Hedging Risks of Demand and Lead Time Variabilities in Healthcare Inventory Management

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This paper proceeds from the premise, derived from the literature, that uncertainty is predominantly a demand-side and/or lead time problem in healthcare inventory management. It conceptually explores how organizational exposure to the risks of uncertain demand and lead time may be hedged, especially considering that forecasting stock-outs and overstocks can be quite challenging in healthcare. We examine these challenges probabilistically. Theoretically, by inquiring into the underlying premises of aggregate demand, order quantity, and reorder point. And practically, regarding the implications of hedging inventory risks under conditions of uncertainty. Three measures that can efficiently hedge against demand and lead time variabilities under a continuous review inventory system are identified and analyzed: safety stock with service level, stock-out and overstock costing, and low-cost reorder point. Mathematical modeling, simulation, and optimization enhance integrated financial and operational problem-solving. With appropriate technology and software, demand forecasting and risk-hedging offer real-time visibility into stock levels. These should help healthcare organizations make critical, data-driven decisions and contain costly understocking and unnecessary overstocking when demand and lead time are stochastic and discreet.

Keywords: inventory, demand, lead time, safety stock, stock-out cost, overstock cost, reorder point

INTRODUCTION

Planning, sourcing, purchasing, storage, and tracking are vital functions in maximizing control, reducing waste, and ensuring the availability of medical supplies and equipment needed for healthcare. After all, the central objective of inventory management in healthcare, like any other industry, is to stock and replenish essential items and products at optimal quantities at optimal times, rates, and prices. That way, total revenue can exceed total cost, and assets are replaced as they wear out (Cleverley et al., 2023).

Stability and predictability of demand (and supply) underpin the basic premises and assumptions built into deterministic approaches and methods in managing inventory items and products. They are considered fixed and constant. Yet, that appears to be the exception rather than the rule in the healthcare sector. Peer-reviewed studies find that variability and unpredictability are more the norms. Forecasting optimality in the quantity, timing, pricing, and holding of inventory in healthcare becomes challenging with unknown or variable demand and/or lead time (Oeser & Romano, 2021).

Han et al. (2011) point to probability, ambiguity, and complexity of treatments and expected health outcomes as main sources of uncertainty. These pertain "to the onset of disease, the benefits and harms of medical treatment, or the practical or personal consequences of illness and its treatment" as well as "misunderstandings of scientific evidence" and "the comprehensibility and coherence of information" (Han et al., 2011, p. 835). Arrow (1963) asserts that vastly intractable uncertainties arise primarily because health is not just a function of (good) healthcare but many other factors. These may include demographics, diet, exercise, work-related issues, environmental and other conditions, preexisting health conditions, and even supply-chain disruptions that are beyond the control of healthcare and can easily result in demand-side variabilities. In this sense, healthcare inventory demand patterns and lead time are generally probabilistic (i.e., stochastic) and discrete (Waters, 2003).

Studies like Poswal et al. (2022) further find that price and supply levels of medical inventory items and products tend to have substantial and reciprocal effects on consumption. The demand function is influenced by price and stock. And because, as Nowicki points out, "a constant demand is unlikely in most healthcare organizations..., the probability of stock-outs and overstocks increases" (Nowicki, 2022, p. 278). For this reason, Knowles (1995) suggests that demand analysis use appropriate measures of consumer expected prices, rather than average or actual prices, and include measures of the degree of price uncertainty in (stochastic and discreet) models which explain both the demand decision to seek care and the choice of provider.

Against the backdrop of the literature on demand variation and lead time uncertainty in healthcare inventories, we chose to undertake this study. We investigate how organizational exposure to these risks can be hedged, especially because "[m]easuring the costs associated with stock-outs and overstocks is admittedly difficult" (Nowicki, 2022, p. 278). We consider these challenges from both a theoretical and practical standpoint. Theoretically, by inquiring into the underlying premises of probabilistic demand, order quantity, and reorder point relative to unit cost. And practically, regarding the implications of hedging inventory risks under conditions of uncertainty.

