutdown, seasonal demand shifts, and weather-induced route closure. The second experiment evaluates the impact of introducing an additional distribution center identified through Greenfield Analysis. The third and fourth experiments impose service radius constraints of 200 km and 150 km respectively, simulating policy-driven initiatives to reduce delivery lead times. Across all scenarios, total logistics cost and service-level fulfilment are measured to quantify the trade-offs associated with alternative network configurations.

This study contributes to literature in three principal ways. First, it demonstrates the structured integration of optimization and simulation within a validated digital twin of a government-operated pharmaceutical supply chain. Second, it establishes a transparent validation procedure based on comparison with actual government expenditure, strengthening methodological credibility in applied healthcare simulation research. Third, it quantifies resilience–cost trade-offs under realistic disruption scenarios, providing actionable insights for public-sector decision makers operating under budget and service-level constraints.

By bridging the gap between simulation-based resilience modelling and public healthcare logistics, this research illustrates how digital twin frameworks can support evidence-based planning in nationally managed pharmaceutical distribution systems.

2. Literature Review

Pharmaceutical supply chains differ fundamentally from other logistics systems. They are characterized by high regulatory complexity, strict traceability requirements, patient safety implications [16]. The products they handle are not ordinary commodities: they are temperature-sensitive, time-critical, and directly consequential for patient outcomes. A delay in the delivery of antibiotics, vaccines, or anesthetics is not merely a service failure—it is a potential threat to life [17, 18]. This inherent sensitivity imposes strict regulatory, handling, and traceability requirements that distinguish pharmaceutical logistics from commercial or industrial supply chains. In addition, coordination, visibility and oversight are required across multiple tiers to maintain safety and compliance [19]. Yet despite these high stakes and increasing digitization, healthcare systems continue to struggle with balancing cost containment and quality service provision.

While the structural fragility of pharmaceutical supply chains is well recognized [20, 21], the application of advanced simulation-based decision support tools to publicly operated pharmaceutical distribution networks remain surprisingly limited [22].

2.1 Pharmaceutical Supply Chain Risks and Resilience

The vulnerability of healthcare supply chains has been repeatedly demonstrated [23]. The COVID-19 pandemic exposed systemic fragilities across both developed and developing countries: sudden demand surges for personal protective equipment, vaccines, and therapeutics overwhelmed networks designed for stable and predictable consumption [2]. Concurrently, border restrictions,

supplier failures, and transport disruptions revealed limited redundancy and insufficient visibility within global medical logistics systems [24].

Subsequent research has consolidated these observations into a broader typology of risks. Internal risks include quality control failures, warehouse capacity constraints, inventory mismanagement, and coordination breakdowns; external risks encompass supplier delays, natural disasters, geopolitical instability, and demand shocks [21]. What unites these risks is not their diversity, but the fact that they are frequently identified retrospectively—after disruption has occurred—through manual audits or ex-post analysis [25]. Proactive, quantitative stress-testing of public pharmaceutical networks remains comparatively rare [22], despite extensive research demonstrating the importance of redundancy, backup facilities, and survivable network design for improving resilience under disruption conditions [26].

Efforts to strengthen resilience have largely concentrated on private-sector hospital logistics or commercial pharmaceutical wholesalers. Ma *et al.*, [19] demonstrate the value of digital traceability and data sharing in enhancing coordination and operational performance. However, these contexts operate under profit incentives, contractual penalties, and competitive pressure. Public healthcare logistics—particularly in centralized, state-funded systems—function under fundamentally different institutional constraints [27]. Budgets are fixed, procurement is centralized, and continuity of supply is a political obligation rather than a market differentiator [27]. It cannot be assumed that resilience strategies developed for private supply chains directly transfer to public systems [15]. This distinction forms the foundation of the present study.

2.2 Simulation Modelling in Supply Chain Risk Analysis

Simulation has long been recognized as a powerful approach for supply chain risk analysis. Unlike deterministic optimization, which prescribes a single optimal configuration under assumed certainty, simulation allows decision-makers to observe network behavior under probabilistic, dynamic, and interdependent disruption scenarios [14]. By modelling variability in demand, transport delays, facility outages, and inventory dynamics, simulation provides insight into system performance beyond static efficiency metrics, complementing optimization-based supply chain planning models that address pricing, inventory, and distribution decisions within integrated frameworks [28].

Hybrid modelling platforms that integrate optimization and discrete-event simulation further enhance this capability [29], particularly in disruption-prone environments where demand forecasting and adaptive recovery planning improve supply chain responsiveness and resilience [30]. In particular, the emerging concept of digital supply chain twins enables the replication of real-world logistics networks in silico, allowing structured stress-testing under compound disruption scenarios [13]. ALX integrates GFA, NO, and risk-modulated discrete-event simulation within a unified modelling environment. Such integration is especially relevant for public-sector logistics systems, where cost efficiency, service equity, and resilience must be simultaneously evaluated. Recent applications of integrated optimization–simulation frameworks to vaccine distribution networks have demonstrated their effectiveness in improving resilience, optimizing inventory and facility allocation, and evaluating disruption scenarios under realistic operational conditions [31].

