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Linking Demand Forecasting to Operational Outcomes: A Cross-Sectional Supply Chain Analysis of Kenyan Public Hospitals

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ABSTRACT

Operational performance within Kenyan public hospitals has become an issue of growing public and policy concern, particularly in the context of frequent medicine stock imbalances and service delivery inefficiencies. Persistent challenges in balancing drug overstocking and stock-outs point to weaknesses in demand planning within hospital supply chains. This study examines the relationship between demand forecasting practices and operational outcomes in public hospitals in Kenya, using evidence from Siaya County. The research is anchored on the Resource-Based View (RBV) and Network Perspective Theory to explain how internal forecasting capabilities and inter-organizational supply chain relationships influence hospital performance. A cross-sectional survey design was employed involving personnel drawn from procurement, pharmacy, stores, and administrative departments across six public hospitals. Data were analyzed using descriptive statistics, correlation analysis, and linear regression modelling. The findings reveal a strong and statistically significant positive relationship between demand forecasting practices and operational outcomes ($\beta = 0.876$, $p < 0.05$). The model explains approximately 70.1% of the variation in operational performance ($R^2 = 0.701$). These results suggest that hospitals that institutionalize structured forecasting practices within their supply chain systems achieve improved operational efficiency and enhanced service delivery outcomes. The study concludes that strengthening forecasting capabilities is critical for improving drug availability and reducing service disruptions in public healthcare systems. The paper recommends adoption of data-driven forecasting approaches, strengthened supply chain coordination, and integration of digital health logistics systems to enhance healthcare service delivery in Kenya.

Keywords: Demand Forecasting, Healthcare Supply Chain, Operational Performance, Public Hospitals.

INTRODUCTION

concern, particularly in the context of frequent medicine stock imbalances and service delivery inefficiencies. Persistent challenges in balancing drug overstocking and stock-outs point to weaknesses in demand planning within hospital supply chains. This study examines the relationship between demand forecasting practices and operational outcomes in public hospitals in Kenya, using evidence from Siaya County. The research is anchored on the Resource-Based View (RBV) and Network Perspective Theory to explain how internal forecasting capabilities and inter-organizational supply chain relationships influence hospital performance. A cross-sectional survey design was employed involving personnel drawn from procurement, pharmacy, stores, and administrative departments across six public hospitals. Data were analyzed using descriptive statistics, correlation analysis, and linear regression modelling. The findings reveal a strong and statistically significant positive relationship between demand forecasting practices and operational outcomes ($\beta = 0.876$, $p < 0.05$). The model explains approximately 70.1% of the variation in operational performance ($R^2 = 0.701$). These results suggest that hospitals that institutionalize structured forecasting practices within their supply chain systems achieve improved operational efficiency and enhanced service delivery outcomes. The study concludes that strengthening forecasting capabilities is critical for improving drug availability and reducing service disruptions in public healthcare systems. The paper recommends adoption of data-driven forecasting approaches, strengthened supply

chain coordination, and integration of digital health logistics systems to enhance healthcare service delivery in Kenya.

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INTRODUCTION

Across the world, healthcare institutions, both public and private, prioritize high levels of operational efficiency and effective service delivery as core performance indicators *(de Vries & Huijsman, 2011)*. Public hospitals, in particular, are mandated to provide continuous, 24-hour services, which requires accurate planning and timely availability of essential medicines and medical supplies. In this context, demand forecasting plays a critical role in anticipating patient needs, guiding procurement decisions, and ensuring uninterrupted healthcare delivery. Where forecasting systems are weak or inaccurate, hospitals often experience stock imbalances that disrupt service provision and compromise operational outcomes *(Stevenson, 2010)*.

In Kenya, public hospitals face persistent challenges in predicting patient demand patterns and determining appropriate stock levels to meet fluctuating healthcare needs *(Toroitich et al., 2022)*. The difficulty of balancing shortages and excess inventory reflects gaps in supply chain forecasting and planning mechanisms. Ineffective demand forecasting can result in stock-outs, delayed treatments, increased patient waiting times, and overall inefficiencies in hospital operations. Consequently, operational outcomes, such as service reliability, responsiveness, and cost efficiency, are directly affected.

Evidence from national policy and health-system assessments indicates that essential-medicine availability constraints remain a significant barrier to effective service delivery, and stock-outs can contribute to avoidable morbidity and mortality *(Ministry of Health [Kenya], 2014; Toroitich et al., 2022)*. In settings where patients are frequently referred to private pharmacies due to public-facility stock-outs, out-of-pocket costs can deter medicine access and undermine treatment continuity *(Toroitich et al., 2022)*. These challenges highlight systemic weaknesses in forecasting and supply chain planning within Kenyan public hospitals. Against this backdrop, the present study adopts a cross-sectional supply chain perspective to examine how demand forecasting practices are linked to operational outcomes in Kenyan public hospitals.

Hyndman and Athanasopoulos *(2021)* describe demand forecasting as the process of estimating anticipated demand within a defined future timeframe. In a similar vein, Lysons and Farrington *(2016)* explain it as the projection of future production or distribution requirements based on historical data and other variables that may influence organizational outcomes. Demand forecasting is commonly operationalized using quantitative and qualitative approaches, including time-series methods that extrapolate historical patterns and causal (explanatory) methods that model relationships between predictors and the forecast variable *(Chopra & Meindl, 2021; Hyndman & Athanasopoulos, 2021; Lysons & Farrington, 2016)*. Within supply chain management, effective forecasting supports inventory strategies such as just-in-time systems, where materials and components are supplied precisely when required in the production or service delivery process, thereby minimizing holding costs and stock imbalances *(Chopra & Meindl, 2021)*.

Operational performance, on the other hand, refers to how well an organization performs relative to established benchmarks and standards. Neely *(2005)* defines it as an organization's performance measured against predefined criteria including regulatory compliance, waste minimization, and productivity. He further emphasizes that operational performance encompasses indicators of efficiency and effectiveness, forming a framework for assessing how well organizational activities achieve intended objectives. According to Neely *(2005)*, key dimensions of operational performance include efficiency, effectiveness, quality, timeliness, flexibility, cost management, and productivity.

Kaplan and Norton *(1992)*, through the Balanced Scorecard framework, propose that organizational performance should be assessed from four complementary perspectives: financial performance, customer outcomes, internal business processes, and learning and growth. This multidimensional approach ensures a balanced evaluation by integrating short- and long-term goals, financial and non-financial indicators, as well as internal efficiencies and external stakeholder outcomes. Within public healthcare systems, such a framework is particularly relevant for

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examining how supply chain capabilities, such as demand forecasting, translate into measurable operational outcomes.