For these reasons, we examine three integrated operational and financial measures that can hedge against demand and lead time variability: safety stock with service level, probabilistic costing of stock-outs and overstocks, and low-cost reorder point. While it may not make much of a difference for risk-hedging purposes, we approach demand and lead time from a continuous review inventory system commonly used in healthcare with its generally high-volume and costly inventories. Continuous review requires ongoing inventory inspections, so that when stock drops to a predetermined level, a fixed quantity is reordered. The other method, known as periodic review inventory, checks inventory stock only at pre-determined time frame intervals, regardless of the level in which inventory might have dropped. At this time, it is replenished to the maximum (Waters, 2003).

Deterministic Demand and Reorder Point

Because inventory methods and strategies in healthcare were mostly adopted from operations or supply chain management in the manufacturing and retail sectors, restocking medical inventory is initially based on a presumption of regularity: Annual demand, rate of production, availability of inventory, lead time for placing orders to and receiving them from suppliers and vendors, and ordering cost are held fixed and constant. And no discounts are deemed available for quantity orders (Nowicki, 2022). Many healthcare finance textbooks concentrate on so-called "known in time" demand for medical inventory, so that the behavior of the inventory level is expectable. While seemingly "unrealistic" to many healthcare organizations, one assumption underlying deterministic modeling is that demand fluctuations "tend to cancel [each other] out so that seasonal demand, or annual demand, appears constant" (Nowicki, 2022, p. 321).

The deterministic model of reorder point, ROP, is illuminating. Built on the assumption that there is little or no uncertainty in the demand and replenishment of inventory, ROP tracks the minimum stock level or threshold for each inventory item or product at which time stock should be replenished. By triggering a new order, ROP can avoid a stock-out - or even overstocking - while waiting for the next batch to ship and arrive:

$$ROP = (D/365)\text{lead t} \quad (1)$$

Since aggregate demand, D, assumes annual purchases or utilization of the inventory item or product at a consistent level, Eq. (1) can apportion it daily (at 365 days a year) and express ROP in number of days. The resulting quotient is multiplied with lead time, lead t, to account for the days between (re)ordering and receiving the next batch. In other words, the deterministic model is one of D under lead t, with both estimated based on historical averages, in-depth analysis of the supply chain, and supplier performance relative to the inventory item (Ramachandram, 2015).

It should be noted that several stages exist between the decision to purchase and their availability for use by the purchasing (healthcare) organization. Variability in this chain is often unavoidable. Raw materials may not be immediately or sufficiently accessible to the supplier. There could be order processing delays at certain levels. Supplier reliability issues can arise (e.g., in identifying, inspecting, and sending the correct quantity of the item). Delivery might involve long distances and could be hampered by bad weather and other natural and human-caused disturbances. And the purchasing organization itself might commit errors, revise, recall, or subsequently delay orders, including to first resolve consumer and supplier bottlenecks. These give rise to three possible uncertainty scenarios that deterministic modeling will find difficult to incorporate: 1) lead t demand from the purchasing organization is constant (e.g., 1,000 units), but lead t itself varies (e.g., way beyond the expected five days due to supplier delays); 2) lead t is constant (five days on the part of the supplier), but demand, D, fluctuates during lead t (e.g., D suddenly surges or drops during a short-term, public health crisis, causing sharply variable reorders from 1,000 units); or 3) both lead t and D are variable during lead t (i.e., supplier and purchaser are simultaneously dealing with issues related to inventory replenishment) (Oeser & Romano, 2021).

Be that as it may, once ROP is established, the healthcare organization is set to reorder the inventory item or product from the supplier or vendor based on the desired unit quantity, Q, per order (using historical order, inventory, and other relevant data), or based on an economic order quantity, Qe, which is the optimal size of a single (re)order for which ordering and carrying costs can be kept at minimum. Unlike Q, which could vary per reorder, Qe does not depend on unit purchase cost (Olofsson, 2024). At least theoretically, leveraging an item's unique Qe (in lieu of Q) avoids or reduces the probability of having a shortage or surplus of goods, and allows storage of their optimal volume relative to annual demand or purchases, D:

$$Qe = \sqrt{2DO/(IP + 2H)} \tag{2}$$

In Eq. (2), O accounts for the ordering cost, namely the overheads and transaction costs per (re)order. I is the "risk-free opportunity-cost" rate forgone on alternative assets, meaning the associated cost of stocking or keeping inventory of a particular material instead of investing organizational cash flow elsewhere (Raturi & Singhal,1990). H covers the annual holding cost of stocking (e.g., warehousing fees, heating, lighting), securing (with barriers, security cameras, alarms, etc.), and insuring (e.g., risk insurance).