Although simulation-based approaches have been widely applied in automotive, retail, and food supply chains [13], their application to pharmaceutical distribution networks is comparatively sparse [22]. When healthcare applications do appear, they often focus on hospital-level operations such as

patient flow or scheduling rather than nationwide pharmaceutical distribution systems [22]. Furthermore, validated benchmarking against actual operational expenditure is rarely reported.

2.3 The Research Gap: Public Healthcare Simulation in WANA

The limited application of simulation-based digital twins to public pharmaceutical supply chains [22] is particularly evident in the WANA region. Rapid population growth, climate variability, geographic dispersion, and centralized public healthcare financing heighten the need for structured, evidence-based pharmaceutical logistics planning.

Oman exemplifies these conditions. Its population is distributed across coastal, mountainous, and desert regions; seasonal migration during the annual Khareef monsoon generates temporary demand shifts; and its healthcare system is centrally funded and administered by the MOH. These characteristics introduce variability and operational complexity that cannot be adequately addressed through static planning tools.

Yet no published study has modelled the Omani MOH's pharmaceutical distribution network using ALX or a comparable simulation-based digital twin framework. More broadly, the literature assumes access to fully digitized datasets, comprehensive commercial software licenses, and institutional familiarity with simulation-based planning—assumptions that do not consistently hold in emerging public healthcare systems. Data fragmentation, confidentiality constraints, and licensing limitations pose practical challenges that are seldom documented in the research record.

Thus, the gap is both contextual and methodological: public healthcare pharmaceutical systems in emerging economies remain under-modelled, and the process of constructing validated simulation frameworks under real-world institutional constraints remains insufficiently described.

2.4 Synthesis and Study Positioning

The literature establishes three critical insights. First, pharmaceutical supply chains are structurally sensitive, highly regulated, and vulnerable to disruption [21, 17, 18]. Second, simulation—particularly integrated optimization—simulation platforms such as ALX—can effectively model network behavior under disruption and support resilience-oriented decision-making [13, 14]. Third, this capability has not been systematically extended to centrally managed public healthcare systems in the WANA region [15].

This study positions itself at the intersection of healthcare logistics, supply chain risk management, and simulation-based decision support. Rather than proposing a new simulation algorithm, the contribution is empirical and methodological: we demonstrate that a validated digital twin of a national public pharmaceutical distribution network can be constructed using real operational data, implemented under practical software constraints, and benchmarked against actual government expenditure.

By doing so, the study extends simulation-based resilience modelling into a domain where it has been largely absent—state-operated pharmaceutical distribution—and provides a transparent, replicable framework for emerging healthcare systems facing similar structural and institutional constraints.

3. Problem Statement and Modeling

This section presents the case setting, data collection procedures, model development process, and validation framework. The objective is to ensure methodological transparency and reproducibility for comparable public healthcare systems while respecting confidentiality constraints imposed by the Omani MOH.

3.1 Case Description: Oman's Public Pharmaceutical Network

The Omani public pharmaceutical distribution network is centrally operated by the MOH through the Directorate General of Medical Supplies (DGMS). As illustrated in Figure 1, the system comprises three principal distribution centers: the DGMS headquarters in Al Khuwair (Muscat), a regional warehouse in Nizwa (Ad Dakhiliyah), and a separate facility in Salalah serving the Dhofar governorate. Two additional specialized warehouses—one dedicated to vaccines (Darsait) and one for emergency reserves (Bawsher)—function as storage nodes but do not operate as primary outbound distribution centers.

The scope of this study is limited to the network supplied by the Muscat and Nizwa hubs. Dhofar is excluded due to its autonomous supply structure and distinct seasonal demand dynamics. Within this boundary, the model includes 72 public health institutions—hospitals, polyclinics, and health centers—that received pharmaceutical deliveries during the 2024 calendar year. These facilities are distributed across Muscat, Al Batinah (North and South), Musandam, Al Buraymi, Ad Dakhiliyah, Al Wusta, Ash Sharqiyah, and Ad Dhahirah.

Transportation is outsourced under a three-year contract to a private Omani logistics provider. In 2024, available vehicle types included air-conditioned trucks with capacities of 3, 7, 10, 12, 18, and 30 tons, and non-air-conditioned trucks with capacities of 7 and 30 tons. Transportation cost is determined by transported weight and travelled distance, differentiated by refrigeration requirement. Pharmaceutical procurement is centralized and conducted through three primary suppliers: Muscat Pharmacy, Alwaleed Pharmacy, and Bahwan Pharmacy.

