Optimizing Health Supply Chains in LMICs with Machine Learning: A Case Study in Sierra Leone

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Abstract This chapter overviews the challenges in pharmaceutical supply chains (PSCs) in Low- and Middle-Income Countries (LMICs), with a focus on Sierra Leone. Furthermore, it describes how traditional supply chain optimization strategies can be used to improve performance of PSCs in Sierra Leone. Finally, it describes the significant potential for using machine learning in this framework for effective demand forecasting. We highlight challenges such as limited data availability, the need to ensure equitable distribution, as well as the potential for transfer learning to address some of these challenges.

Keywords Global health · Machine learning · Healthcare supply chains

1 Introduction

According to the World Health Organization (WHO), nearly 2 billion people in the world lack access to essential medicines. Stockouts of essential medicines present a barrier to universal health coverage[1] in Low- and Middle-Income Countries (LMICs), potentially leading to increased avoidable morbidity and mortality, economic losses, and poverty (World Health Organization et al., 2017).

[1] Target 3.8 of the UN Sustainable Development Goals (SDGs).

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Maximizing access to essential medicines requires well-functioning supply chain systems capable of optimally allocating limited supplies to healthcare facilities in alignment with their demand. Inefficiencies in healthcare supply chains can result in stockouts, expired products, delayed deliveries, and other issues that jeopardize people's lives and well-being; furthermore, medicine shortages have the potential to encourage illicit trade of medicines between government hospitals, drug importers, and retailers (Humanitarian, 2012).

Supply chain management has been a well-studied topic in operations management, and there has been interest in applying these techniques to improving healthcare supply chains. For example, previous studies have explored how to reduce costs and improve care in the healthcare industry through lessons learned from the retail industry in the US (Agwunobi and London, 2009). However, a number of unique challenges make it difficult to apply existing strategies to supply chains in LMICs; Project Last Mile—a project aiming to adapt The Coca-Cola Company's supply chain optimization techniques to improve the availability of life-saving medicines in LMICs—has found that translating existing strategies is not straightforward (Linnander et al., 2017, 2018).

In this book chapter, we describe the challenges facing pharmaceutical supply chains in LMICs, with a case study focusing on Sierra Leone, one of the poorest countries in the world (Worldbank, 2022). One of the key challenges in optimizing the pharmaceutical supply chain in Sierra Leone is the high rate of missing data, likely a consequence of low digital penetration and heavy reliance on manual data entry. The unreliable data poses challenges for existing demand forecasting methodologies, which make strong assumptions about data availability.

Machine learning has proven to be an effective, general-purpose prediction methodology for high-dimensional data; accordingly, there has been a great deal of interest in leveraging machine learning for demand forecasting (Ban and Rudin, 2019). We describe how a specific form of machine learning called *transfer learning* (Bastani, 2021) can be applied to demand forecasting pharmaceutical supply chains in LMICs. In particular, it addresses the challenge of missing data by combining data across different locations. Intuitively, this strategy can obtain accurate forecasts even in locations with a large amount of missing data by leveraging trends from similar locations with more complete data. Our recent work in this direction has demonstrated the promise of transfer learning for optimizing the pharmaceutical supply chain in Sierra Leone (Chung et al., 2023).

We begin by surveying the challenges facing pharmaceutical supply chains in developing countries (Sect. 2), with Sierra Leone as an in-depth case study (Sect. 3). Finally, we describe how a combination of supply chain optimization and machine learning can be used to improve supply chain performance (Sect. 4).

2 Pharmaceutical Supply Chains in Developing Countries

In this section, we survey the key challenges in optimizing healthcare supply chains in LMICs compared to more traditional retail supply chains, focusing on pharmaceutical supply chains (PSCs) (Agwunobi and London, 2009; Privett and Gonsalvez, 2014; Yadav, 2015; Yadav et al., 2010):

Limited Data and Lack of Technology Historically, the absence of data collection technologies is a central problem for PSCs in developing countries (Yadav et al., 2010). In particular, information sharing (Aviv, 2001) and access to accurate demand data (Cachon and Fisher, 2000) are often infeasible in LMICs. As a consequence, there is heavy reliance on manual demand forecasting. Unfortunately, manual forecasting can be ineffective (Yenet et al., 2023) since accurately estimating market size is challenging due to limited knowledge about the population (Levine et al., 2008).