Stevenson *(2009)* notes that performance concerns within supply chain and inventory systems typically revolve around two key issues: service levels and cost control. From a service perspective, organizations must ensure that the right products are available in the correct quantities, at the appropriate location, and at the required time. From a cost perspective, attention is directed toward minimizing ordering and holding costs. In hospital settings, inaccurate demand forecasting can compromise both dimensions, resulting in stock-outs that affect patient care or excess inventory that strains limited budgets.

Service quality measurement is therefore central to operational success in healthcare institutions *(Asubonteng et al., 1996; Gefen, 2002; Parasuraman et al., 1988)*. Gefen *(2002)* conceptualizes service quality as the gap between patients' expectations and their actual service experience, while Asubonteng et al. *(1996)* similarly define it as the difference between anticipated and perceived service performance. In public hospitals, this gap is often influenced by the reliability of forecasting systems that determine drug availability, staffing levels, and resource allocation.

Operational outcomes in healthcare can be evaluated using indicators such as efficiency, effectiveness, regulatory compliance, cycle time, productivity, and waste reduction *(Abdel-Maksoud et al., 2008; Neely, 2005)*. Improving operational efficiency requires monitoring both input variables (e.g., medical supplies, staff time) and output measures (e.g., number of patients served, treatment outcomes) *(Abdel-Maksoud et al., 2008)*. In public hospitals, efficiency may be reflected in reduced patient waiting times, optimal bed occupancy rates, shorter lengths of stay, timely admissions and discharges, reduced mortality rates, and improved coordination across departments.

Empirical studies in Kenya and comparable settings associate operational performance in health facilities with essential medicine availability, timeliness of service delivery, reduced lead times, and patient satisfaction *(Toroitich et al., 2022)*. These indicators underscore the importance of robust supply chain planning mechanisms.

This study was grounded in two complementary theoretical lenses: The Resource-Based View (RBV) and the Network Perspective Theory, both of which provide a foundation for understanding how demand forecasting capabilities relate to operational outcomes in public hospitals. The Resource-Based View, originally advanced by Edith Penrose *(1959)*, conceptualizes the organization as a bundle of tangible and intangible resources structured to achieve productive purposes. Wernerfelt *(1984)* further developed this perspective by arguing that firms derive superior performance from valuable, rare, inimitable, and well-organized resources and capabilities. RBV therefore emphasizes that sustainable performance improvements arise not merely from possessing resources, but from effectively deploying them through coordinated processes and routines *(Ray et al., 2004)*. In the context of Kenyan public hospitals, demand forecasting systems, data analytics capabilities, skilled personnel, and integrated information systems can be viewed as strategic resources. When embedded within supply chain processes, these capabilities enhance service reliability, cost control, and overall operational efficiency.

Complementing RBV, the Network Perspective Theory, traced to Jacob Moreno's *(1930)* early work on sociograms, emphasizes the importance of relationships among interconnected actors. The theory examines how nodes (individuals, groups, or organizations) are linked through various ties, including communication, formal authority, trust-based relationships, workflow exchanges, and resource flows *(Wasserman & Faust, 1994)*. In supply chain contexts, these ties extend beyond interpersonal relations to include interactions between hospitals, suppliers, government agencies, and regulatory bodies. Effective demand forecasting in public hospitals depends not only on internal capabilities but also on timely information sharing, supplier coordination, and collaborative planning across the healthcare network *(Borgatti & Li, 2009)*.

A key criticism of the Network Perspective Theory is that, although it strongly emphasizes collaboration and knowledge exchange, it offers limited explanation regarding how networks are initiated, structured, or sustained over time. The theory has often been applied in large organizations with complex stakeholder arrangements, potentially limiting its applicability in smaller or less formalized institutional contexts. Additionally, certain informal or tacit dimensions of knowledge sharing may not be fully captured through network analysis

frameworks *(Bosua & Scheepers, 2007)*. Despite these limitations, the theory remains relevant to this study as it helps explain the link between demand forecasting and operational outcomes. In Kenyan public hospitals, effective forecasting depends on coordinated interactions among procurement units, pharmacists, clinicians, suppliers, and government agencies. These interconnected actors form a healthcare supply network whose collaborative functioning enhances forecasting accuracy and responsiveness within the hospital system.

Empirical evidence also underscores the importance of structured inventory practices in improving organizational outcomes. For example, inventory classification approaches(e.g., ABC analysis) have long been

shown to improve inventory control and operational decision-making *(Flores & Whybark, 1986)*.

Kalchschmidt *(2014)* investigated demand forecasting practices among manufacturing firms in Italy and established that forecasting is a critical mechanism for aligning production planning with broader supply chain activities. The study employed a descriptive research design with simple random sampling and utilized both descriptive and inferential statistical methods in data analysis. Findings revealed that many firms adopted Material Requirements Planning (MRP) systems and Economic Order Quantity (EOQ) models to structure their forecasting processes. Operational performance was evaluated mainly in terms of cost efficiency and delivery reliability, and the results demonstrated that firms embedding forecasting within their inventory systems achieved measurable improvements in performance. Despite these contributions, the study was largely confined to a manufacturing context characterized by relatively stable production cycles and predictable demand patterns. Such conditions differ significantly from the healthcare environment, where demand is often uncertain, emergency-driven, and influenced by epidemiological trends.

Evidence from health systems research indicates that supply chain weaknesses, including inadequate forecasting and inventory practices, are associated with essential medicine stock-outs and compromised service continuity *(Leung et al., 2016; Toroitich et al., 2022)*.

The Kenya Health Policy emphasizes the government's commitment through the Ministry of Health to collaborate with public health institutions to ensure timely delivery of medical goods and services as a foundation for quality healthcare *(Ministry of Health [Kenya], 2014)*. Similarly, the Constitution of Kenya *(2010)* mandates the Ministry of Health to formulate policies, set standards, regulate service provision, and create an enabling framework for effective healthcare delivery. Under Kenya's devolved governance structure, county governments are thus responsible for managing county health services, including pharmacies, ambulance services, primary healthcare promotion, food safety licensing, and public health functions such as waste management.

At the operational level, sub-county hospitals prepare annual procurement plans, which are consolidated at the county level. Major pharmaceutical supplies are typically sourced through the Kenya Medical Supplies Authority (KEMSA), while minor items may be procured locally through quotation processes when urgent needs arise. Kenya's public health system continues to face pressures related to access and affordability, with poverty dynamics shaping reliance on public facilities *(Kenya National Bureau of Statistics, 2021)*.