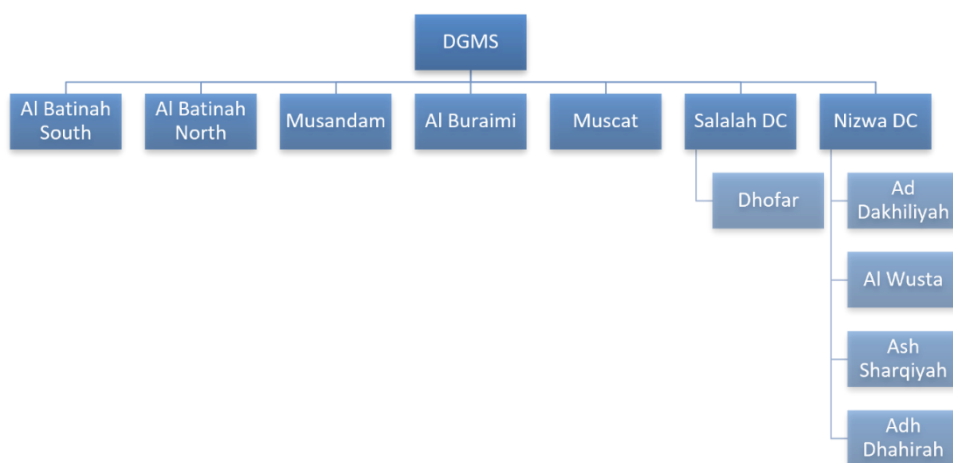


Fig. 1. Health Institute Structure in Oman

Transportation is outsourced under a three-year contract to a private Omani logistics provider. Available vehicle types in 2024 included air-conditioned trucks of 3, 7, 10, 12, 18, and 30 tons, and non-air-conditioned trucks of 7 and 30 tons. Transportation cost is determined by weight transported and distance travelled, differentiated by refrigeration requirement.

All pharmaceutical procurement is centralized and conducted through three primary suppliers: Muscat Pharmacy, Alwaleed Pharmacy, and Bahwan Pharmacy.

3.2 Data Collection and Constraint Management

Data were collected through semi-structured interviews with DGMS personnel and structured questionnaires administered to IT, finance, and warehouse departments (Appendix 1). The reference period is the full 2024 calendar year.

The available datasets included the names and GPS coordinates of all 72 supplied institutions, product descriptions and shipment-level ordered quantities, transportation dates, truck types and capacities per shipment, a historical disruption register, and total annual procurement expenditure by product category.

Due to confidentiality and software limitations associated with the ALX PLE, certain parameters required estimation.

Transportation rates are contractually confidential. However, historical rate templates provided internal benchmarks of 12 OMR per tonne per kilometre for air-conditioned trucks and 6 OMR per tonne per kilometre for standard trucks. Using the 2024 exchange rate (1 OMR = 2.6 USD), these values correspond to 31.2 USD/tonne/km and 15.6 USD/tonne/km, respectively.

The PLE version limits the number of product classes to ten. Consequently, more than 200 pharmaceutical SKUs were aggregated into ten functional categories. Unit cost per category was calculated as total annual expenditure divided by total units ordered and then converted to USD. The resulting values are reported in Table 1, which should be placed immediately after this paragraph.

Shipment-level quantities in pieces were not recorded in transportation logs. However, truck capacity and delivery dates were available. Quantities were therefore reconstructed using weight-based estimation. Based on DGMS consultation, solid-dose pharmaceuticals were assumed to weigh 200g per unit and vaccines, insulin, and consumables 500g per unit. A weighted average conversion yielded 3,400 pieces per tonne. Assuming full truckload utilization—a standard practice confirmed by DGMS—shipment quantity was estimated as:

$$\text{Estimated Quantity (pcs)} = 3,400 \times \text{Truck Capacity (tonnes)}$$

The validity of this assumption is indirectly verified through cost calibration in Section 3.4.

Table 1
Product Cost Per Unit

Product category	Unit	Cost (\$)
Penicillin	pcs	3.1
Antibiotics	pcs	0.8
Insulin	pcs	0.2
Hormonal non	pcs	20.2
Alkaloids	pcs	25.3
Consumables	pcs	7.3
Anti-Malaria	pcs	3.9
Vitamins	pcs	0.7
Vaccines	pcs	68
Placebos	pcs	0.1

3.3 Simulation Model Architecture in AnyLogistix

The model was developed in AnyLogistix PLE using a three-stage architecture integrating GFA, NO, and stochastic Simulation with Risk Analysis.

In the GFA stage, the physical network topology was defined. Customer nodes correspond to the 72 health institutions. Muscat and Nizwa were specified as fixed distribution centres, and the three suppliers were modeled as production nodes. Ten product categories were defined, and 2024 historic shipment-level demand was imported. The GFA configuration was subsequently converted into a Network Optimization experiment. Unit costs (Table 1), transportation cost structures, vehicle capacities, and lane definitions were specified. Facility fixed costs were set to zero, reflecting state-owned infrastructure, and selling price was set to zero since the objective was cost minimization. The NO experiment was solved to optimality, producing baseline least-cost flows under disruption-free conditions.

The optimized configuration was then imported into the Simulation module. Service-level thresholds were set at 96% (failure threshold) and 98% (recovery threshold), consistent with MOH operational standards. Three primary disruption types were modeled: temporary DGMS facility failure (40% probability, first quarter, seven-day duration), seasonal demand shift during Khareef, and rain-induced route closure between Muscat and Nizwa (70% probability, two-day duration). Deterministic recovery events were linked to each disruption. Each configuration was simulated over a 365-day horizon with 10 replications.