For illustration, let us assume demand D, is known and fixed for medical-grade hydrogen peroxide (3% strength), which is among the most commonly used antiseptics in hospitals and other treatment facilities, especially for disinfecting and treating minor cuts and abrasions, and as a gargle or rinse. To compute for this disinfectant's economic order quantity, Qe, assume further that this hypothetical hospital obtains hydrogen peroxide from a supplier at a fixed price, P, per bottle:

where: P = $6.00/bottle
D = 10,000/year
O = $4.00/order
I = 0.06 risk-free rate
H = $0.10/bottle
lead t = 5 days

$$Q_e = \sqrt{2DO/(IP + 2H)}$$

$$= \sqrt{\frac{2(10{,}000)(4)}{(.06)(6) + 2(0.10)}}$$

$$= 378 \text{ units (bottles)}$$

Reorder point, ROP, is then set by the hospital:

$$ROP = (D/365)\text{lead t}$$

$$= \frac{10{,}000}{365} 5$$

$$= 137 \text{ units (bottles)}$$

Therefore, with aggregate demand, D, held constant, the hospital should reorder 378 bottles of hydrogen peroxide each time inventory goes down to approximately 137 bottles.

However, the academic literature finds that most healthcare inventories are less likely to follow definitive rules. D and/or lead t are oftentimes unknown and variable (Waters, 2003; Oeser & Romano, 2021). Even controlling for the effects of price (uncertainty) on order quantity, Q, probabilistic modeling, rather than deterministic modeling, appears to be better suited to these situations, as it incorporates randomness and uncertainty into its predictions and classifications. It estimates and assigns different probabilities or weights to all potential outcomes. And each random variable can have a corresponding probability distribution. ROP may be determined with constant or variable D and lead t. Q can be set along the same dimensions (Saha & Ray, 2019; Oeser & Romano, 2021). The two major concerns in probabilistic modeling, D variation and lead t uncertainty, thus draw attention to the distribution of D during lead t. Variations beyond these variables can be addressed for the most part by adjusting the timing and size of the next reorder based on unit Q or the economic order quantity, Q_e.

Each of the succeeding three sections is conceptually devoted to a selected, albeit less explored, method or strategy for hedging D and/or lead t variability, along with their intertwining operational and financial implications for healthcare inventory management.

Safety Stock

When aggregate demand, D, is uncertain, and stock level could be depleted at a much faster rate during a given lead time, lead t, healthcare organizations might choose to build in a safety stock level, SS, for an inventoried item or product, assuming it is affordable enough, particularly in terms of ordering and carrying costs. The reorder point, ROP, adds in SS, being the item or product quantity in which ROP would exceed the expected (or average) lead t demand. ROP with SS replaces the deterministic ROP method based on D under lead t. SS can, of course, be replenished separately once it decreases to an organizationally predetermined level. But doing so tends to be costlier, both logistically and price-wise. Either way, SS equals the quantity of the material that the organization will consider holding in stock as a hedge against understocking, but without having to resort to excessive overstocking (Gonçalves et al., 2020). If delivery is delayed (variable lead t), or D increases suddenly or quickly for whatever reason (variable D), SS can also cover for the shortage until the next reorder is placed.

Therefore, a safety stock, SS, determines the probability of and hedges against a stock-out during lead t. The higher the inventory on hand, the likelier D will be met (Gonzatto Junior et al., 2022). Service level, SL, is the complement of this probability. SL is the probability that a stock-out will not be incurred during any lead t (Barrros et al., 2021). An SL = 0.85 indicates an 85% probability that D will be met during lead t and a 15% probability of a stock-out. Stated in another way, the (healthcare) organization, in this example, has chosen to meet D at 85% of D from stock, but has opted not to meet the remaining 15% of (variable) D. Theoretically, D variability requires an infinite SS in order to ensure a 100% SL. But that would be impractical. Anywhere close to 100% becomes prohibitively costly to the organization, although the actual financial or monetary burden would depend on the type of inventory item or product and its purchase price, P (Barrros et al., 2021; Cleverley et al., 2023).