Recently, information sharing and data collection technologies have increased in prevalence, as state governments have realized their importance (Bastani et al., 2021; Wong et al., 2023; Saha et al., 2022). However, Saha et al. (2022) points out that challenges such as lack of digital literacy can reduce the effectiveness of these technologies on improving PSCs. For instance, Lugada et al. (2022) finds that in Uganda, despite an emphasis on digitalization, many nodes in their PSC still rely on manual data entry, which can lead to data loss and limit information sharing.

Ineffective Regulatory Agencies A reliable and efficient PSC requires an effective regulation. However, in LMICs, regulatory agencies are often limited by issues such as lack of resources and limited organizational capacity (Yadav, 2015). Regulatory agencies for PSCs in African countries also tend to focus on registration of medicines, neglecting supervision of PSCs (Tetteh, 2009).

Government-Operated Supply Chains In developed countries, patients typically access medicines through retail or hospital pharmacies, which are supplied by a network of private distributors and wholesalers. In contrast, in many LMICs, government-operated PSCs remains the dominant approach. The public nature of these PSCs can pose challenges such as lack of accountability, the bullwhip effect, and limited incentives.

Lack of accountability stems in part from the limited power of regulatory agencies described above. It can be exacerbated by the complexity of PSCs; a study across 13 African countries finds that on average, their distribution model involves three tiers and a large number of stakeholders at each tier (Wong et al., 2023; Lu et al., 2011). This complexity can lead to a lack of accountability among actors in the supply chain (Wong et al., 2023); for instance, each actor may attribute the inefficiency or failure of the supply chain to others (Yadav, 2015). The limited data availability discussed above can also exacerbate lack of accountability, since it makes it difficult to create measurable performance metrics, thereby hindering the ability to hold actors accountable.

Coordinating different actors in public PSCs can also be more challenging. For instance, while contracts can be used to facilitate coordination (Cachon, 2003), these contracts are difficult to leverage in public PSCs since limited regulatory power can make it difficult to ensure compliance (Yadav et al., 2010). The lack of coordination can contribute to the bullwhip effect (Yadav, 2015; Wong et al., 2023), which exacerbates the mismatch between supply and demand and further decreases access to medicine.

Finally, incentives are not always aligned for public PSCs. Political leaders typically have many priorities competing for their attention, and may be more eager to invest in tangible capital projects than in operating expenses such as truck maintenance or driver salary (Yadav, 2015; Adebisi et al., 2022). Similarly, in the public sector, penalties for failure often significantly outweigh rewards for success, which incentivizes a conservative approach that maintains the status quo (Ostroff, 2006). Even when there is a desire to improve PSCs, doing so can be difficult since it often requires skilled labor that may be in short supply (Radnor and O'Mahoney, 2013). Furthermore, changes can pose risks to many stakeholders, necessitating coordination and approvals from all relevant parties.

Long Resupply Interval In contrast to retail supply chains, which tend to have high frequencies of shipments, lead times in PSCs are typically long due to the complex processes that occur at each level of the PSC, often to fulfill regulatory requirements (Yadav et al., 2010). As a consequence, replenishment may only occur every few months, meaning health facilities must accurately forecast demand over a long time horizon, which can be noisy and difficult.

Limited Human Resources and Distribution Points Medications and medical supplies must typically be dispensed at designated locations, due to the need for proper storage facilities; these sites can be limited due to the costs associated with proper storage. Furthermore, in many cases, only qualified pharmacists are permitted to dispense medicines, but qualified pharmacists tend to be scarce in LMICs. Finally, different nodes in PSCs such as distribution centers and warehouses often require skilled staff to operate, and these staff can be in short supply (Yadav et al., 2010).