Although universal healthcare was prioritized under the government's Big Four Agenda, persistent medicine availability challenges continue to undermine service delivery in many counties *(Toroitich et al., 2022; Walukana et al., 2021)*. Ensuring uninterrupted drug availability requires robust demand forecasting and coordinated supply chain planning rather than reliance on reactive procurement practices.

Despite significant investments by Siaya County, in collaboration with the World Health Organization, in areas such as service delivery, health governance, infrastructure, and information systems, limited emphasis has been placed on strengthening forecasting-driven supply chain systems. Ministry of Health reports (2025) further indicate that Siaya County has recorded high mortality rates, with malaria and HIV/AIDS among leading causes of death, often exacerbated by medicine unavailability. This context underscores the critical need to examine how improved demand forecasting within hospital supply chains can enhance drug availability, strengthen service delivery, and ultimately improve operational outcomes in Kenya's public healthcare system.

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Statement of the Problem

Public hospitals are mandated to operate continuously, providing round-the-clock healthcare services. To fulfill this responsibility effectively, health facilities must maintain adequate and timely availability of essential medicines and medical supplies. However, inefficiencies in pharmaceutical inventory management remain a persistent challenge in many public healthcare systems, particularly in low- and middle-income countries. Weak demand forecasting practices often lead to imbalances between supply and patient demand, resulting in either overstocking or frequent stock-outs of essential medicines. Such supply chain inefficiencies disrupt healthcare delivery, increase treatment delays, and ultimately compromise operational performance within health facilities (de Vries & Huijsman, 2011; Leung et al., 2016). In Kenya, medicine availability challenges continue to undermine the effectiveness of public healthcare delivery despite ongoing policy reforms aimed at improving access to healthcare services. Studies examining pharmaceutical supply chains in Kenya have reported that medicine stock-outs remain common across public health facilities, often forcing patients to seek medications from private pharmacies where costs may be prohibitive (Toroitich et al., 2022). These supply disruptions are frequently linked to weaknesses in forecasting systems, procurement planning, and coordination across healthcare supply chain actors. The situation is particularly pronounced in counties with high disease burdens such as Siaya County. Located along Lake Victoria, Siaya experiences relatively high prevalence rates of malaria and HIV/AIDS, which place significant pressure on the county's public health facilities. Ensuring reliable availability of essential medicines in such settings requires effective forecasting systems capable of anticipating fluctuating disease patterns and patient demand. However, inconsistent forecasting practices within hospital supply chains often result in unpredictable drug availability and service delivery challenges. These operational challenges have important implications for Kenya's ongoing efforts to achieve Universal Health Coverage (UHC), which seeks to ensure that all individuals have access to essential health services without financial hardship. Evidence from Kenya's UHC pilot implementation indicates that although healthcare access has improved, persistent shortages of medical supplies and medicines continue to constrain service delivery within public health facilities (Walukana et al., 2021). Anchored on the Resource-Based View and Network Perspective Theory, the study investigates how forecasting capabilities and supply chain coordination mechanisms contribute to improved operational efficiency and service delivery within public healthcare institutions. Public hospitals are mandated to operate continuously, providing round-the-clock healthcare services. To fulfill this responsibility effectively, they must maintain adequate levels of essential medicines and medical supplies. Inefficiencies in stock management have been widely associated with disruptions in healthcare delivery and diminished service quality *(Leung et al., 2016; Toroitich et al., 2022)*. A persistent challenge for public hospitals is determining optimal inventory levels that can meet patient demand without resulting in either excess stock or frequent shortages. Achieving this balance between overstocking and stock-outs remains a significant operational concern *(Leung et al., 2016)*. Evidence from Kenyan health-system research indicates that public facilities can experience shortages of critical items, with patients frequently referred to private pharmacies due to stock-outs, and affordability constraints limiting medicine uptake *(Toroitich et al., 2022)*. Against this backdrop, and aligned with the broader objective of linking demand planning to service outcomes, the present study sought to examine the effect of demand forecasting practices on operational performance in public hospitals in Siaya County, Kenya.

METHODOLOGY

Research Design

The study employed a cross-sectional survey research design. According to Cooper and Schindler (2014), a cross-sectional survey involves collecting data at a single point in time to describe and examine the prevailing conditions of a given population. This design was considered appropriate because it enabled the researcher to obtain a comprehensive snapshot of existing demand forecasting practices and operational outcomes across public hospitals in Siaya County. A cross-sectional approach is particularly suitable for gathering primary data from a relatively large population efficiently by selecting a representative sample. It allows for the assessment of attitudes, practices, and institutional processes without the need for prolonged follow-up. By capturing data concurrently from multiple facilities, the design facilitated comparative analysis and strengthened the reliability of findings regarding prevailing supply chain practices. In alignment with the study objective, this design

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provided a practical framework for examining the relationship between demand forecasting practices and operational performance in public hospitals, thereby generating empirical evidence on how forecasting capabilities are linked to service delivery and efficiency outcomes within the county's healthcare system.

Area of study

Siaya County is one of Kenya's 47 devolved units and is situated in the former Nyanza region in the western part of the country. The county is administratively divided into six sub-counties: Ugenya, Ugunja, Gem, Bondo, Rarieda, and Alego-Usonga. Siaya County was selected as the study site due to its documented public health challenges. Reports from the Ministry of Health (2018) indicated that the county recorded among the highest mortality rates in the country, with residents facing an elevated risk of premature deaths largely associated with the high burden of HIV/AIDS and malaria. Furthermore, data from the World Health Organization (2017) ranked Siaya among the counties with the highest HIV prevalence rates nationally, second only to Homa Bay County. These epidemiological realities underscore the critical importance of ensuring consistent availability of essential medicines and efficient supply chain systems within public hospitals. The high disease burden in the county makes it an appropriate context for examining how demand forecasting practices are linked to operational outcomes in public healthcare facilities.

Target Population of the Study

The study targeted a total population of 106 personnel drawn from key functional departments involved in supply chain and operational management across six sub-county hospitals in Siaya County. These facilities included Sigomere Sub-County Hospital, Bondo Sub-County Hospital, Malanya Sub-County Hospital, Yala Sub-County Hospital, Madiany Sub-County Hospital, and Siaya County Referral Hospital. The target population comprised staff from procurement, stores, pharmacy, and hospital administration, as these departments play a central role in demand forecasting and supply chain coordination. Specifically, the population consisted of 34 administrators, 33 pharmacists, 18 procurement officers, and 21 storekeepers. The distribution of the total target population of 106 respondents is presented in Table 2.1.