3.4 Model Validation

Model validity was assessed through cost calibration against actual 2024 procurement expenditure. The actual procurement cost was 4,908,044,735 USD, while the simulated baseline cost was 4,907,849,227 USD. The absolute deviation of 195,508 USD corresponds to a relative error of 0.00397% (Table 2). This extremely low deviation indicates that product aggregation introduced negligible distortion, estimated transportation rates are consistent with contractual structures, and the shipment reconstruction assumption is reasonable. No post-calibration adjustments were performed. The model is therefore accepted as a validated baseline representation of the 2024 MOH pharmaceutical distribution network. All subsequent experiments are conducted relative to this configuration.

Table 2
Actual supply cost

Category	Cost per PC (\$)	Total Cost (\$)	Total Quantity Sent
Alkaloids	25.5	24,925,791	977,482
Antimalaria	3.9	754,599	193,487
Antibiotics	0.83	13,962,962	16,822,846
Consumables	7.3	4,637,357,905	635,254,508
Hormonal	20.2	58,360,749	2,889,146
Insulin	0.15	8,794,510	58,630,069
Penicillin	3.1	2,401,086	774,544
Placebos	0.13	303,634	2,335,645
Vaccines	68	145,611,052	2,141,339
Vitamins	0.73	15,572,446	21,332,117

Category	Cost per PC (\$)	Total Cost (\$)	Total Quantity Sent
Total	—	4,908,044,735	741,351,183

4. Computational Experiments and Results

Four computational experiments were conducted to address the research questions. Experiment 1 evaluates the baseline resilience of the existing network. Experiment 2 assesses the impact of adding one strategically located distribution centre. Experiments 3 and 4 impose maximum service radii of 200 km and 150 km, respectively.

All experiments share identical demand data, cost parameters, and disruption configurations (Table 3). Only network structure varies. Performance is evaluated using total logistics cost (procurement plus transportation) and service level (proportion of demand fulfilled under disruption).

Table 3
Distribution event configuration

Event	Event type	Occurrence	Trigger	Probability
DGMS Failure	Facility state-temporarily closed	Randomly through the first quadrant		40%
DGMS Recovery	Facility state-open	Seven days delay	DGMS Failure	100%
Demand decrease	Demand coefficient = 0.7	Randomly between JUL and AUG		90%
Demand increase	Demand coefficient = 1.1	SEP	Demand decrease	100%
Rainy season	DGMS-Nizwa path temporarily closed	May		70%
End of rainy season	DGMS-Nizwa path reopens	Two days delay	Rainy season	100%

4.1 Network Configuration Outcomes

GFA was used to identify structural adjustments required under imposed constraints rather than to redesign the network entirely. In the baseline configuration, DGMS Muscat supplies 56 institutions and Nizwa supplies 16 (Figure 2a). Allowing one additional DC (Experiment 2), GFA selects Sohar as the optimal location. This redistributes ten northern institutions from Muscat to Sohar while leaving Nizwa unchanged (Figure 2b). Imposing a 200 km service radius (Experiment 3) requires two additional DCs in Sohar and Duqm. DGMS coverage reduces to 41 institutions and Nizwa to 12 (Figure 2c). Reducing the radius to 150 km (Experiment 4) requires four additional DCs (Figure 2d).

A notable structural pattern emerges: a 25% reduction in service radius (200 km to 150 km) doubles the required number of new facilities. This non-linear expansion reflects Oman's dispersed geography.

4.2 Cost Outcomes

Table 4 and Figure 3 reports total logistics cost under disruption-free optimal conditions. Procurement cost remains constant across all experiments; all variation is attributable to transportation.