Safety stock, SS, is usually computed based on a preset service level, SL, during lead t. The deterministic SS formula deducts the product of average lead t and average D from the product of lead t and D (Gapenski, 2016). With stochastic and discreet D and lead t, the SS formula needs to incorporate SL and initially determine the number of standard deviations in D to meet such SL. Both measures are intended to mitigate the risk of stock-outs arising from variable D or supply chain delays and disruptions:

$$SS = (Z)(\sigma_d) \sqrt{\text{lead t}} \quad (3)$$

where: z = standard deviations of SL
lead t = lead time
σd = standard deviation of D during lead t

Let us illustrate Eq. (3) using the hypothetical hospital from the preceding section: If the hospital opted to stock hydrogen peroxide at SL = 0.95, the corresponding z-score will be approximately 1.645 (z-score table omitted here). The hospital would need historical order, inventory, and other relevant data to reliably determine aggregate D for peroxide, and then average D at a given time frame (e.g., daily), μd, as well as the standard deviation of demand, σd. Assume μd = 27 bottles daily with σd = 5 peroxide bottles daily. Average lead t = 5 days based on our original illustration. Therefore, given a variable demand for hydrogen peroxide, the hospital needs to keep approximately 18 bottles for a daily safety stock, SS, at a 95% service level, SL:

$$SS = (1.645)(5) \sqrt{5}$$

$$= 18 \text{ units (bottles)}$$

Safety stock, SS, for hydrogen peroxide can then be added to ROP = 137 bottles, so that the next reorder will be placed for 155 bottles. Some healthcare organizations might allow SS to drop below 18 bottles (e.g., at a preset level of 10% less or until 16 bottles are left) for an ROP < 155 bottles, following the rule, "order a replacement unit whenever one is [or some are] used" (Waters, 2003, p. 308). As previously pointed out, cost-savings (e.g., from shipping) would more likely incentivize organizations to integrate SS replenishment with ROP. Regardless of how soon the organization chooses to replace SS, there are ordering and carrying costs to consider in keeping it. And they are not inexpensive.

Probabilistic Costing

While admittedly challenging, the probability of understocking and overstocking due to variabilities in demand, D, and lead time, lead t, maybe probabilistically costed out for the order quantities set by the healthcare organization. Doing so not only helps to better forecast and budget for stock-out and overstock costs. It compels the organization to consider less prominent expenses that it might incur (or even realize savings from), including during lead t when it might start running out of stock, or discover it has excess stock. Probabilistic costing, in this sense, hedges against variability by pointing to item or product cost differences and encouraging the ranking (for opportunity cost) and selection of inventories that might be more or less risky to understock (and overstock), including at certain periods in time.

Direct stock-out costs arise from foregone purchases relative to patient needs and physician prescriptions, thus lost revenue, reduced profit/income margins, and increased supply chain and transportation/delivery costs (e.g., for orders on short notice). To these may be added lost productivity and the cost of handling consumer complaints. Indirect expenses can also be incurred, including from the transaction cost of expediting replenishment orders and (the harder to quantify) reputational damage to the organization due to poor service and failure to meet consumer expectations (Anderson et al., 2006; Yeung, 2023). Besides the risks on revenue, margins, and profitability, consumers might be permanently lost, too, which, in turn, signifies a lost stream of future cash flows (Anderson et al., 2006).

Stock-out cost per unit of inventoried material is traditionally computed from: 1) days out of stock, DOS; 2) average number of units used/purchased by consumers (usually per day), μd; and 3) the selling (i.e., not purchase) price per unit, SP, set by the organization (ICAI, 2021). A fourth component, called the cost of consequences, CO, might be added to the equation by other sectors or industries besides healthcare (ICAI, 2021). It has been omitted here since CO applies only to stock-outs of raw materials or sub-assemblies (e.g., in manufacturing and retail) instead of finished goods in healthcare.