Table 2.1: Target Population

	Section	**Ungenya (Sigomere SubCounty Hospital)**	**Ugunja (Malanya SubCounty Hospital)**	**Gem (Yala SubCounty Hospital)**	**Bondo (Bondo SubCounty Hospital)**	**Rarieda (Madiany SubCounty Hospital)**	**AlegoUsonga (Siaya County Referral Hospital)**	**Total**
1.	Administration	05	05	05	05	05	09	34
2.	Pharmacy	06	04	03	05	04	11	33
3.	Procurement	03	03	02	03	02	05	18
4.	Stores	03	03	03	03	03	06	21
Total								**106**

Source: Siaya County MoH, (2025)

Sample Size and Sampling Procedure

This section outlines the determination of the study's sample size and describes the sampling procedures employed. The details are presented in the subsections that follow:

Sample Size

The sample size is a representative of a large population (Bryman, 2012). Yamane, (1967) formula was used in determining the sample size. The sample size in each stratum was obtained proportionately. In the field the respondents were selected using random sampling.

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According to Yamane, (1967): $n = \frac{N}{[1+(Ne^2)]}$ ……………………………….Eq.2.1

Where n = is the sample size

N = is the population e = is the error limit (0.05 on the basis of 95% confidence level)

Therefore, $n = 106 / [1 + 106 (0.05)^2]$

$n = 106/1.265$

$n = 84$

Using a population of 106 staff members in public hospitals in Siaya County and considering an error limit of 5%, a sample size of 84 was used in the study. This sample size was representative enough and was spread in each stratum proportionately as illustrated in Table 2.2.

Table 2.2: Sample Frame

	Section	**Population (X)**	**Sample Size X/N x 84**	**Sigomere**	**Malanya**	**Yala**	**Bondo**	**Madiany**	**Siaya County Referral Hospital)**
1.	Administration	34	27	4	4	4	4	4	7
2.	Pharmacy	33	26	5	3	2	4	3	9
3.	Procurement	18	14	2	2	2	2	2	4
4.	Stores	21	17	2	2	2	3	3	5
Total		**106**	**84**	**13**	**11**	**10**	**13**	**12**	**25**

Source: Researcher's own conceptualization, (2025)

Sampling Procedure

In view of the researcher's inability to reach out to the entire population, and in order to gain the advantage of an in-depth study and effective coverage, Yamane formula was used to establish the sample size from the study population.

Stratified proportionate sampling was used to get sample size for each stratum. In the field, respondents were selected using simple random sampling.

Data Collection Instruments

The study used structured questionnaires and interview guide in collecting primary data.

Questionnaires

The questions were based on a 5-point Likert scale. The questionnaire would capture information on the variables and was divided into sections. Preliminary section captured general information of the respondents. The other sections covered information on operational performance, and finally the last section covered information on Demand Forecasting in Siaya County public hospitals.

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Interview Guide

Interview with randomly selected respondents from sample size was used to compliment information derived from the questionnaire items. This was an enhancement to gather information that may not have otherwise been anticipated during the construction of the questionnaire.

Data Collection Procedure

Prior to data collection, the researcher obtained an introductory letter from Jaramogi Oginga Odinga University of Science and Technology to facilitate the acquisition of a research permit from the National Commission for Science, Technology and Innovation (NACOSTI). This authorization allowed access to the selected hospitals for field data collection. Structured questionnaires were distributed to respondents using a drop-and-pick-later approach at their respective workstations to minimize disruption of hospital operations. Follow-up was conducted through telephone calls to remind participants of the agreed collection dates, after which the completed questionnaires were retrieved. In addition, group interviews were organized with selected categories of staff to complement the survey data. Upon collection, all questionnaires were reviewed to ensure completeness and accuracy of responses before proceeding to data coding and analysis.

Pilot Testing

A pilot study was carried out at Kombewa Sub-County Hospital involving staff drawn from the four departments targeted in the main study. Pilot studies are widely recommended to test feasibility and improve instrument quality (van Teijlingen & Hundley, 2001). The purpose of the pilot test was to assess the clarity, relevance, and reliability of the research instruments, as well as to estimate the time required to complete the questionnaire and identify any structural or content-related weaknesses. According to Abuya (2018), between 10% and 30% of the intended sample is adequate for pilot testing in survey research. In this study, 10% of the anticipated respondents were selected for the pilot phase. Consequently, 10 staff members from Kombewa Sub-County Hospital were randomly chosen to participate in the pre-test. Following the pilot exercise, the researcher examined response patterns, evaluated participant feedback, and analyzed preliminary data to detect ambiguities or inconsistencies. The insights obtained were then used to refine and improve the final data collection instruments before the main study was undertaken.

Validity Test

Content validity was used to determine the validity index. Content validity measurement are used to emphasize clarity on what CVI reflects and how it is reported (Polit & Beck, 2006). The questionnaires were given to the two supervisors in the School of Business and Economics to evaluate and rate each item in relation to the objectives as “not relevant” or “relevant” on a scale of the 1-4 such that; 1 = *not relevant*, 2 = *somehow relevant*, 3 = *relevant* and 4 = *very relevant*. Content validity index would then be determined from the supervisors’ agreement scale as K/N, where K being the number of items marked 3 or 4 and N the total number of items assessed.

The rated finding was used to calculate content validity index (CVI) using the formula:

$CVI = {}^{K}/_{N}$ ………………………………………………………. Eq.2.2

Where: K = Total number of items in the questionnaire declared valid by both experts; and N = Total number of items in the questionnaire. This was solved as follows:

$$CVI = {}^{K}/_{N} = \frac{39}{48} = 0.8125$$

The computed instrument content validity index (CVI) was ε=0.8125 > ε=0.7. The computed CVI was greater than the minimum acceptable index of 0.70 as recommended in the survey studies by Amin, (2005) hence the instrument was valid for the study.

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Reliability Test

Reliability of the instrument was checked through split-half reliability coefficient test. The items in the questionnaire was divided into; odd items represented by "x" and even items represented by "y". The scores from both halves would then be correlated. Usually, the internal consistency of a measurement scale is assessed by using Cronbach's co-efficient alpha (Cronbach 1951) which was calculated using Flanagan Formula shown in Eq. 2.3.

$$R_t = 2[1 - \frac{\delta_1{}^2 + \delta_2{}^2}{\delta_t{}^2}] \quad \text{.. Eq.2.3}$$

Where: R_t = Reliability Coefficient of the Test; δ_1= Standard Deviation (S.D.) of Scores of 1st Half; δ_2= Standard Deviation (S.D.) of Scores of 2nd Half; and δ_t= Standard Deviation (S.D.) of Scores of Whole Tests

For overall analysis on reliability using Cronbach's alpha, the items analysed for this study were summed to create the different scores, which formed a scale on which Cronbach's alpha was computed. The computed Reliability Coefficient of the instrument was checked against the minimum acceptable index of 0.70 as recommended in the survey studies by Nunnally and Bernstein (1994).

