The Impact of Diversity, Inclusion and Equity Product Offering and Forecast Bias on Supply Chain Decisions

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ABSTRACT

U.S. demographic change brings new product offerings, production planning, and distribution challenges. While many companies embrace diversity, inclusion, and ethnicity product offering, their practice often renders mixed results, potentially negatively impacting their profitability. We offer an interdisciplinary marketing and supply chain perspective in addressing demand distribution change and its impact on inventory and distribution decisions. In addition, we demonstrate the importance of developing culturally adapted inventory and customer analytics models for manufacturing and supply chain distribution. We examine demand forecast bias in the apparel industry through the product demand distribution analysis at the product size level. We propose supply chain solutions to alleviate the situation by product size re-positioning, distribution channel choice, multistage execution plan, lead time and safety stock, and planning and revenue management approach. We also recognize the potential of addressing the problem by better understanding the consumer behavior change process and allowing a more extended period of marketing campaigns. In the apparel industry, the planning and supply chain decisions assume product demand follows a normal distribution. However, our research found that the demand distribution is highly skewed with significant kurtosis. Therefore, during the planning stage, inventory policy must be adjusted to count for the bias in the demand distribution. Moreover, managers can orchestrate other supply chain and marketing solutions such as centralized operation, leading time and safety stock trade-offs, and more extended marketing campaigns to match supply and demand better. Our work offers some analytical and practical approaches to increase a better supply and demand match.

Keywords: *Demand distribution, Diversity, Ethnicity, Forecast bias inclusion.*
JEL Classification: *C53.*

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Highlights of this paper

- Most inventory planning models used in practice assume a normal distribution of demand.
- Yet, our research has shown significant skewness and kurtosis exacerbated by product size proliferation.
- Therefore, managers must orchestrate comprehensive supply chain and marketing solutions to account for the forecast bias.

1. INTRODUCTION

U.S. demographics have become more diverse over the years. Nearly four of 10 Americans identify with a race or ethnic group other than white in the 2020 census data. Another salient trend is the increased diversity in the younger population. According to the U.S. Census, in 2019, for the first time, more than half of the nation's population under age 16 identified as a racial or ethnic minority. Among this group, Latino or Hispanic and Black residents comprise nearly 40% of the population. Businesses embrace this trend by offering more inclusive products. In 2021, Old Navy set out to make clothes shopping more inclusive for women of all body types by launching the "BODEQUALITY" campaign. It ended up with too many extra-small and extra-large items and too few of the rest. A problem that frustrated customers and contributed to falling sales (Kapner, 2022). Old Navy's inclusive push includes offering all clothing styles in sizes 0-30 and XS-4X. The CEO called it the "largest integrated launch" in Old Navy's history and an "important growth driver for … years to come." Despite the initial doubling the number of extended-size customers in the company's database, stores were scrambling to get rid of surplus merchandise- most of which was on opposite ends of the size range (Merritt, 2022).Victoria's Secret decided to shift brand association with female empowerment by introducing new product lines for women of different ethnicities, body types, and ages. Still, the revenue and profit did not catch up (Safdar, 2022). A common problem facing businesses with diversity, equity, and inclusive (DEI) offerings is product mix and stock-keeing units (SKU) proliferation, which usually makes operations less efficient and more costly with more frequent supply-demand mismatches. In the Old Navy's case, it has invested millions of dollars into its size-inclusivity campaign. It developed new technology to design garments that fit well across many body types. It adjusted its supply chain to work with factories that could manufacture across sizes. It changed its pricing strategy so that garments cost the same regardless of size. It also redesigned its stores by not separating plus and straight sizes so that women could shop by style rather than size (Segran, 2022). These efforts were essential to launching the "BODEQUALITY" rollout, but the problem is that it does not know how much inventory to hold in each size for each store. Therefore, stores sold out of medium sizes but were stuck with too many very small and very large sizes, which meant they had to deeply discount those items.