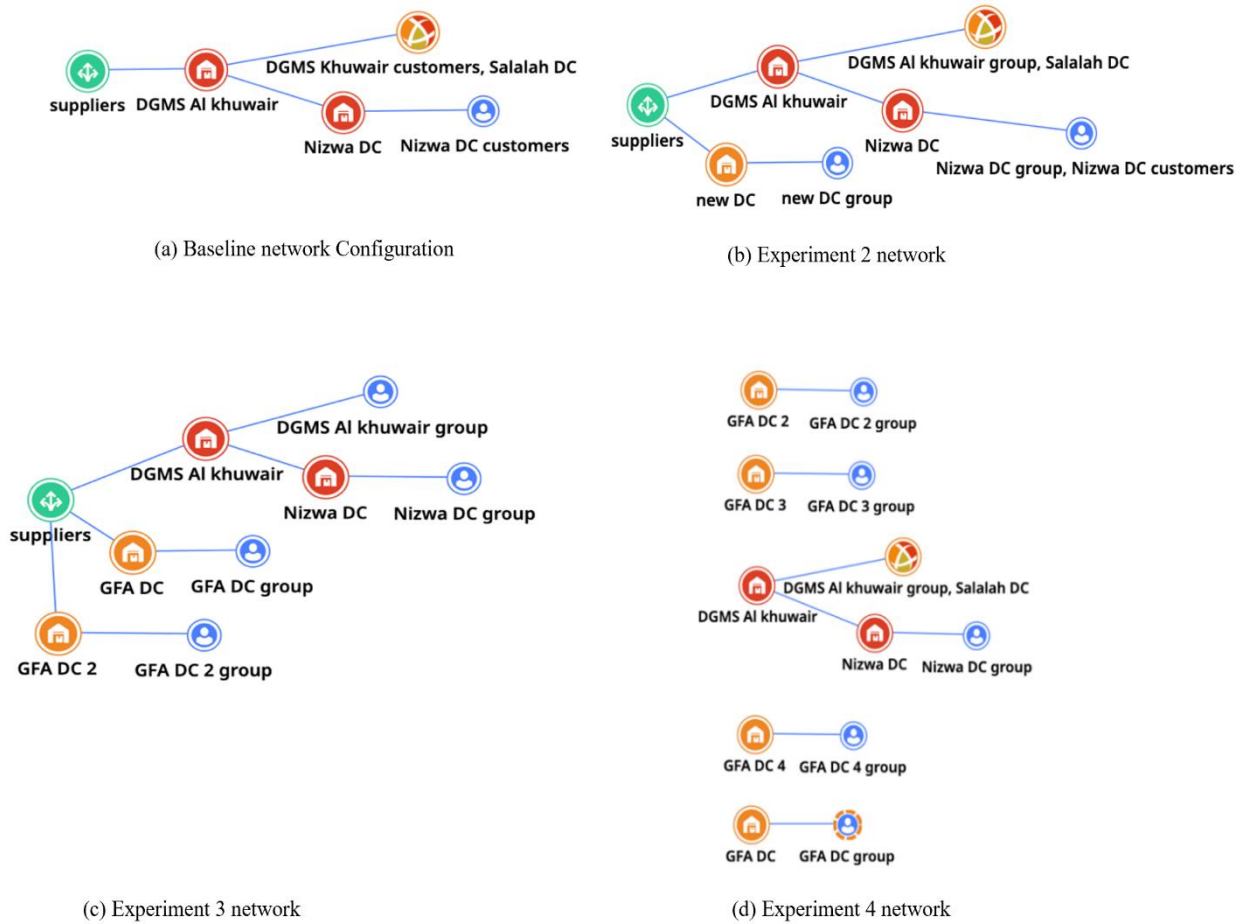


Fig. 2. Configuration of the four experimental scenarios

Table 4

Cost Outcomes (USD) from NO

	Total Cost	Supply Cost	Transport Cost
1 (Baseline)	5,190,991,427	4,907,849,227	283,142,199
2 (+1 DC)	5,222,919,699	4,907,849,227	315,070,472
3 (200km)	5,224,554,557	4,907,849,227	316,705,329
4 (150km)	5,251,848,634	4,907,849,227	343,999,407

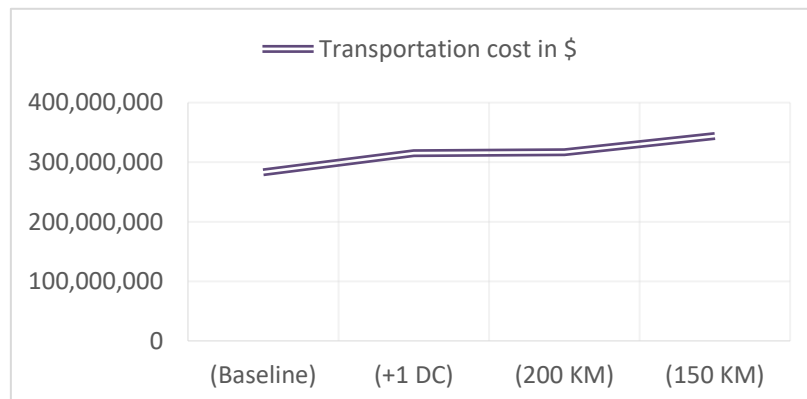


Fig. 3. Transportation cost in USD

Adding a single DC increases transportation cost by 3% [17]. Imposing 200 km and 150 km radii increases transport cost by 9% and 21.5%, respectively [17]. The marginal cost of reducing the radius from 200 km to 150 km is nearly as large as the entire previous expansion. Under disruption-free conditions, decentralization yields no operational efficiency gains.

4.3 Resilience Outcomes

Service-level results under disruption are summarized in Tables 5 and 6.

Table 5
Service Level by Product for Different Experiments

#	Experiment 1		Experiment 2		Experiment 3		Experiment 4	
	Replication	Value	Replication	Value	Replication	Value	Replication	Value
1	R10	0.652	R10	0.434	R10	0.325	R10	0.329
2	R1	0.658	R1	0.465	R1	0.328	R2	0.340
3	R2	0.661	R2	0.471	R2	0.338	R3	0.346
4	R4	0.667	R3	0.459	R4	0.335	R4	0.332
5	R5	0.658	R4	0.467	R5	0.335	R5	0.343
6	R6	0.636	R5	0.455	R6	0.335	R6	0.342
7	R7	0.669	R6	0.466	R7	0.329	R7	0.346
8	R8	0.658	R7	0.466	R8	0.334	R8	0.339
9	R9	0.641	R8	0.466	R9	0.341	R9	0.336
10	-	-	R9	0.450	-	-	-	-

Table 6
Service Level Summary

Experiment	Min	Mean	Max	Transport Cost (USD)
1 (Baseline)	0.636	0.671	0.694	283,142,199
2 (+1 DC)	0.434	0.513	0.598	315,070,472
3 (200km)	0.325	0.404	0.489	316,705,329
4 (150km)	0.329	0.412	0.501	343,999,407

The baseline configuration achieves a minimum service level of 0.636, implying that 36.4% of demand is unmet in the worst replication. While the network demonstrates moderate resilience, this shortfall represents a significant public health risk.