Reliabilities ranging from 0.5 to 0.60 are usually sufficient for exploratory studies (Nunnally & Bernstein, 1994), while those in the range of 0.70 are acceptable and over 0.80 are good (Sekaran, 2003). The reliability obtained was as summarized in Table 3.3a and Table 2.3b.

Table 2.3(a) Reliability Statistics

Cronbach's Alpha Based on Un-Standardized Items	Cronbach's Alpha Based on Standardized Items	No. of Items
0.834	0.821	48

Source: Survey Data (2025)

Table 2.3(b) Reliability Statistics

Factor	No. of Items	Cronbach's Alpha Based on UnStandardized Items	Cronbach's Alpha Based on Standardized Items
Background	03	0.987	0.983
Demand Forecasting	08	0.863	0.854
Operational Performance	06	0.835	0.819
Overall	48	0.834	0.821

Source: Survey Data (2025)

The overall alpha for the Demand Forecasting items under investigation had a Cronbach's alpha of 0.854 indicating good internal consistency, operational performance had a good Cronbach's alpha coefficient of 0.819.

The minimum alpha for the items was 0.819 while the highest alpha was 0.983 both of which conformed to the project by George and Mallery (2003) thus the items formed a scale that had excellent internal consistency reliability.

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Data Analysis

Upon completion of data collection, the responses were carefully edited, categorized, coded, and entered into a computer for analysis. Statistical analysis was conducted using the Statistical Package for Social Sciences (SPSS), Version 24, which is widely recognized for its robust data management capabilities and ability to perform diverse statistical procedures suitable for both small and large datasets (Muijs, 2004). The study generated both qualitative and quantitative data. Qualitative data obtained from interviews were analyzed using thematic and content analysis techniques to identify recurring patterns and key insights. Quantitative data were analyzed using descriptive and inferential statistical methods. Descriptive statistics included graphical and numerical summaries such as frequencies, percentages, means, and standard deviations to describe the characteristics of the data. Inferential analysis involved correlation and regression techniques to examine the relationship between demand forecasting practices and operational outcomes. Correlation analysis was used to determine the strength and direction of the linear association between variables, while regression analysis was applied to estimate the predictive effect of demand forecasting on operational performance (Mutai, 2000). In addition, Analysis of Variance (ANOVA) was performed to test the overall significance of the regression model. Individual regression coefficients were further examined to assess the extent to which demand forecasting practices significantly influenced operational performance in public hospitals. The study hypothesis was formulated to guide this analytical process as follows:

H_{O1}: Demand Forecasting has no statistically significant effect on operational performance of public hospitals in Siaya County.

The following regression model to establish the relationship between the study variables guided the study:

$Y = \beta_0 + \beta_1 X_1 + e$……………………………………….***Eq.2.4***

Where: Y = Operational Performance; X_1 = Demand Forecasting Practice; e- Error Term; β_0 -represents the Model Constant; and β_1 -are Regression Coefficients.

The regression model assumed independent, identical and normally distributed random variables with a zero mean and a constant variance at 5% significance level.

Diagnostic Tests for Inferential Statistics

Prior to inferential analysis, a series of diagnostic tests were conducted to verify that the data satisfied the underlying assumptions of regression analysis. These assessments included tests for normality, multicollinearity, homoscedasticity, and linearity. Normality of the data distribution was evaluated using the Kolmogorov–Smirnov (K–S) test as part of exploratory data analysis. Numerical normality tests compare observed sample scores with those expected under a normal distribution.

The K–S test is particularly appropriate for sample sizes greater than 50. A non-significant result ($p > 0.05$) indicates that the data do not significantly deviate from normality. In this study, the K–S test yielded $p = 0.55$, which exceeds the 0.05 threshold, confirming that the data were normally distributed. Multicollinearity among independent variables was assessed using pairwise correlation analysis together with Tolerance and Variance Inflation Factor (VIF) statistics. All correlation pvalues exceeded 0.05, indicating no significant intercorrelation among the predictors. This result confirmed the absence of multicollinearity and supported the suitability of the variables for regression modelling. Homoscedasticity was examined using the Breusch–Pagan approach based on the observed R-squared statistic. The resulting p-value (0.3285) was greater than 0.05, leading to acceptance of the null hypothesis of constant error variance. This indicates that the residuals were homoscedastic, a desirable condition for reliable regression estimates. Linearity was assessed by plotting standardized residuals against predicted values. The scatterplot showed no systematic curvature or bowed pattern, and the residuals were symmetrically distributed around the horizontal axis with approximately constant spread. This pattern confirmed that the relationship between the study variables satisfied the linearity assumption required for regression analysis.

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FINDINGS

Descriptive Statistics on Demand Forecasting

Descriptive analysis was done on the effect of demand forecasting practice on operational performance. The results were summarized in table 3.1a

Table 3.1a: Descriptive Statistics for Demand Forecasting Practice and Operational Performance

Demand Forecasting and Operational Performance (Operational Efficiency)	Response				
	N	% Frequency	% Frequency	Mean	Std. Dev
Our constant usage of proper MRP System in our inventory management have led to improved operational efficiency through the pharmacy that is always well	80	75 (60)	25 (20)	2.754	0.354
stocked with required drugs Our constant usage of proper EOQ Model in our inventory management have led to improved operational efficiency through the pharmacy that is always well	80	69 (55)	31 (25)	2.769	0.332
stocked with required drugs The use of MRP System in our inventory management has led to well stocked surgical and non-surgical inventory required by medics hence improved	80	87 (70)	13 (10)	2.716	0.318
The use of EOQ Model in our inventory management has led to well stocked surgical and non-surgical inventory required by medics hence improved	80	84 (67)	16 (13)	2.675	0.322
AVERAGE		**79**	**21**	**2.136**	**0.129**
Demand Forecasting and Operational Performance (Service Delivery)	**N**	**(63) % Frequency**	**(17) % Frequency**	**Mean**	**Std. Dev**
Our constant usage of proper MRP System in our inventory management have led to improved operational efficiency through the pharmacy that is always well	80	77 (62)	23 (18)	2.625	0.401
stocked with drugs required hence improved service Our constant usage of proper EOQ Model in our inventory management have led to improved operational efficiency through the pharmacy that is always well	80	81 (65)	19 (15)	2.763	0.315
stocked with drugs required hence improved service The use of MRP System in our inventory management has led to well stocked surgical and non-surgical inventory required by medics hence improved service	80	85 (68)	15 (12)	2.469	0.116
The use of EOQ Model in our inventory management has led to well stocked surgical and non-surgical inventory required by medics hence improved service	80	83 (66)	17 (14)	2.845	0.347
AVERAGE		**82 (66)**	**18 (12)**	**2.676**	**0.295**