Derivation of companies' production, inventory, and distribution planning policies requires the knowledge of the demographic-based specific demand distribution, which often can't be observed directly. In addition, instruments used in production planning are often culturally insensitive due to not being culturally adapted to reflect differences in body shape and composition across ethnic groups (Patt, Lane, Finney, Yanek, & Becker, 2002), (Kronenfeld, Reba-Harrelson, Von Holle, Reyes, & Bulik, 2010). Therefore, it exacerbates the mismatch problem due to demographic changes in the U.S. population, which has become more racially and ethnically diverse, with blacks, Hispanics, Asians, and other minorities making up 42% of the population (Pew Research Center, 2019). Furthermore, product proliferation that caters to the diverse needs in the market also has caused more challenges in managing inventory and production. In this work, we want to examine the forecast bias introduced in the demand distribution due to more diverse product offerings. We also discuss how this bias is amplified along the supply chain and misleading decisions on procurement, production, and distribution. Moreover, Managers can use other supply chain and marketing solutions such as centralized operation, leading time and safety stock trade-offs, and longer marketing campaigns in an orchestrated fashion to better match supply and demand.

In the following sections, we discuss the background information and literature review in section 2. The data analysis and result were presented in section 3, along with discussion and managerial implications. And in section 4, we discuss future research direction.

2. BACKGROUND AND LITERATURE

Supply and demand mismatches are nothing new in the retail industry. Consumers encounter sales events and piles of surplus products in retail stores almost on a cyclical basis. One of the primaries focuses within supply chain management is to reduce the mismatch by trading off between service level and inventory investment. Delivering the right product at the right size, quantity, location, and time require tremendous coordination among many supply chain subsystems, which include forecasting, order management, supplier management, procurement, production planning and control, warehousing and distribution, and product development. The demand forecast is crucial information in all these subsystem operations that forms the foundation of sourcing, manufacturing, and distribution decisions. Mature products, such as pasta, soup, etc., usually have stable demand and are generally easy to forecast. However, forecasting and related managerial decisions are complicated when the supply of raw materials or the market for the finished product is highly unpredictable (Chopra & Meindl, 2013). Newly introduced products, fashion goods such as those offered at Old Navy and Victoria's Secret, and many high-tech products are examples of products that are difficult to forecast. The demand forecasting challenge is further complicated for the diverse product offerings that lead to product size and packaging change that eventually produces more stock keep units (SKU).

In addition to the intrinsic bias of forecast data, the major shift in the demographics and body shape of the U.S. population exacerbates the challenge in forecasting. According to the U.S. Department of Health and Human Services, the average U.S. woman wears a size 16-18. But plus-size fashion has only recently begun to break through and become included within the mainstream industry. To further complicate the problem, with a diverse population group in the U.S., each ethnic group's body type/size composition also varies greatly. Therefore, in response to the market reality, some retailers offer sizes 00 to 40, a vast variation in product size.

Demand forecast falls into the judgmental prediction category. There are three major approaches to critical predictions, i.e., point forecasts, interval forecasts, and probability density forecasts. We review articles through google scholar using search words demand forecast bias and inventory models. The exact search phrase has been used in "ABI/Infroms Global database" to check relevant articles. Wan and Sanders (2017) state that increased stock-keeping-unit (SKUs) deteriorate decision quality and can introduce forecast bias- the tendency to consistently over or under-forecast into the system. They used balanced panel data and empirically tested the mediation relationship of forecast bias on inventory levels. They found that firms can mitigate the negative effect of product variety on inventory level by using strategies to reduce forecast bias.

As Niu and Harvey (2022) demonstrated, prediction approaches and volatility in past data could lead to higher overall error, making people overconfident and increasing bias. In short, when facing a more volatile demand pattern, people's decision process could lead to even higher bias, which could make inventory decisions, such as order quantity, safety stock, and lead time decisions, less accurate, causing oversupply or loss of sales. In practice, forecast bias is rarely incorporated into inventory calculations. Most mathematical models for determining the amount of on-hand inventory and safety stock required to meet demand assume the normality of forecast errors. The chance of miscalculation of inventory increases as forecasts become more biased. The situation is exacerbated as planning production to the wrong inventory levels further complicates efforts along the entire supply chain. One example from the industry does make mention of the importance of dealing with this issue. Steve, Kuettner, and Cargille (2002) provide a case study of the impact of forecast bias on a product line produced by Hewlett-Packard. Their experiments verified that eliminating demand bias from forecasts resulted in a 20 to 30 percent reduction in inventory while maintaining high product availability levels. Manary and Willems presented a case about Intel setting safety-stock targets in the presence of forecast bias. Managing the forecast bias by directly modifying the raw sales forecast data was not an option because sales and marketing controlled and loaded the data into the manufacturing resource planning system before the planning organization received it. The only adjustment that the planning organization could make was to change the inventory target (Manary & Willems, 2008).