Potential Solutions Many efforts have been made to enhance PSCs in LMICs to increase access to essential medicines (e.g., Alayande et al., 2016; Chandani et al., 2014; Daff et al., 2014; Seidman and Atun, 2017; Lesego et al., 2023; Vledder et al., 2019). Importantly, improving integration and coordination along components of the PSC has proven to be an effective strategy across multiple African countries (Chandani et al., 2014; Mueller et al., 2016). Despite this progress, there remains a significant need for more powerful data-driven tools that integrate with existing data systems and operational processes to manage various stages of distribution. In the remainder of this chapter, we describe the limitations of existing approaches in the context of a case study on Sierra Leone, and discuss the potential for machine learning to address some of these challenges.

3 Case Study: Sierra Leone

In this section, we describe some of the challenges facing the pharmaceutical supply chain (PSC) in Sierra Leone, based in part on our own discussions with government officials. Sierra Leone is one of the five poorest countries in the world (Worldbank, 2022). The average life expectancy at birth is only 60.8 years, significantly lower than the global average of 73.3 years (WHO, 2020). The child and maternal mortality rates are also among the highest in the world (Carshon-Marsh et al., 2022).[2]

In 2010, the country launched the Free Healthcare Initiative (FHCI) to provide free health care service and medicines for pregnant women and children under five. The National Medical Supplies Agency (NMSA),[3] a part of the Ministry of Health and Sanitation (MoHS), was established to be responsible for ensuring the transparent, cost-effective and timely availability of medical supplies and free healthcare products to every public health facility. However, as of 2019, only 39% of the country has achieved universal health coverage in Sierra Leone (Higgins et al., 2023). The NMSA has been facing difficulties in allocating limited supplies of essential medicines to over a thousand health facilities across the nation. Because of unstable and insufficient supplies, digital immaturity, and technical challenges of demand prediction with limited data, the NMSA currently uses an Excel-based tool to decide the allocation, which is labor-intensive and prone to errors. In 2022 Q1, 42% of the needs across health facilities in the country remained unfulfilled.

3.1 Essential Medicines Allocation in Sierra Leone

Allocation Problem The NMSA allocates essential medicines to health facilities at the beginning of each quarter. They follow a two stage, centralized push system. The allocation is first sent from central government to district first, and then delivered to local health facilities. Each quarter, they allocate around 70–100 free health care products (specifically for women and children under five), depending on the availability of stock and the quantity of medicines donated. Most of the products have a shelf life longer than the lead time.

Health facilities in Sierra Leone are categorized based on the district and the facility type. There are a total of 16 districts, and three types of health facilities—including District Medical Stores (DMS), District Hospitals (DH), and Western Area Hospitals (WAH). Before the allocation is performed, each district puts in a request for how much medicine they need for the next quarter, typically based on their 3 month rolling average of historical demand. DMSs are further categorized

[2] Maternal mortality rates was 510 deaths per 100,000 livebirths; child mortality was 31.1 deaths per 1000 livebirths respectively.

[3] Established and evolved from the National Pharmaceutical Procurement Unit (NPPU) in 2017.

into four sub-types: Community Health Centers (CHC), Community Health Posts (CHP), Maternal and Child Health Posts (MCHP), and Clinics.

Allocation Strategy Once the NMSA has received all of the requests, they first decide the percentage of total stock at their central warehouse to send to each of the three facility types (e.g., 70% to DMS, 15% to DH, and 15% to WAH). The percentage depends on various factors, most notably, whether the product is only for hospital use. Second, the NMSA decides the proportion of the first stage calculation to allocate to each district. For example, if the proportion for DMS at district A is 10%, then this DMS at district A will receive a (total stock) $\times$ 0.7 $\times$ 0.1 quantity. This proportion is chosen based on the product type, district population, and the district's request. Finally, the NMSA will deliver the first mile allocation to all the districts. Each district will complete the last mile to the health facilities based on the product and facility types.

As of the beginning of 2023, the entire process is performed based on a complex Excel tool. While Sierra Leone started using District Health Information Software 2 (DHIS2) (Braa and Muquinge, 2007) to manage health data—including consumption and stock balance—in 2019, the NMSA has had difficulty incorporating this data into their Excel tool to better inform their allocation decisions. As a consequence, the Sierra Leone government could significantly benefit from a new system that enables efficient, data-driven essential medicines allocation.