Source: Survey Data (2025*)*

The study sought to investigate the effect of Demand Forecasting practice on operational performance of public hospitals in Siaya County. Table 3.1a shows that majority of Siaya County public hospitals believe that Demand

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Forecasting would have an effect on operational performance of public hospitals in Siaya County, with a mean response of 2.136 (for operational efficiency) within the range of $2.675 \leq \mu \leq 2.769$ at 79% (S.D=.129) and a mean response of 2.676 (for service delivery) within the range of $2.469 \leq \mu \leq 2.845$ at 82% (S.D=.295). This finding is consistent with the findings of Kalchschmidt (2014), Louis (2015), Ngai-Hang et al (2016) and Oballa et al (2015). Kalchschmidst (2014) established that demand forecasting is considered crucial process for effectively guiding several activities within a manufacturing industry. Ngai-Hang et al (2016) found out that manual guesswork in forecasting demand is directly liked to inventory stock outs, the study recommended scientific demand forecasting practices to be adopted to experience improved performances. Oballa et al (2015) established that having accurate future demand would lead to a positive influence on the organizational performances. Louis (2015) recommended proper demand forecasting with efficient coordination within the supply chain.

Descriptive Statistics on Operational Performance

Descriptive analysis was done on operational performance. The results were summarized in table 3.1b

Table 3.1b: Descriptive Statistics for Operational Performance

Operational Performance (Operational Efficiency)	N	% Frequency (Agree)	% Frequency (Disagree)	Mean	Std. Dev
The hospital always handles a large number of out- patient's cases on daily basis	80	55(44)	45(36)	2.933	1.216
It takes the shortest time possible for patients to go through the treatment process (for out-patient)	80	58(46)	42(34)	2.628	1.137
For the last two years the hospital has recorded reduction in mortality rates	80	56(57)	44(43)	2.917	1.313
In-patients cases normally stay in the hospitals for a shorter period before being discharged	80	51(41)	49(39)	3.007	1.144
AVERAGE		**55(44)**	**21(17)**	**2.871**	**1.203**
Performance in Terms of Service Delivery	**N**	**% Frequency (Agree)**	**% Frequency (Disagree)**	**Mean**	**Std. Dev**
The suggestion box is easily accessible to patients	80	60(48)	40(32)	3.726	1.321
On average, patients are always satisfied with the hospital services	80	51(41)	49(39)	4.238	1.421
Action is always taken on feedbacks from the suggestion box	80	76(61)	24(19)	2.416	1.232
On average, patients do get the prescribed drugs in the hospital pharmacy	80	87(70)	13(10)	2.118	1.279
AVERAGE		**69(55)**	**31(25)**	**3.125**	**1.313**

Source: Survey Data (2025)

Table 3.1b shows that majority of Siaya County public hospitals believe that operational performance of public hospitals in Siaya County is good. Specifically, operational efficiency had a mean response of 2.871 within the range of $2.628 \leq \mu \leq 3.007$ at 55% (S.D=1.203). This implies that 55% of the respondents in Siaya County public hospitals do agree that operational efficiency was considerably good. In addition, service delivery was also considerably good at a mean response of 2.522 within the range of $2.118 \leq \mu \leq 2.726$ at 69% (S.D=1.313).

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Inferential Statistics

Hypothesis stated that there is no significant statistical effect of Demand Forecasting practice on operational performance of public hospitals in Siaya County. The effect of Demand Forecasting on operational performance of public hospitals in Siaya County was investigated through linear regression analysis using the model in equation 3.0:

$$P = \beta_0 + \beta_1 X_1 + \varepsilon_1 \quad \text{..............................} \textbf{Eq. (3.0)}$$

where *P* is operational performance, while β_0 is the intercept (a constant), β_1, is the slope associated to the independent variables X_1, and ε is the error term which is assumed to be independent, identical normally distributed random variable with a zero mean and a constant variance. The results were as captured in Table 3.2, Table 3.3, and Table 3.4.

Table 3.2 Model Summary

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.837	.701	.678	.021

Source: Survey Data (2019)

The Model Summary table 3.2 gives the R square (0.701) and Adjusted R square (0.678). Thus, in this model, demand forecasting is predicting 70.1% of the variance in operational performance of public hospitals in Siaya County.

This leaves 29.9% of the variation in operational performance of public hospitals in Siaya County being explained by the error-term or other variables other than demand forecasting. This finding also indicated the model's goodness of fit as exemplified by the coefficient of determination value of (R2 value) of 0.701 adjusted to of 0.678.

The standard error of the estimate, of 0.021 being a measure of standard deviation around the fitted line suggests that about 95% of the prediction error in demand forecasting - operational performance model of public hospitals in Siaya County is less than ±1.96 (0.046) = 0.041.

Table 3.3 ANOVA

Model		df	F-Change	Sig. F-Change	Durbin - Watson
1	Regression	1	9.195	0.001	1.602
	Residual	79			
	Total	80			

Source: Survey Data (2025)

The ANOVA table 3.3 shows that the computed F statistic was 9.195, with an observed significance level (pvalue) of 0.001 which was also less than p<0. 05. This shows that the significance can be extended to 0.01, or 99.99% confidence interval.

The independence of residuals in this model was analysed using Durbin-Watson statistic. Considering a Durbin-Watson statistic of 1.602, it was deduced that there was no serial correlation of the residuals as the values were within the accepted threshold of between 1.5 to 2.5 as was recommended by Hayes, (2013).

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Table 3.4: Regression Coefficients of Demand Forecasting and Operational Performance

Model	Unstandardized Coefficients		Stand. Coef.	t	Sig.
	B	Std. Er.	Beta		
1(Constant)	2.382	.820		2.905	.000
Demand Forecasting	.876	.191	.685	4.578	.000
R	0.837				
R-squared	0.701				
Adjusted R-squared	0.678				
F-statistics	9.195				
Prob(F-statistics)	0.001				

Source: Survey Data (2025)

Considering the hypothesis that there is no statistically significant effect of demand forecasting practices on the operational performance of public hospitals in Siaya County, the results of the regression analysis in, Table 3.4, revealed a strong and statistically significant positive relationship between demand forecasting and operational performance ($\beta = 0.876$, $p < 0.05$). This indicates that improvements in demand forecasting practices are associated with corresponding improvements in hospital operational outcomes. Specifically, the regression coefficient suggests that a one-unit increase in demand forecasting capability is associated with a 0.876-unit improvement in operational performance among public hospitals in Siaya County. Consequently, the null hypothesis was rejected and the alternative hypothesis, which posits that demand forecasting practices significantly influence operational performance, was accepted.