Some of the basic forecast principles that the industry often uses include 1) understanding that forecasts are always inaccurate and should include the expected value of the forecast and a measure of forecast error; 2) long-term forecasts are usually less accurate than short-term forecasts; 3) aggregate forecasts are usually more accurate than disaggregated forests, as they tend to have a minor standard deviation of error relative to the mean; 4) father up the supply chain a company is, the greater is the distortion of information it receives, as evidenced in the bullwhip effect.

Forecast bias comes from several different sources. In the retail industry, forecasts are often a sales goal the marketing department sets rather than a realistic demand appraisal. This practice often leads to positive forecast bias and higher inventory levels. Moreover, the aggregate forecasting model often used in the consumer goods industry depends on accurate data to allocate a high-level forecast to manufacturing plants. Pragmatic methods, such as triangle forecast, could misallocate, resulting in higher bias. Furthermore, the dynamic nature of the business and demand characteristics make it challenging to recenter forecast over time.

We want to examine the highly volatile demand for a fashion product and break down the order at the cloth size level. Using descriptive statistics and visualizing demand distribution, we want to examine the gap between the actual data and the theoretical inventory models used in management, hence bringing awareness of the necessity of recenter, and adjusting demand forecasts to reflect the cultural shift and diverse product offering.

3. METHODOLOGY AND ANALYSIS

3.1. Examine the Actual Demand Distribution

Working with a national sports apparel brand, we have obtained the 2021 demand data for 176 different products. This type of sports apparel typically sells for one season from April to August. Products are sourced from all over the world with lead time varies from six months to three weeks. The demand planning and inventory management practice typically assume product demand follows a normal distribution. We analyze the demand data. The descriptive statics result is presented in Table 1.

As Table 1 has demonstrated that the distribution of demand varies drastically for different sizes of apparel as well as for different gender products. One counterintuitive observation is that the larger cloth sizes, such as men's XXL and 3XL, and women's XL, even though demand is relatively small, the demand shows less variance as indicated in the smaller standard deviation. The most significant COV value, 1.57, is shown in Menswear size XL, while the smallest one, 0.02, is for menswear XXL, as shown in Table 1. In Table 2 we present the combined size result for menswear, womenswear, and overall combined men's and women's wear data.

Another important observation is the skewness and kurtosis in the demand distribution. Very often we define normal distributions with two factors, mean and standard deviation. Skewness is a standard measure of the symmetry of the data, or more precisely, the lack of symmetry. Kurtosis measures whether the data is heavy-tailed or light-tailed compared to the normal distribution.

Table 1. Descriptive statistics about apparel type and size.

Menswear	Mean	Standard deviation	Skewness	Kurtosis	COV
S	47	49	2	1	1.05
M	87	118	3	7	1.35
L	105	161	3	7	1.53
XL	87	136	2	4	1.57
XXL	73	1	0	0	0.02
3XL	9	1	-2	-2	0.11
Womenwear	Mean	Standard deviation	Skewness	Kurtosis	COV
XS	99.8	82.4	1.9	3.4	0.83
S	93	93	1	2	1.01
M	104	113	2	6	1.09
L	55	76	2	7	1.39
XL	81	65	1	0	0.79

For a normal distribution, the skewness value is zero, and any symmetric data should have a skewness near zero. In our data, we have seen the skewness varying in the range of -2 to 7, as shown in Table 1 and 3-13 in Table 2. The negative value for the skewness indicates skewed left, i.e., lower demand volume, and the positive value indicates skewed right, i.e., higher demand volume. A standard normal distribution has a kurtosis of 3 and is recognized as mesokurtic. An increased kurtosis (>3) indicates a "thin" bell curve with a high peak, whereas a decreased kurtosis corresponds to a broadening of the peak and a "thickening" of the tails. As the data shows, almost all the demand distributions do not follow the normal distribution. We further explore the demand distribution by plotting the different demand distributions against the normal distribution with the same mean and standard deviation. The results are shown in Figure 1 through Figure 3. The graph in Figure 1 clearly indicates the non-normal feature of demand distribution of overall products, while Figure 2 and Figure 3 have shown the non-normal characteristics of the demand in men's wear and women's wear respectively.