Counterintuitively, all structural expansions reduce resilience. Adding one DC lowers the minimum service level to 0.434. Imposing 200 km and 150 km constraints further reduces minimum service levels to approximately 0.325–0.329. The centralized structure appears to benefit from inventory pooling and operational predictability. Decentralization fragments coverage and reduces cross-coverage flexibility.

Moreover, reducing the service radius from 200 km to 150 km yields no measurable resilience improvement but increases transportation cost by approximately 27.3 million USD. This suggests a resilience threshold at or above 200 km within the Omani geographic context.

4.4 Synthesis of Findings

Three principal findings emerge: (1) The current MOH network is moderately but not sufficiently resilient. A 36% service failure rate under plausible disruptions exceeds acceptable public health tolerance. (2) Network expansion reduces resilience while increasing cost. This challenges the common assumption that decentralization inherently improves robustness in public healthcare logistics. (3) Reducing service radius below 200 km yields zero resilience benefit but substantial cost increase.

This provides a clear, actionable policy implication. MOH should not pursue sub-200 km service targets unless accompanied by investments in surge capacity, inventory redundancy, or dynamic coordination mechanisms. The broader managerial and theoretical implications of these findings are discussed in Section 5.

5. Conclusion

This study developed and validated a simulation-based representation of Oman's MOH pharmaceutical distribution network using AnyLogistix. In collaboration with the DGMS, the model was calibrated using real 2024 operational data and validated against actual procurement expenditure with a relative error of 0.004%. To our knowledge, this constitutes the first peer-reviewed application of AnyLogistix to a national public pharmaceutical supply chain in the WANA region under real-world public-sector data constraints.

The computational experiments yield four principal insights. First, the current MOH network is moderately but not sufficiently resilient. Under three realistic disruption scenarios—facility failure, seasonal demand shifts, and weather-induced route closure—the baseline configuration fulfilled only 63.6% of demand in the worst-performing replication, revealing a material vulnerability not captured by conventional manual risk assessments.

Second, structural decentralization consistently reduced resilience while increasing cost. Adding a single distribution centre decreased minimum service level by 31.8% and increased transportation cost by 3% [17]. Imposing 200 km and 150 km service radius constraints further degraded resilience while increasing transportation cost by 9% and 21.5%, respectively [17]. These findings challenge the common assumption that decentralization inherently enhances robustness. In the Omani context, centralized coordination and inventory pooling appear to provide stability that is weakened when responsibilities are fragmented across additional facilities.

Third, reducing service radius below 200 km produced no measurable resilience benefit. The 150 km configuration increased annual transportation cost by approximately USD 27.3 million without improving service performance relative to the 200 km scenario. This identifies a practical infrastructure threshold for policy planning.

Fourth, the study demonstrates that high-fidelity simulation-based decision support is feasible even under significant data and software constraints. The use of the ALX PLE, combined with transparent parameter estimation, did not prevent the construction of a validated and analytically robust model. Advanced supply chain simulation is therefore accessible to public health ministries in emerging economies.

From a managerial perspective, three implications follow. Infrastructure expansion, particularly sub-200 km service targets, should not be pursued without complementary investments in coordination and surge capacity. Simulation-based “what-if” analysis should be institutionalized as a routine decision-support tool within MOH. Finally, strengthening shipment-level data capture would substantially enhance future modelling precision.

This study has limitations. The exclusion of Dhofar restricts analysis to the northern and central network. Software constrains limited product and facility granularity. Shipment quantities were reconstructed using weight-based assumptions, and disruption mitigation strategies were not optimized. Future research may extend the model to full national coverage, integrate defense and private-sector facilities, and embed multi-objective optimization to identify cost–resilience trade-offs explicitly.

Overall, this work demonstrates that rigorous, validated simulation modelling of public pharmaceutical supply chains is both practicable and policy relevant. Beyond the Omani case, it contributes to the growing recognition of public healthcare logistics as a distinct and strategically important domain for operations research in emerging economies.