The findings of this study provide empirical support for the theoretical propositions of the Resource-Based View (RBV) and Network Perspective Theory in explaining operational outcomes within healthcare supply chains. From the RBV perspective, demand forecasting capability can be conceptualized as a strategic organizational resource that enhances institutional performance. RBV suggests that organizations achieve superior outcomes when they effectively deploy valuable, rare, inimitable, and well-organized capabilities (Barney, 1991). In the context of public hospitals, forecasting systems, inventory planning tools, data management practices, and skilled supply chain personnel constitute critical internal capabilities that determine how effectively healthcare facilities plan procurement and manage pharmaceutical inventories. The strong explanatory power of the regression model ($R^2 = 0.701$) further reinforces the argument that forecasting capability represents a critical operational resource in healthcare supply chain systems.

The findings demonstrate that hospitals that systematically apply structured forecasting techniques, such as demand planning models, inventory control systems, and data-driven procurement processes, are better positioned to maintain optimal pharmaceutical stock levels and minimize service disruptions associated with medicine shortages or excess inventory. These findings align with earlier studies that emphasize the strategic importance of forecasting for operational performance. For example, Kalchschmidt (2014) established that forecasting is a crucial mechanism for coordinating supply chain activities and guiding operational planning. Similarly, Oballa et al. (2015) demonstrated that accurate demand forecasting contributes significantly to improved performance in healthcare institutions. Other studies have also shown that effective forecasting reduces stock-out costs, enhances inventory optimization, and improves service delivery outcomes (Ngai-Hang et al., 2016; Kisaka, 2016; Louis, 2015; Haruna, 2019). It is therefore evident that structured forecasting improves operational planning and inventory outcomes *(Chopra & Meindl, 2021; Fildes et al., 2009)*. Additionally, evidence from health supply systems links weak inventory management to stock-outs and service disruptions *(Leung et al., 2016; Toroitich et al., 2022)*.

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Beyond traditional forecasting methods such as Material Requirements Planning (MRP) and Economic Order Quantity (EOQ), recent developments in forecasting highlight the role of machine learning and advanced analytics in improving predictive performance *(Sezer et al., 2020)*. In healthcare supply chains, analytics-driven decision support has been increasingly reviewed as a pathway to improve supply responsiveness and operational efficiency *(Subramanian, 2021)*. Contemporary research suggests that AI-driven forecasting systems integrate historical consumption data, epidemiological trends, and real-time demand signals to generate more accurate predictions of healthcare supply requirements. These technologies enable healthcare organizations to optimize inventory management, improve demand forecasting, and streamline procurement processes, thereby enhancing operational efficiency and service delivery outcomes.

Similarly, predictive analytics tools have been shown to transform healthcare supply chains by improving inventory management and enabling more responsive procurement systems. By leveraging machine learning algorithms and real-time data analytics, healthcare supply chains can significantly enhance forecasting accuracy and operational efficiency. In pharmaceutical supply chains, AI-driven forecasting models can outperform traditional forecasting techniques by identifying complex demand patterns and anticipating potential supply disruptions. These advancements suggest that integrating digital forecasting technologies into hospital supply chain systems could significantly strengthen pharmaceutical availability and operational resilience.

The relevance of these findings becomes even more significant when viewed through the lens of Network Perspective Theory, which emphasizes the role of collaborative relationships and information exchange among supply chain actors in influencing organizational performance. Healthcare supply chains are inherently networked systems involving multiple stakeholders including hospitals, pharmaceutical suppliers, procurement agencies, regulatory institutions, and central distribution bodies. Effective demand forecasting therefore depends not only on internal organizational capabilities but also on the quality of coordination and communication across the healthcare supply network.

In the Kenyan context, hospitals depend heavily on the Kenya Medical Supplies Authority (KEMSA) for procurement and distribution of essential medicines. Consequently, forecasting accuracy within hospitals is closely linked to the effectiveness of information sharing and coordination between hospitals and central supply agencies. Weak communication within this network can lead to procurement delays, inaccurate demand projections, and frequent stock-outs of essential medicines.

Qualitative evidence obtained from respondents in this study reinforces this interpretation. One respondent observed that although hospitals attempt to forecast pharmaceutical demand, unpredictable disease outbreaks such as epidemics and pandemics often distort historical demand patterns, resulting in cases of both overstocking and understocking of medicines. In such situations, hospitals may procure quantities that either exceed or fall below actual demand levels, thereby generating inefficiencies in inventory management and negatively affecting service delivery outcomes. Another respondent emphasized that improving demand forecasting systems could significantly reduce cases where patients leave hospitals without receiving prescribed medicines, highlighting the direct relationship between forecasting capability and healthcare service accessibility.

Kenya’s pursuit of Universal Health Coverage has highlighted persistent operational constraints, including medicine availability and facility readiness (Walukana et al., 2021). Stock-outs and affordability barriers can undermine effective access even where service utilization improves (Toroitich et al., 2022). Universal health coverage aims to ensure that all individuals have access to quality healthcare services without financial hardship. Kenya has prioritized UHC as a major health sector reform through national policy initiatives and pilot programs implemented since 2018. However, several studies have noted that persistent supply chain challenges, particularly medicine shortages and delayed procurement processes, continue to undermine the effectiveness of UHC implementation. For instance, evidence from Kenya’s UHC pilot phase shows that although access to healthcare services improved, facilities continued to experience challenges related to inadequate medical supplies and inconsistent pharmaceutical availability.

In this context, strengthening demand forecasting capabilities within hospital supply chains becomes a critical policy priority for achieving sustainable universal health coverage. Accurate forecasting systems can help ensure that essential medicines are available in the right quantities, at the right time, and in the right locations, thereby

supporting continuous service delivery within public health facilities. Furthermore, integrating advanced forecasting technologies such as predictive analytics and AI-based demand modelling could enable healthcare systems to better anticipate disease outbreaks, respond to fluctuations in patient demand, and enhance supply chain resilience.

Overall, the findings of this study suggest that improving demand forecasting systems, through investments in digital forecasting technologies, enhanced data integration, and stronger coordination across healthcare supply networks, can significantly improve operational performance in public hospitals. By strengthening both internal forecasting capabilities (as emphasized by RBV) and external supply chain collaboration mechanisms (as emphasized by Network Perspective Theory), healthcare institutions can improve drug availability, reduce service disruptions, and ultimately enhance the effectiveness of healthcare delivery within Kenya's evolving universal health coverage framework.