Table 2. Descriptive statistics about men, women and overall apparels.

Overall		Men_descriptive		Women_descriptive	
Mean	65	Mean	75	Mean	52
Standard error	7	Standard error	12	Standard error	8
Median	32	Median	28	Median	32
Mode	5	Mode	12	Mode	0
Standard deviation	97	Standard deviation	115	Standard deviation	68
Sample variance	9412	Sample variance	13125	Sample variance	4671
Kurtosis	13	Kurtosis	10	Kurtosis	8
Skewness	3	Skewness	3	Skewness	3
Range	640	Range	636	Range	370
Minimum	0	Minimum	4	Minimum	0
Maximum	640	Maximum	640	Maximum	370
Sum	11376	Sum	7266	Sum	4110
Count	176	Count	97	Count	79

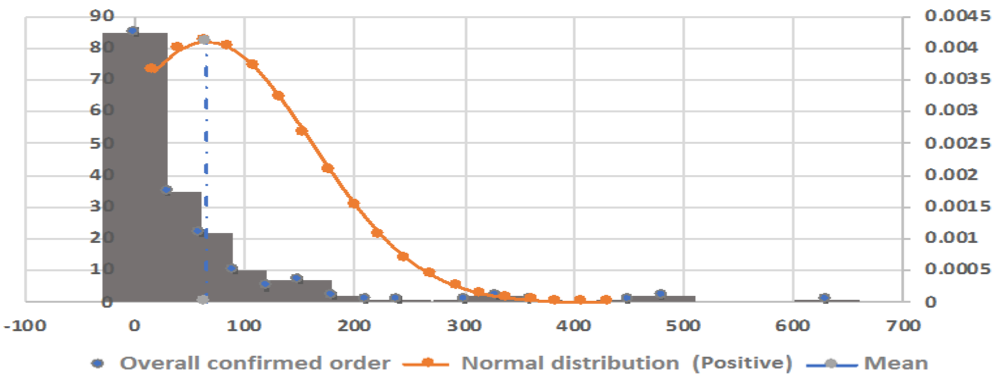

Figure 1. Overall confirmed order quantity.

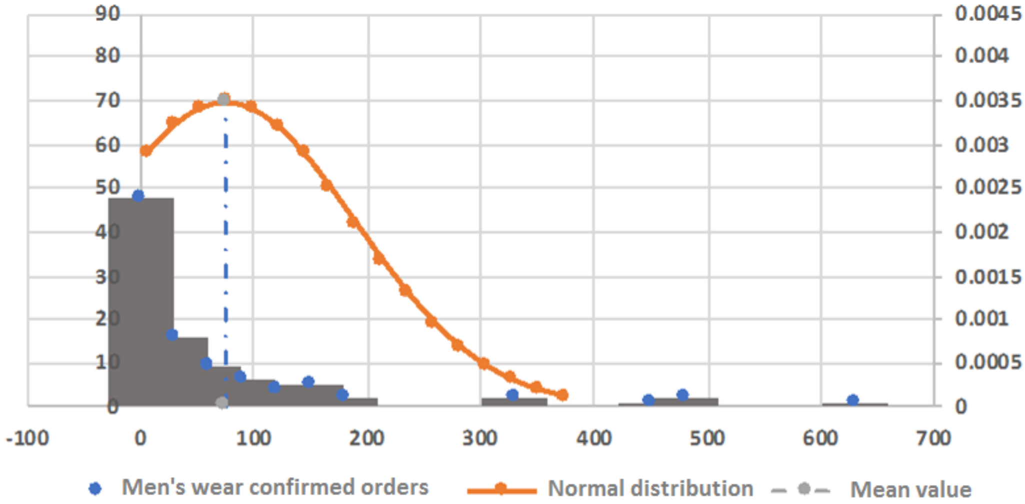

Figure 2. Men's wear confirmed order.