3.2 Challenges

To develop a more efficient allocation strategy rooted in real needs, we have been working closely with Sierra Leone government officials to better understand the situation they are facing. Here, we summarize several of the key challenges we have identified; these challenges pose methodological challenges, necessitating novel solutions to achieve efficient allocation.

Truck Capacity and Transportation Since the total number of trucks budgeted to deliver medicines is usually insufficient, the NMSA schedules deliveries at different dates for each district. This schedule needs to incorporate political constraints; for instance, if the President or any senior government official is visiting a particular district, then the schedule should align with that visit. Usually, it takes almost a month to complete delivery to all districts for each round of allocation. However, the timeline can be delayed during the flooding season or due to other unexpected events (e.g., political unrest before the election). To account for these uncertainties, the NMSA carefully adjusts delivery dates and tends to overstock during these parts of the year.

Data Infrastructure Sierra Leone has been using mSupply and the DHIS2 system to manage their health supply chain and healthcare data across the country since 2019. mSupply is primarily used for logistics data tracking, such as warehouse management, stock balance, and distribution. In contrast, DHIS2 documents drug consumption, disease cases, and broader healthcare data. Prior to the adoption of these software, most of the data collection and documentation were paper-based or recorded in local Excel sheets. With the government's focus on digitization in recent years, the reporting rate of mSupply and DHIS2 data has been increasing, but it still remains incomplete. On average, approximately 40% of historical monthly drug consumption data at the facility level is missing across essential medicines and medical supplies. In addition, since these two pieces of software are managed by different government entities, they sometimes exhibit inconsistent records that require cautious use of the data.

Warehouse Management In Sierra Leone, all nine central warehouses are located in the capital city, Freetown. The operations of these warehouses have not yet been fully digitalized. Consequently, the counting and tracking of stock is conducted manually, with the data then being entered into mSupply. In addition, the organization of stock within these warehouses can be inconsistent in terms of expiration dates and package sizes. This lack of systematic organization poses challenges for warehouse staff in terms of efficient allocation such as prioritizing expiring products, which can lead to unnecessary waste.

Allocation Policy To ensure security and equity of the allocation, the NMSA enforces a mandatory reserve on a fraction of the total stock, and also imposes an upper bound on the quantity allocated to each facility based on its historical consumption. The NMSA also requires a lower bound on the quantity allocated according to the facility's request, its size and type, the essential medicine in question, and the catchment population of the facility.

Unstable Supply Each quarter, 70%-80% of the essential medicines supply comes from international donors such as UNICEF and FCDO. This supply varies drastically—the standard deviation is often on par with the mean—across different years. Table 1 shows the descriptives of supply from 2022–2023 across six essential medicines.

Human Resources A skilled workforce is critical to optimal performance of all PSC processes and functions. However, the number of staff available to conduct the allocation in Sierra Leone is extremely limited. The NMSA has been relying on

Table 1 Supply descriptive statistics for sample essential medicines from 2022–2023

Product	Amoxicillin	Implant (Jadelle)	Magnesium sulphate
Mean	2,861,950	167,825	20,671
Standard deviation	2,432,835	74,895	20,538
Product	ORS[a]	Oxytocin	Zinc sulphate
Mean	849,419	204,311	12,800,050
Standard deviation	779,711	78,768	13,394,754

[a] Oral rehydration salts

the support of a nonprofit to implement and maintain its current Excel tool and for making allocation decisions. Due to a shortage of human resources and the absence of a reliable information sharing system, the processes for collecting allocation requests from each facility and for counting, picking, and packing stock can be very time consuming. One consequence is that allocation decisions are sometimes made based on requests from the previous quarter instead of the current requests.

4 Optimizing Pharmaceutical Supply Chains

Next, we describe how Sierra Leone's pharmaceutical supply chain (PSC) can be formalized within existing supply chain optimization frameworks. In particular, the allocation problem in the case of Sierra Leone involves a single supplier (the NMSA) and more than 1000 facilities in a multi-echelon supply chain. Every quarter (i.e., every 3 months), the NMSA is responsible for allocating inventory of dozens of essential medicines to the 16 districts, who are then responsible for allocating their supply to individual health facilities.