Appendices A. Questionnaire

- *Health Facilities Information*

1. Could you provide a complete list of public health facilities in Muscat (hospitals, clinics, health centres)?

2. What are the GPS coordinates or physical addresses of each facility?

3. What are the typical pharmaceutical storage capacities at each facility?

- *Distribution Network and Logistics*

4. Where are the main pharmaceutical warehouses or distribution centres (DCs) located?

5. What are the transportation modes used (e.g., trucks, vans)? Who provides the logistics (MoH-owned, third party)?

6. What are the typical delivery routes and schedules from warehouses to facilities?

7. What is the average lead time for deliveries to different types of facilities?

- *Inventory and Demand Data*

8. What are the top most critical or commonly distributed pharmaceutical items?

9. What are the average monthly demand volumes (units) for key pharmaceuticals at each facility?

10. Are there seasonal or emergency demand spikes (e.g., during flu season or pandemics)?

11. How is stock replenishment triggered—fixed intervals, demand-based, or emergency response?

- *Costs*

12. What are the transportation costs per route, per shipment, or per km?

13. What are the storage and handling costs per pharmaceutical unit or batch?

14. Are there penalties or costs associated with stockouts or late deliveries?

- *Risk and Disruption Information*

15. What types of disruptions have occurred in recent years (e.g., supplier failure, pandemics, transportation issues)?

16. What contingency plans are in place for pharmaceutical shortages or delivery failures?

17. Are there any known bottlenecks or vulnerable points in the current network?

- *Policies and Strategic Goals*

18. Are there current MoH goals or plans for expanding, consolidating, or changing the distribution network?

19. Are there regulatory or compliance constraints on how pharmaceuticals must be stored, handled, or delivered?

Acknowledgement

This research was not funded by any grant.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] C. Årdal, E. Baraldi, P. Beyer, Y. Lacotte, D. J. Larsson, M. C. Ploy and I. Smith, "Supply chain transparency and the availability of essential medicines," *Bulletin of the World Health Organization*, vol. 99, no. 4, p. 319, 2021. DOI: 10.2471/BLT.20.267724.
- [2] D. Ivanov and A. Das, "Coronavirus (COVID-19/SARS-CoV-2) and supply chain resilience: A research note," *International Journal of Integrated Supply Management*, vol. 13, no. 1, p. 90–102, 2020. DOI: 10.1504/IJISM.2020.107780.
- [3] W. W. Jifar, G. B. Geneti and S. D. Dinssa, "The impact of COVID-19 on pharmaceutical shortages and supply disruptions for non-communicable diseases among public hospitals of South West, Oromia, Ethiopia," *Journal of Multidisciplinary Healthcare*, p. 1933–1943, 2022. DOI: 10.2147/JMDH.S377319.
- [4] M. L. S. De La Pava and E. L. Tucker, "Effects of geopolitical strain on global pharmaceutical supply chain design and drug shortages," *European Journal of Operational Research*, 2025. DOI: 10.1016/j.ejor.2025.05.002.
- [5] R. Doroudi, P. Sequeira, S. Marsella, O. Ergun, R. Azghandi, D. Kaeli and J. Griffin, "Effects of trust-based decision making in disrupted supply chains," *PLOS ONE*, vol. 15, no. 2, p. e0224761, 2020. DOI: 10.1371/journal.pone.0224761.
- [6] S. Zandkarimkhani, H. Mina, M. Biuki and K. Govindan, "A chance constrained fuzzy goal programming approach for perishable pharmaceutical supply chain network design," *Annals of Operations Research*, vol. 295, no. 1, p. 425–452, 2020. DOI: 10.1007/s10479-020-03677-7.

- [7] J. M. Lawrence, N. U. I. Hossain, R. Jaradat and M. Hamilton, "Leveraging a Bayesian network approach to model and analyze supplier vulnerability to severe weather risk: A case study of the US pharmaceutical supply chain following Hurricane Maria," *International Journal of Disaster Risk Reduction*, vol. 49, p. 101607, 2020. DOI: 10.1016/j.ijdr.2020.101607.
- [8] F. Lücker, R. W. Seifert and I. Biçer, "Roles of inventory and reserve capacity in mitigating supply chain disruption risk," *International Journal of Production Research*, vol. 57, no. 4, p. 1238–1249, 2019. DOI: 10.1080/00207543.2018.1504173.
- [9] O. Badejo and M. Ierapetritou, "Optimization of pharmaceutical supply chains: Navigating disruptions and operational uncertainty utilizing risk measures," *AIChE Journal*, vol. 71, no. 6, p. e18770, 2025. DOI: 10.1002/aic.18770.
- [10] A. Al Zadjali, S. Nabati and M. Kamran, "Impact of port infrastructure and policies on supply chain efficiency in Oman," *Journal of Maritime Research*, p. 118–126, 2026.
- [11] S. Nabati, R. Babazadeh and M. A. Kamran, "Designing the supply chain of microbial proteins from municipal solid waste and sewage," *Journal of Cleaner Production*, vol. 490, p. 144712, 2025. DOI: 10.1016/j.jclepro.2025.144712.
- [12] J. M. Phuong, J. Penm, B. Chaar, L. D. Oldfield and R. Moles, "The impacts of medication shortages on patient outcomes: A scoping review," *PLOS ONE*, vol. 14, no. 5, p. e0215837, 2019. DOI: 10.1371/journal.pone.0215837.
- [13] D. Ivanov, "Supply chain simulation and optimization with anyLogistix," Berlin School of Economics and Law, 2021.
- [14] W. Klibi, A. Martel and A. Guitouni, "The design of robust value-creating supply chain networks: A critical review," *European Journal of Operational Research*, vol. 203, no. 2, p. 283–293, 2010. DOI: 10.1016/j.ejor.2009.06.011.
- [15] M. Kamalahmadi and M. M. Parast, "A review of the literature on supply chain risk management," *Open Journal of Business and Management*, vol. 4, no. 3, p. 21–33, 2016.
- [16] A. Ghadge, M. Bourlakis, S. Kamble and S. Seuring, "Blockchain implementation in pharmaceutical supply chains: A review and conceptual framework," *International Journal of Production Research*, vol. 61, no. 19, p. 6633–6651, 2023. DOI: 10.1080/00207543.2022.2125595.
- [17] P. Kelle, J. Woosley and H. Schneider, "Pharmaceutical supply chain specifics and inventory solutions for a hospital case," *Operations Research for Health Care*, vol. 1, no. 2–3, p. 54–63, 2012. DOI: 10.1016/j.orhc.2012.07.001.
- [18] N. Shah, "Pharmaceutical supply chains: Key issues and strategies for optimisation," *Computers & Chemical Engineering*, vol. 28, no. 6–7, p. 929–941, 2004. DOI: 10.1016/j.compchemeng.2003.09.022.