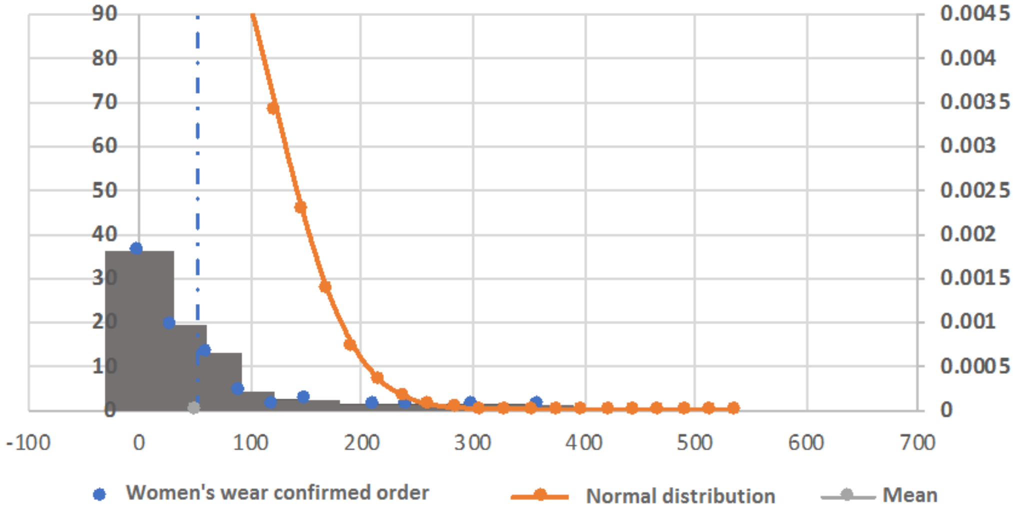

Figure 3. Women's wear overall confirmed orders.

3.2. The Use of Normal Distribution in Planning and Distribution

In production and distribution planning, companies typically use normal distribution in probabilistic models to adjust for uncertainty. With uncertainty rising both from demand and lead time, managers must maintain an adequate service level with safety stock, a buffer stock that usually was added to the reorder point to respond to the fluctuations in demand and supply.

The traditional safety stock model takes into consideration of the mean demand, mean lead time, the variance of demand as well as the variance of lead time. The model assumes forecast errors are independent and randomly distributed according to a Normal Distribution.

$$Safety\ Stock = Z \times \sqrt{L \times \sigma_d^2 + d^2 \times \sigma_l^2}$$

Where Z representing the service level,

L: *is the lead time*.

σ_d^2: *is the variance of demand*.

d: *is daily demand*.

σ_l^2: *is lead time variance*.

It is generally accepted in probability theory that according to the central limit theorem, in many situations, when the population with mean μ and standard deviation σ, and takes sufficiently large random samples from the populations with replacement, the distribution of the sample means will be approximately normally distributed. But in practice, when the forecast errors do not form a normal distribution, companies don't have an effective mechanism to adjust for bias. Moreover, due to the current high variability in the global supply chain, the traditional safety stock formula could lead to a very high level of safety stock and excessive reorder quantities.

In the single-period inventory model, also known as the news vendor model, only one order is placed for a product at each selling period. Any remaining product at the end of the period has little or no value. This is a typical problem for seasonal goods, high-fashion apparel, bakery goods, newspapers, magazines, etc. Because the exact demand for such seasonal products is never known, managers typically use a probability distribution for product demand. More often, a normal distribution would be used.

For product i, with a price of p and sourcing cost of c, and salvage value of s,

$$C_u = cost\ of\ shortage\ (underage\ cost) = p - c$$

$$C_o = cost\ of\ overage = c - s$$

The expected profit maximizing service level is set as $Critical\ ratio = \frac{C_u}{C_o + C_u}$

In this model, the demand is also assumed to follow normal distribution without considering the potential skewness and kurtosis.

This sports apparel company's product characteristics and ordering pattern fall into a single-period inventory model, in which only one order is placed for a product during the selling season. Given the highly biased demand distribution, the news vendor model often fails to provide an effective inventory policy, resulting in over or under-supply in the season.

4. FINDINGS AND DISCUSSION

While improving demand forecast and reducing bias could facilitate better inventory management policies. Other supply chain strategic approaches could also be used for better supply and demand Match.