4.1 Overview

First, in Sect. 4.2, we describe how to formulate this problem as an optimization problem given the demand distribution, and then describe existing approaches for demand forecasting. In particular, the operations management literature has proposed a number of approaches for making optimal allocation decisions (Porteus, 1990; Veinott Jr, 1966; Chen, 2000; Veinott Jr, 1965; Rosling, 1989; Clark and Scarf, 1960; Chen and Zheng, 1997; Graves, 1996; Svoronos and Zipkin, 1988; McGavin et al., 1993). Approaches have also been proposed for improving distributional efficiency and equity (McCoy and Lee, 2014; Jbaily et al., 2020; Gallien et al., 2021).

However, many existing approaches assume the demand distribution is known, which is not true in practice. To address this challenge, data-driven approaches have been proposed for using historical data to approximate the optimal policy (Aviv, 2001; Huh and Rusmevichientong, 2009; Keskin et al., 2023). In addition, robust optimization (Bertsimas and Thiele, 2006) can be used to conservatively account for uncertainty in the demand estimates. In Sect. 4.3, we describe a number of standard strategies used for demand forecasting in LMICs, including the approaches implemented by the Excel tool used in Sierra Leone.

These approaches work well when the demand distribution has a simple structure; however, they require an intractably large amount of data when the demand depends on high-dimensional covariates. In high-dimensional settings, machine learning can be used to predict demand; for example, Ban and Rudin (2019) show the advantages of using feature information and machine learning for a newsvendor problem. Finally, in Sect. 4.4, we describe the challenges and opportunities for using machine learning to improve allocation performance.

4.2 Supply Chain Optimization

Optimization Problem Formulation Our problem is to allocate a limited quantity of a single resource (e.g., a medicine) to a set of facilities (e.g., hospitals, clinics, etc.) and the goal is to minimize the *expected shortfall* (or *unmet demand*)—i.e., the amount of demand from customers (e.g., patients) across facilities for which supply is unavailable. We assume that the amount to be allocated in any given quarter is a constant $a_{\max} \in \mathbb{R}$, and our goal is to allocate this resource across $N \in \mathbb{N}$ facilities. Each facility $n \in [N]$ has demand Ξ_n, where $\Xi \in \mathbb{R}^N$ is a real-valued random vector with distribution $\mathbb{P}_\Xi$. We denote our allocation decision by $a \in \mathbb{R}^N$, where a_n is the allocation intended for facility n. Our objective is the *expected unmet demand*

$$\mathbb{E}_\Xi\left[\sum_{n\in[N]} \max\{\Xi_n - a_n, 0\}\right],$$

which measures the amount of unmet demand on average across facilities and in expectation over Ξ.

Optimization Strategy First, when $\Xi = \xi$ is constant, the optimal policy can be straightforwardly expressed as a linear program. To account for the randomness in Ξ, we use *sample average approximation (SAA)*, which takes K samples $\xi^{(k)} \sim \mathbb{P}_\Xi$ (for $k \in [K]$), and then optimizes the objective on average across these samples. The resulting optimization problem is

$$a^* = \operatorname*{arg\,min}_{a\in\mathbb{R}^N} \frac{1}{K}\sum_{k=1}^{K}\sum_{n=1}^{N} c_n^{(k)} \quad \text{subj. to} \quad c^{(k)} \geq \xi^{(k)} - a, \quad c \geq 0, \quad \sum_{n=1}^{N} a_n \leq a_{\max}, \tag{1}$$

where vector inequalities are element wise; $c_n^{(k)}$ denotes the unmet demand. The first two constraints ensure $c_n^{(k)} = \max\{\xi_n^{(k)} - a_n, 0\}$ (one of the constraints must bind to minimize the objective), and the last ensures the allocation would not exceed total available stock.

Demand Prediction and Distribution So far, we have assumed that the distribution of demand Ξ is known. However, in our problem setting, the demand distribution is unknown. We need to learn a model to predict it from data. To this end, we assume given a dataset $M = \{(x^{(m)}, \xi^{*(m)})\}_{m\in[M]}$, where $x^{(m)} \in \mathbb{R}^d$ is a feature vector (e.g., demand during the last few periods) and $\xi^{*(m)} \in \mathbb{R}^N$ is the demand vector we are trying to predict. As we need a distribution over demand rather than a point estimate to account for the uncertainty, we draw samples from the historical demand distribution.