- [19] J. Y. Ma, L. Shi and T. W. Kang, "The effect of digital transformation on the pharmaceutical sustainable supply chain performance: The mediating role of information sharing and traceability using structural equation modeling," *Sustainability*, vol. 15, no. 1, p. 649, 2023. DOI: 10.3390/su15010649.
- [20] G. K. Yoseph and Y. Sunitiyoso, "Navigating supply chain risk in the pharmaceutical industry: A bibliographic mapping and systematic review using global supply chain risk framework," *Journal of Global Operations and Strategic Sourcing*, vol. 18, no. 4, p. 670–701, 2025. DOI: 10.1108/JGOSS-06-2024-0050.
- [21] D. Ivanov and A. Dolgui, "A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0," *Production Planning & Control*, vol. 32, no. 9, p. 775–788, 2021. DOI: 10.1080/09537287.2020.1768450.
- [22] F. Alidoost, N. Mustafee, T. Monks and A. Harper, "Simulation in healthcare supply chains with perishable products: A scoping review," *Journal of the Operational Research Society*, p. 1–36, 2025. DOI: 10.1080/01605682.2025.2509698.
- [23] M. A. Kamran, B. Karimi, H. Bakhtiari and S. Masoumzadeh, "A resource allocation model in a healthcare emergency center using goal programming," *Journal of Engineering Research*, vol. 4, no. 4, p. 81–97, 2016. DOI: 10.1016/S2307-1877(25)00891-0.
- [24] R. Lotfi, B. Kargar, M. Rajabzadeh, F. Hesabi and E. Özceylan, "Hybrid fuzzy and data-driven robust optimization for resilience and sustainable health care supply chain with vendor-managed inventory approach," *International Journal of Fuzzy Systems*, vol. 24, no. 2, p. 1216–1231, 2022. DOI: 10.1007/s40815-021-01209-4.
- [25] G. K. Getele and X. Ruoliu, "Service supply chain risk management in the public healthcare sector," *International Journal of Emerging Markets*, vol. 19, no. 11, p. 4259–4285, 2024. DOI: 10.1108/IJOEM-04-2022-0627.
- [26] S. Masoumzadeh, M. Solimanpur and M. Abdollahi Kamran, "A multi-objective fuzzy goal programming P-hub location and protection model with back-up hubs considering hubs establishment fixed costs," *Scientia Iranica*, vol. 23, no. 4, p. 1941–1951, 2016. DOI: 10.24200/sci.2016.3939.
- [27] Y. Yanuarisa, G. Irianto, A. Djamhuri and M. K. Rusydi, "Exploring the internal audit of public procurement governance: A systematic literature review," *Cogent Business & Management*, vol. 12, no. 1, p. 2485411, 2025. DOI: 10.1080/23311975.2025.2485411.
- [28] F. Salehi, M. A. Kamran, S. M. Al-E-Hashem and H. Mohammadi, "Sustainability in organic and non-organic agricultural supply chain: An integrated planning-pricing model with demand dynamics and hybrid metaheuristic optimization," *Transportation Research Part E: Logistics and Transportation Review*, vol. 206, p. 104545, 2026. DOI: 10.1016/j.tre.2025.104545.

- [29] I. Jackson, M. Jesus Saenz and D. Ivanov, "From natural language to simulations: Applying AI to automate simulation modelling of logistics systems," *International Journal of Production Research*, vol. 62, no. 4, p. 1434–1457, 2024. DOI: 10.1080/00207543.2023.2276811.
- [30] R. Babazadeh, H. Taraghi Nazloo and M. A. Kamran, "A hybrid ANN-MILP model for agile recovery production planning for PPE products under sharp demands," *International Journal of Production Research*, vol. 63, no. 2, p. 758–778, 2025. DOI: 10.1080/00207543.2024.2313100.
- [31] S. Khalilpoor, M. A. Kamran and M. Solimanpur, "Resilient COVID-19 vaccine supply chain: An optimization and simulation approach for multi-objective management," *Transportation Research Part E: Logistics and Transportation Review*, vol. 201, p. 104168, 2025. DOI: 10.1016/j.tre.2025.104168.