Over the last few years, brands across the fashion industry have embraced the practice of inclusive size offering to reach large-size customers. Many successful size-inclusive brands tend to be startups selling most of their products online. Universal Standard, an online apparel retailer that sells comfortable wear, has redesigned its product size. While rolling out the products varying in size from 00 to 40, the company has focused on the most common size in the U.S., which is size 18. The brand made the radical decision to make 18, its size "medium", while the rest of the industry uses size 8 (Segran, 2022). This is a very important step in reducing the skewness in the demand distribution. On the contrary, Old Navy's practice was much more aggressive in rolling out inclusive-size products for all its product lines. It developed new technology to design garments that fit well across many body types. In addition, it adjusted its supply chain to work with factories that could manufacture across sizes. It also made entire sizes available at each retail store and changed its pricing strategy so that garments cost the same regardless of size. These practices, though well intended, ignore supply chain strategies for reducing forecast bias, and better responding to demand uncertainty.

1. Not all styles are equally popular. Therefore, taking incremental steps in product offering could reduce overstock risk.

   When expanding the size range, a more gradual multi-stage process could reduce the potential supply and demand mismatch risk and gain important accurate demand data, which could help build a better demand forecast model. In addition, not all styles are equally popular; a portfolio approach with different product characteristics in scaling up size offerings could reduce the potential risk.

2. Leaving out 5% of tail-end products could reduce inventory uncertainty.
   It is an excellent intention to offer all the products to every customer. Yet, it is not customary to design and produce for everyone. The few at either end of the normal curve may be so extreme that an encompassing design could become too large or expensive to make (Tilley, 1993). The military chose to exclude 5% at the small end and 5% at the large end, thus accommodating 90% of the measured population in the military standards. Any other percentile values may be chosen as the company's strategy fits.
3. Offer tail-end products only online.
   In a centralized multi-echelon supply chain, the aggregated inventory level at the central location responds better to the uncertainty of demand due to more accuracy in the aggregated demand forecast. For tail-end products that typically have higher uncertainty in demand data, aggregating the demand forecast and preparing inventory online in a more centralized manner could reduce inventory while also maintaining certain service levels.
4. Using a pricing strategy to leverage the price elasticity and manage revenue.
   Price elasticity tells us that product demand responds to price change. Therefore, while offering price discounts, companies can stay profit positive if the proper pricing strategies are used. In our sports apparel company's case, each product has about 30+ different prices with various offering conditions. Given the difference in demand frequency, different product sizes could adopt different pricing strategies.
5. Reducing lead time to maintain the same service level without increasing safety stock.
   The safety stock and lead time could trade-off at a given service level. Thus, while maintaining the same service level, if the company could focus on logistics operations by reducing the lead time, it could also reduce the safety stock level. Given the extended supply chain, reducing the lead time very often is challenging. But with more American companies re-shoring by moving their production back to the United States, the reduced lead time in transportation could eventually mean reduced safety stock.
6. Allow enough time for consumers to adapt.

Old Navy traditionally offers clothes between sizes 0 and 14. It also provides a plus-size collection featuring styles ranging from 16 to 30. For large-size women, it has been a more common practice for them to turn to retailers that specialize in plus sizing. Even though Old Navy ran a large commercial and public relationship campaigns before the launch of BODEQUALITY, many plus-size women were not used to thinking of Old Navy as their target store. And customers in this plus-size group are extraordinarily ad-blind to brands that are speaking to them for the first time (Garcia-Astolfi, 2022). For Old Navy, this requires multiple tries to connect to the plus sizing group of customers. The initial data has shown that Old Navy has doubled extended-size customers in its database, evidence that inclusive offering could help the company to reach a broader customer base.

Developing culturally adapted inventory and customer analytics models for the supply chain is critical in leading to better overall supply chain performance. A better understanding of forecast bias and its impact on inventory management policy, production, and cost will give supply chain managers the capability to deliver improved customer service levels. In addition, these new models represent a significant incremental step in understanding the complex logistical trade-offs that firms must perform daily to remain competitive in the consumer goods industry. The entire fashion industry is going in inclusivity, and brands willing to go through these growing pains will benefit more in the future.

5. FUTURE WORK

Our work uses a relatively small data set in this study. To better understand the bias in demand distribution given the extended product size and mix, a more extensive data set could offer more insight into inventory policy and demand forecast bias. It will also be helpful to analyze different inventory policies given the centralized and de-centralized supply chain network structure. Detailed trade-off analysis between safety stock, lead time, and network structure could help logistics managers proactively and reactively plan for demand uncertainty. Using a proper pricing model, managers could also explore the revenue, profit, and inventory trade-offs. Overall, we demonstrate the importance of developing culturally adapted inventory and customer analytics models for manufacturing and supply chain distribution.

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