4.3 Existing Demand Forecasting Strategies

In LMICs, common strategies for demand forecasting include consumption-based approaches, morbidity-based approaches, and proxy consumption approaches (FUND et al., 2016; USAID | DELIVER PROJECT, Task Order 4, 2014; Reproductive and Maternal Health Services Unit, Ministry of Health, 2016).

Consumption-Based Approaches Consumption-based approaches for forecasting demand use historical data to predict future needs. It involves the following steps:

1. *Data collection and analysis:* Determine the list of medicines and their lead times. Collect and analyze historical consumption data and the number of days out of stock.
2. *Forecasting required quantity:* Calculate the average monthly consumption (AMC) using

$$C_A = \frac{C_T}{R_M - M_{OS}},$$

where C_A is the average monthly consumption adjusted for stockouts, C_T is the total consumption across historical periods, R_M is the number of months covered in the historical total consumption calculation, and M_{OS} is the estimated number of months an item experienced stockout during historical periods. This forecast may be adjusted based on anticipated changes. Negative adjustments can be made for potential spoilage, expiration, or pilferage; positive adjustments can be made for supply received from an alternative source.
3. Decide the quantity to order using

$$C_A \times (\text{lead time}) + (\text{safety (buffer) stock}) - (\text{stock on hand}).$$

Adjustments may need to be made based on the availability of the medicines.

This approach relies on access to historical consumption data and the ability to make appropriate adjustments based on expected changes. One issue that must be carefully dealt with is the potential to perpetuate understocking for facilities that have had stockouts in the past; if these stockouts are not properly accounted for, since the average consumption would then be underestimated compared to the true average consumption. In general, other forecasting methods follow similar steps, but differ in terms of their prediction techniques.

Morbidity-Based Approaches These approaches estimate the quantities of medical commodities needed for prevention and treatment based on the prevalence of diseases at a particular region. It usually requires data on catchment population, number of cases of common diseases, and standard treatment patterns of the diseases in consideration. Then, consumption is estimated using

$$Q_T = E_T \times Q_E \times P_T,$$

where Q_T is the total required quantity; E_T is the expected number of treatment episodes, Q_E is the amount of each medicine per treatment episode, and P_T is the number of cases anticipated to receive treatment. Depending on data availability, there are two ways to estimate P_T:

- *Demographic/population based:* We can estimate P_T based on the population served by the health facility and an estimate of the number of people affected by the diseases in question.
- *Service-level based:* We can estimate P_T based on healthcare data such as the number of visits, number of services provided, relevant lab tests conducted, or the number of patients being treated.

Proxy Consumption Method Proxy consumption approaches are an alternative when consumption-based and morbidity-based approaches are infeasible. These approaches extrapolate consumption patterns from one set of facilities to estimate the demand in another set that serves the same type of population in similar geographic and environment.

Current Approach As described in Sect. 3, the Excel-based allocation tool used in Sierra Leone as of early 2023 employs a consumption-based approach while additionally accounting for population factors. However, the complexity of data patterns and the challenges previously highlighted lead to a significant mismatch between estimated and realized demand using their tool.

4.4 Machine Learning

An alternative approach to demand forecasting is to use machine learning to train a predictive model from historical data (Ban and Rudin, 2019). The key advantage of machine learning is that it can incorporate a much larger number of factors for prediction, beyond standard factors such as seasonality effects. Thus, we might hope that machine learning can be used to improve demand forecasts in LMICs by combining multiple sources of information to make better decisions. For instance, rather than base predictions purely on historical data, we may forecast it on a mix of features that includes historical data, catchment population, and demographic