To the three factors we propose to build into Eq. (4) the probability, p, of a stock-out based on order quantity, Q or Qe. Incorporating p provides a second-line of hedging against lead t demand as well as price uncertainty. For each order quantity, p can be established by first taking the unit Q per order subtracted by the average (or mean) order quantity. The difference is then divided by the corresponding standard deviation from the mean to locate the average amount of variability in the order dataset. The resulting quotient matches the k value (or coverage factor) in a probability table (omitted here). The k value determines the confidence level in the data points within a certain standard deviation value. The probability, p ($Q > k$), assigned to the value of a discrete random variable indicates the likelihood of each value of Q. Stock-out cost, S, under conditions of uncertainty may thus be calculated:

$$S = (DOS)(\mu d)(SP)(p) \tag{4}$$

Using our previous hydrogen peroxide illustration of inventory stock:

where: DOS = 5 days
μd = 27 bottles (10,000/365)
SP = \$7.00/bottle
p = 0.05

The stock-out cost per unit, S = \$47.25. This figure represents the lost income from each bottle of hydrogen peroxide priced at \$7.00 for the 5 days that the hospital is out of stock.

S can nonetheless be susceptible to challenge. For one, many hospital or healthcare inventory or materials managers might find it difficult to accurately forecast annual demand, D, in order to average for daily demand, μd, where significant variances or fluctuations exist in historical purchases that skew averaging. This may be the case even after inventory turnover ratios, ITRs, are calculated. Hydrogen peroxide demand during the COVID-19 pandemic exemplifies this issue to a broader extent. Selling price, SP, on the other hand, might continue to be based on the regularity presumption behind rate of production, availability of inventory, lead t, and/or ordering cost if it becomes difficult to anticipate or predict D or lead t (e.g., due to high or rising inflation and interest rates). Some studies further suggest that the likelihood of a stock-out is directly proportional to the frequency of reorder. Specifically, the more often inventory stock is reordered, the more often there is a stock-out probability for the item or product (Arnold et al., 2008). In this case, demand depletes its own supply.

Overstocking can also occur, although likely on a smaller scale, as the literature suggests (Ovezmyradov, 2022). Overstock cost, L, can arise relative to demand-side economics, independent of the interplay of supply chain factors. Inaccurate forecasting of and inadequate inventory planning for (reduced) demand can rack up inventory, especially carrying costs. These can leave the organization with expired or obsolete inventory ("dead stock") and diminish cash flow, further risking the bottom line (Nowicki, 2022).

Calculating unit cost of overstocking is by no means less challenging. One common method initially obtains the difference between average inventory value, μinv (i.e., the total value of an inventory item held during a specific period divided by the number of days during that period) and the target or optimal inventory value during that period as denoted by x^*i. The difference is multiplied by holding cost, H, during the overstock period (for which H may or may not increase). Note: H in Eq. (5) is the cost of holding a single unit of an inventory item or product for a specific period. It covers the costs of storing, securing, and insuring it (Arnold et al., 2008). To complete Eq. (5), the product should be multiplied with the probability of overstocking, similar to stock-out costing, in order to generate unit overstock cost, L:

$$L = (\mu inv - x^*inv)(H)(p) \quad (5)$$

Using again our hydrogen peroxide illustration, let the same values remain: annual demand, D = 10,000 bottles; mean daily demand, μd = 27 bottles; daily standard deviation of demand, σd = 5 bottles; and selling price per bottle, SP = $7.00. But this time around, assume a hypothetical overstock equivalent to 5 days, with a probability, p = 0.04:

where: μinv = $2,100.00 ($7.00/bottle @300 bottles)
x^*inv = $1,400.00 ($7.00/bottle @200 bottles)
H = $0.10/bottle
p = 0.04

Therefore, with an overstock of 100 peroxide bottles, the expected L = $2.80 per unit. This represents unearned revenue per bottle, priced by the hospital at $7.00 per bottle, as it continues to sit in storage for 5 days. L is likely to increase after the lead t of 5 days.