SUMMARY OF FINDINGS

The objective sought to establish the effect of Demand Forecasting on Operational Performances of public hospitals in Siaya County. 79% (Mean 2.136: SD=.129) of the public hospital workers believe that demand forecasting influences the level of operational efficiency in public hospitals. 82% (Mean 2.676: SD=.295) of the public hospital workers believe that demand forecasting influences the level of service delivery in public hospitals. The Hypothesis stated that there is no significant statistical effect of demand forecasting practice on operational performance of public hospitals in Siaya County. This was, however, rejected based on the findings which showed that demand forecasting had a statistically significant effect on performance of public hospitals in Siaya County with a coefficient of β=.876. This implies that when keeping the effects of other factors constant, a unit increase in demand forecasting would increase operational performances of public hospitals in Siaya County by 0.876 units.

CONCLUSION

The study sought to establish the effect of Demand Forecasting on Operational Performances of public hospitals in Siaya County. The study finding indicated that Demand Forecasting has statistically significant effect on operational performances of public hospitals in Siaya County. From the findings obtained herein, it was concluded that the efforts a public hospital put in Demand Forecasting as an inventory management practice would eventually become critical in realizing an improved operational performance in terms of service delivery for the patients. Further to this, it was also evident that Demand Forecasting does not necessarily determine operational performance independently but rather in addition to other inventory management practices.

RECOMMENDATION

Objective one sought to establish the effect of Demand Forecasting on Operational performances of Public hospitals in Siaya County. The study thus recommends that accurate demand forecasts should always be done to avoid service delivery disruptions.

Implications for Theory and Practice

Implications for Theory

This study contributes to the growing body of literature on healthcare supply chain management by providing empirical evidence on the role of demand forecasting capabilities in shaping operational outcomes within public hospitals. By integrating the Resource-Based View (RBV) and Network Perspective Theory, the study extends theoretical understanding of how internal organizational capabilities and external supply chain relationships jointly influence healthcare system performance. From the perspective of the Resource-Based View, the findings reinforce the argument that organizational performance improvements are strongly linked to the effective deployment of strategic capabilities rather than merely the possession of resources. In this study, demand forecasting capability emerges as a critical strategic resource within hospital supply chain systems. Forecasting tools, data management systems, and skilled personnel collectively constitute an operational capability that

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enables hospitals to anticipate pharmaceutical demand and manage inventory more efficiently. The statistically significant relationship between demand forecasting and operational performance supports RBV's proposition that well-developed organizational capabilities can generate superior performance outcomes. The findings also expand the application of RBV within the healthcare supply chain context. While RBV has traditionally been applied within manufacturing and private sector organizations, this study demonstrates its relevance within public healthcare institutions where operational capabilities, such as forecasting systems and inventory management practices, play a critical role in service delivery outcomes. In addition, the study contributes to theory by highlighting the complementary role of Network Perspective Theory in explaining healthcare supply chain performance. Healthcare supply chains operate within complex institutional networks involving hospitals, procurement agencies, pharmaceutical suppliers, regulatory bodies, and logistics providers. Effective forecasting therefore depends not only on internal organizational competencies but also on the strength of relationships and information exchange across the supply network. The findings, therefore, demonstrate that forecasting effectiveness is partly influenced by coordination between hospitals and supply chain actors such as the Kenya Medical Supplies Authority (KEMSA). Weak coordination or delayed information sharing within this network can reduce forecasting accuracy and contribute to medicine shortages. By illustrating how forecasting capability operates both as an internal resource and a network-dependent operational process, this study contributes to the theoretical integration of RBV and Network Perspective Theory within healthcare supply chain research. Furthermore, the study highlights the growing importance of digital supply chain capabilities, including predictive analytics, artificial intelligence, and integrated health logistics information systems, in improving forecasting accuracy. Incorporating such technological capabilities into theoretical frameworks may provide new directions for future research on healthcare supply chain resilience and operational efficiency.

Implications for Practice

The findings of this study also have significant practical implications for healthcare managers, supply chain practitioners, and policy makers responsible for improving healthcare service delivery within public health systems. First, the results emphasize the importance of strengthening demand forecasting systems within public hospitals. Hospital managers should prioritize the adoption of structured forecasting approaches supported by reliable consumption data, inventory monitoring systems, and integrated supply chain planning processes. Improving forecasting accuracy can help hospitals maintain optimal stock levels, minimize medicine shortages, and enhance service delivery efficiency.

Second, the study highlights the need for capacity building among healthcare supply chain personnel. Forecasting systems are only effective when supported by skilled staff capable of interpreting demand data and applying forecasting models in procurement planning. Continuous training programs for pharmacists, procurement officers, and supply chain managers can significantly enhance forecasting capability within healthcare institutions.

Third, the findings underscore the importance of digital transformation within healthcare supply chains. Many public hospitals still rely on manual forecasting methods that are unable to capture complex demand patterns driven by epidemiological trends and seasonal disease outbreaks. Integrating digital forecasting tools such as predictive analytics platforms, Electronic Logistics Management Information Systems (e-LMIS), and artificial intelligence-based demand modelling can significantly improve forecasting accuracy and supply chain responsiveness.

Fourth, the study highlights the importance of strengthening coordination within the healthcare supply network. Effective forecasting requires continuous communication and information sharing between hospitals, procurement agencies, suppliers, and distribution bodies. Strengthening coordination mechanisms between public hospitals and KEMSA could significantly reduce procurement delays and improve the availability of essential medicines.

Finally, the findings have important implications for health policy and the implementation of Universal Health Coverage (UHC) in Kenya. One of the key objectives of UHC is to ensure equitable access to essential healthcare services and medicines. However, persistent medicine stock-outs continue to undermine service delivery in many public hospitals. Strengthening forecasting systems within hospital supply chains can therefore play a critical

role in supporting the successful implementation of UHC by ensuring the continuous availability of essential medicines and medical supplies.

Policy makers should therefore consider investing in national forecasting systems, integrated health supply chain data platforms, and digital logistics infrastructure that enable real-time monitoring of medicine demand and supply. Such investments would enhance healthcare system resilience and improve the efficiency of pharmaceutical supply chains across the country.

Implications for Future Research

This study also opens several avenues for future research. First, future studies could examine the role of advanced forecasting technologies, such as machine learning and artificial intelligence, in improving pharmaceutical demand forecasting within healthcare supply chains. Second, longitudinal studies could provide deeper insights into how forecasting capability influences operational performance over time. Third, comparative studies across different counties or national healthcare systems could help identify contextual factors that influence forecasting effectiveness within public health supply chains.

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