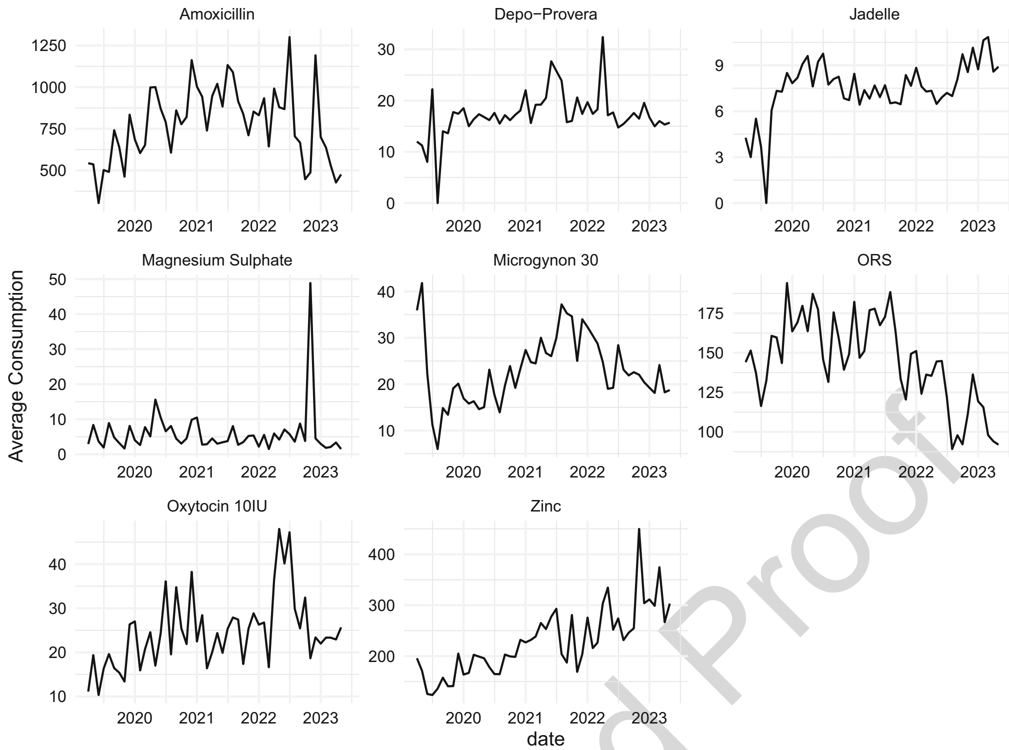

Fig. 1 Consumption patterns for selected essential medicines

features. However, applying machine learning to demand forecasting for Sierra Leone faces several challenges:

- *Small data:* Demand data has only been collected quarterly since 2019, meaning we have very few data points available for each facility-product pair. As a consequence, it is difficult to estimate demand for each facility-product pair separately. This challenge is exacerbated by the highly stochastic demand pattern observed in Sierra Leone. Figure 1 shows that the demand of each facility-product pair fluctuates greatly over time, and the degree of fluctuations also differ greatly across facilities and products.
- *Missing data, demand censoring, and data equity:* Compounding this issue is the substantial amount of missing data, with some pairs having no data at all. In addition, we do not observe demand in excess of available stock; this is also known as the *lost sales problem*. These issues have equity implications because certain regions systematically have lower quality data, meaning they may be consistently understocked. Our framework uses missingness- and censoring-aware learning algorithms from the literature to handle these issues.

Multi-task learning is a form of transfer learning (Bastani, 2021) that can be used to address some of these challenges, especially small and missing data. The basic idea in multi-task learning is to learning a single model across many different tasks, rather than learning a separate model for each task. For demand forecasting, we can use multi-task learning to train a single predictive model across different facilities and products. Intuitively, this strategy shares knowledge across different facilities and medicines to improve predictive accuracy. To capture facility- or medicine-specific effects, we can augment the features with facility features (e.g., facility type, geographic location, etc.) and medicine-specific features (e.g., relevant diseases, purpose, etc.). This strategy has been studied in our recent work (Chung et al., 2023), which demonstrates that multi-task learning is a promising way to improve predictive accuracy.

5 Conclusion

In this chapter, we have described some of the challenges facing pharmaceutical supply chains in LMICs. In addition, focusing on Sierra Leone, we have described how existing supply chain optimization strategies can be applied to reduce unmet demand, and have discussed the potential for machine learning to perform demand forecasting. The insights in this chapter hold the potential to improve performance of essential medicines allocation in resource-constrained settings, and furthermore highlights the potential for using machine learning to improve decision-making problems in traditional operations management settings.

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