Low-Cost Reorder Point

To mitigate the adverse effects of demand uncertainty in healthcare organizations, including on lead time, lead t, the reorder point, ROP, can be stochastically tracked, but differently from a built-in safety stock, SS, at a particular service level, SL. This alternative method will yield another ROP that the organization might consider useful, especially if it finds SS rather expensive or impractical to keep (and reorder). It consists of estimating the probability, p, of each potential demand level, D, relative to a probable reorder point, ROP, and then computing for the order cost of every corresponding pair or match of D and ROP, with the use of either unit stock-out, S, or overstock, L, cost. To begin with, a matrix should be created for this purpose (Table 1). Assume no safety stock, SS, is opted. The product of the standard deviation of D variability and the z-score associated with a particular service probability is added to the average daily demand, μd, and lead t, in determining demand p in Table 1. All costs corresponding to each pair are added horizontally to find which ROP offers the lowest possible cost to the organization (Berman et.al., 1994).

TABLE 1
EXCESS DEMAND AND LOWER SUPPLY OF INVENTORY ITEM

		Potential demand					
		135	136	137	138	139	
	p	**0.1**	**0.2**	**0.3**	**0.2**	**0.1**	
ROP							**Cost ($)**
135		0	9.45				
136							
137							
138							
139							

Each column in Table 1 indicates the probability, p, of a (consumer or patient) demand level, D, for hydrogen peroxide. D may be equal to, less than, or more than the ROP for which it is paired. We will use for this illustration the same unit stock-out cost, S ($47.25), and overstock cost, L ($2.80) from the preceding section. There is no cost implication because D for 135 bottles equals the ROP in the first vertical cell. However, in the next cell, with D = 136 bottles at p = 0.2, the hospital stock of hydrogen peroxide (ROP = 135) falls short of one unit (or bottle) of the inventoried item, q. The stock-out thus produces a unit cost, UC = $9.45 based on Eq. (6):

$$UC = (S)(p)(q) \tag{6}$$

Conversely, the second row of Table 2 indicates a slightly greater stock of one peroxide bottle (ROP = 136) relative to D =135 bottles, at p = 10%. The added cost to the hospital of a single overstocked unit (or bottle), q, amounts to $0.28 following Eq. (7):

$$UC = (L)(p)(q) \tag{7}$$

The remainder of the cells can be filled using either the stock-out, S, or overstock, L, equation depending on which of the paired values is greater, as exemplified by Tables 1 and 2 (i.e., use S if D is greater than its paired ROP, and L if vice versa). Once all values have been computed, each horizontal ROP row should be tallied to determine total cost, as shown in Table 3. The ROP equivalent to the lowest total cost in the last column of Table 3 triggers the reorder (Berman et.al., 1994). In Table 3, this corresponds to ROP = 139 peroxide bottles (unit cost = $5.04) under conditions of uncertainty. This contrasts with the 137 peroxide bottles we calculated earlier based on the assumption of constant or fixed demand, D, in Eq. (2). Because this is a hypothetical illustration, the two ROPs do not markedly differ.

TABLE 2
EXCESS SUPPLY AND LOWER DEMAND FOR INVENTORY ITEM

	Potential demand					
		135	136	137	138	139	
	p	**0.1**	**0.2**	**0.3**	**0.2**	**0.1**	
ROP							**Cost ($)**
135		0	9.45				
136		0.28					
137							
138							
139							

TABLE 3
DEMAND PROBABILITIES AND LOW-COST REORDER POINT

	Potential demand						
		135	136	137	138	139	
	p	**0.1**	**0.2**	**0.3**	**0.2**	**0.1**	
ROP							**Cost ($)**
135		0	9.45	28.35	28.35	18.90	85.05
136		0.28	0	14.18	18.90	14.18	47.54
137		0.56	0.56	0	9.45	9.45	20.02
138		0.84	1.12	0.84	0	4.73	7.53
139		1.12	1.68	1.68	0.56	0	5.04

It goes without saying that accurate and reliable forecasting methods underpin any probabilistic reorder point, ROP, as they should for safety stock, SS, and service level, SL, as well as stock-out, S, and overstock, L, costs, especially at stochastic and discreet levels. Inventory forecasting typically relies on: 1) the utilization of advanced algorithms and predictive analytics to determine lead t demand and other inventory uncertainties more precisely; 2) the availability and extensiveness of historical order, utilization, and consumption data, market trends, and seasonality to incorporate in these models; and 3) the adoption of machine learning algorithms (and some assert, AI) to continuously improve reliability and gain full access to real-time data (Arnold et al., 2008; Gapenski, 2016).

DISCUSSION

While uncertainties abound relative to supply/ier, item or product pricing, and patient treatment, the academic literature finds that managing inventory risks is predominantly a demand-side issue in much of the healthcare industry. Even with lead time, lead t, uncertainty and supply chain delays and disruptions methodically accounted for, lead t demand is often problematic. This is because the requirements for inventoried items and products are patient-specific, procedure-specific, and provider-specific. However, there is no gainsaying that reduction in lead t can produce significant risk or cost reductions to a healthcare organization (Moon & Choi, 1998; Ouyang & Chang, 2002).

In addressing aggregate demand, D, and lead t variabilities, probabilistic methods and strategies can be (proactively) adopted to contain understocking and overstocking risks. In contrast to deterministic models, which generally assume uncertainties barely exist, or are not significant enough, probabilistic or stochastic modeling acknowledges that unpredictability in D pattern and lead t is more the norm than the exception in healthcare inventories. Essentially, there are three variations to the uncertainty theme, each of which we conceptually explored in this study: 1) constant lead t demand, but lead t is variable; 2) constant lead t, but D fluctuates during lead t; and 3) both lead t and D are variable during lead t.

Three probabilistic strategies were identified and analyzed for this study — though there are certainly a few more — given their joint or intertwining operational and financial implications and because they exemplify the critical importance of managing inventory risks from both ends or a dual-purpose approach under conditions of uncertainty. The first of these three (safety stock, SS, with service level, SL) offers an operational hedge against understocking with potential gain (or loss) outcomes on healthcare inventory. The second one (probabilistic costing of stock-outs and overstocks) represents financial measures whose practical value depend on certain operational arrangements and economic factors. The last (low-cost reorder point) may be considered a blended operational and financial measure intended to establish a new threshold for re-ordering at the optimal price when D and/or lead t uncertainties increase unexpectedly and prove costly. All three nonetheless assume a continuous review inventory policy, rather than periodic review, although no distinction is made between the two approaches in this study. Continuous review is appropriate for high volume and/or critical stock items that characterize most medical inventories. Inventory under this scheme is reviewed constantly, so that once inventory falls to an organizationally preset reorder threshold, a fixed quantity should be ordered. Continuous review is also preferred in healthcare for consistently outperforming periodic review (van Beek, 2023).

A safety stock, SS, strategically opted for by an organization should be replenished based on the service level, SL, the organization has chosen during lead time, t. The probability of a stock-out is generally higher during this time, although understocking may also arise before SS and reorder point, ROP, are reached. The z-score (number of standard deviations needed for SL) offers the advantage of incorporating randomness into the probabilistic SS equation in comparison to the traditional, demand under lead t model of ROP. This first alternative, probabilistic model of ROP is derived by adding SS (inclusive of SL) to demand under lead t. It contains variations in demand and lead t uncertainty. That said, finding the right balance between ordering and holding costs and SS is vital to the risk-hedging value of SS.

Stock-out and overstock costing based on their occurrence probabilities hedges against selling price, and inevitably demand, D, fluctuations that are shown by the literature to be strongly influenced by purchase price and stock (Poswal et al., 2022). The (re)order method used, such as desired unit quantity, Q, per order, or economic order quantity, Qe, could depend largely or solely on price risk. Pricing is also critical in the procurement process, as it influences logistical cost as well as the organization's and supplier's operational decisions (Choi et al., 2017). In this sense, probability costing or forecasting responds to changes in supply and demand driven by economic factors and other variabilities, especially in lead t demand. It equally draws attention to the trade-off between over-ordering and then having to sell excess stock for salvage value, and not ordering enough which can leave an organization short of needed supplies and incapable of providing for patient needs and medical prescriptions at the right time. Defining cost of excess and shortage probabilistically are the organization's marginal costs.

Probabilistic forecasting and costing of stock-outs and overstocks underpin another alternative model of reorder point, ROP. This can be useful when the (healthcare) organization finds it expensive or impractical to maintain and reorder safety stock, SS, at (or even without) a service level, SL. In contrast to the ROP deterministic model based on D under lead t, this second alternative specifies and plots an array of potential demand levels and their respective probabilities against different reorder points or stock quantity. The projected cost for each combination incorporates the stock-out, S, or overstock, L, probabilistic forecast. The objective is to locate out of these combinations or pairs a probabilistic ROP for reordering at the lowest possible cost to the healthcare organization when D patterns and lead t substantially vary. The lowest possible cost is chosen from among the various total cost calculations. One logistical imperative that supports this alternative ROP method is periodic inventory auditing. Automating and digitizing it helps keep data both accurate and current (Khokar, 2023).

Stochastic forecasting is doubtless essential to the measures we have examined in this study. Its methods and techniques consider the entire distribution or spread of potential random values in a way that aggregate demand, D, and replenishment of inventoried items and products are based on the extent of data dispersal in relation to the mean (Buchanan, 2023). Rather than seeking to perfectly predict the future, stochastic modeling strives to identify and understand (or test) possible outcomes. These methods and techniques can be grouped into mathematical, simulation, and optimization models of D uncertainty. The choice of which type of model/s to use would necessarily depend on the inventory question or issue at hand.

Mathematical modeling includes input-output analysis, laplace transformation, inventory theory, and Markov chain analysis (Barrros et al., 2021). For instance, the Markov model sets up so-called inventory states (i.e., low, normal, and excess inventory) and the probability of transitioning from one state to the other. By repeatedly multiplying the transition matrix by itself, each inventory state's steady-state probabilities can be computed to define, adjust, or reverse optimal order quantities, Qs, and reorder points, ROPs. Each one is representative of the long-term behavior of inventory levels. In this case, a steady-state probability of low inventory falling below a given threshold suggests that ROP should be increased or that larger order quantities are needed (Moon & Choi, 1998; Kuntz et al., 2013).

Simulation techniques quantify uncertainty in demand planning with appropriate probability distributions. These techniques can establish the likelihood of different demand and supply scenarios relative to inventory risks. Among them are the Monte Carlo simulation, discrete event simulation, infinitesimal perturbation analysis, event-driven simulation, and continuous simulation. Monte Carlo simulation is the most widely used (Barrros et al., 2021). This simulation computationally generates multiple possible demand scenarios by repeatedly sampling from the different probability distributions. The resulting simulations enhance organizational capacity to objectively and comprehensively assess the range of possible demand, D, outcomes and related risks to minimize carrying costs, prevent or minimize the risk of stock-outs, and enhance supply chain efficiency (Farahani et al., 2011; Kuntz et al., 2013; Buchanan, 2023).

The last stochastic group consists of optimization models that specify and evaluate procedures for maximizing or minimizing objective functions when stochastic problems, for example, of D and lead t uncertainty combinations are considered. These include the heuristics technique, dynamic programming, mixed-integer nonlinear programming, linear programming, and genetic algorithms (meta-heuristic) (Barrros et al., 2021). Heuristic methods are experience-based and generally employed to rapidly find a solution as close as possible to the optimal, especially when mathematical models are slow or fail to do so. Among the most frequently used (meta)heuristic for discrete and continuous review inventory in healthcare is simulated annealing (Barrros et al., 2021), a technique for approximating the global optimum of a given function. Its primary objective is to locate the optimal (re)ordering quantity and time for perishable (e.g., drugs) and non-perishable inventory items and products (Farahani et al., 2011; Atiya et al., 2016).

With reliable and extensive stock inventory and supplier information, and the proper technology and software to analyze them, demand forecasting and risk-hedging offer real-time visibility into stock levels. These allow healthcare organizations to make strategic, data-driven decisions and avoid or contain costly understocking and unnecessary overstocking, especially when D and lead t are stochastic and discreet. Integrating financial and operational problem-solving and decision-making to the extent possible helps, as demonstrated in the hedging measures we chose for conceptual exploration in this study. The future of effectively hedging inventory risks in healthcare is on the horizon. And it looks bright.

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