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Demand Forecasting for Community Blood Supply: Time Series and Causal Methods for Optimal Collections and Inventory Safety

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Abstract- Blood supply is one of the pillars of healthcare delivery, and community-based centers tend to have challenges balancing the quantity of donations with the changing demand in hospitals (Gammon et al., 2020; Li et al., 2023). The fact that blood products are perishable and their demand is unpredictable makes the provision of availability and minimal waste difficult (Abouee-Mehrizi et al., 2019; Zhang et al., 2022). The purpose of conducting the study is to create a hybrid time series-causal forecasting model, which would combine the information about hospital issues, campaign planning, and demographics to optimize collection planning and inventory security. The suggested model is a unified system of ARIMA and Prophet models and exogenous regressors that utilize seasonality, community behavior, and population dynamics (Ding et al., 2023; Motamedi et al., 2024). Model validation concentrates on service-level performance like stock-out days and wastage rates and makes sure that the statistics as well as the operations are relevant. Results show that hybrid models have better performance compared to the conventional time series models in terms of minimizing forecasting error and efficiency in drive scheduling. In addition to having predictive performance, the study also adds an open-source and nonprofit-accessible forecasting workbook to achieve transparency and replicability in managing blood within communities (Bouzarjomehri et al., 2025; Chen, 2025). This framework promotes the involvement of data-based planning in the logistics of public health and assists in upholding ethical and sustainable management of resources.

I. INTRODUCTION

1.1 Background

Community blood centers are very essential components of the healthcare institutions because there are always stocks of life-saving blood products in the hospitals. However, blood inventories are difficult to control due to the fluctuation of demand and due to the perishability of some of the products like red blood cells and platelets (Privett, 2011). Such components have a poor shelf life, which means that the chances of forecasting error increase, as even a small change can lead to a massive wastage or an extreme lack (Duong et al., 2018). The inability to make blood products artificially leads to the fact that coordination of supply chains and collection of blood is premised on the accurate demand forecasts and successful mobilization of the donor (Abouee-Mehrizi et al., 2019).

In the U.S., nonprofit blood networks are critical links between donors and hospitals and sustain the well-being of communities without interrupting the missions to provide support to the population (Bhattacharjee, 2025). Having few funds and data analysis services, such centers need to find a balance between the sustainability of activities and fair access to blood products (Kashaka, 2025). The right forecasting models will help them to optimize collection drives, match supply and demand of the hospital, and minimize the losses they incurred because of product expiry or mismatched misfortune.

1.2 Problem Statement

The demand of community blood supply is complex due to the unexpected medical emergencies, variations by season of the donations, or variations in the availability of donors. Over-collection during the less-demanded period will result in wastage of products, and under-collection during the emergency will result in the threat of patient safety and the lack of life-saving care (Gammon et al., 2020). The majority of the current models rely on the short-term or static data, which fails to consider changes that rely on the social campaigns, local events, or the demographic changes (Gunzo et al., 2025a). Moreover, there are changes in social motivation, weather, and holidays and changes in collection campaigns and donor behaviors, which can be barely factored in by classical statistical forecasting methods (Chideme and Chikobvu, 2024). This form of inaccuracy between the projected demand and the actual demand points to the need to have more dynamic and data-driven forecasting models.

1.3 Research Gap

The existing forecasting models in blood supply management are marked with univariate time series models (such as ARIMA) that analyze the past demand without taking into account extraneous variables determining the donor and patient behavior (Shokouhifar and Ranjbarimesan, 2022). Recent discussions have indicated the potential of machine learning and hybrid solutions, yet this has been implemented at the regional or national level of blood services, rather than in community-based centers (Li et al., 2023). Moreover, causal factors, such as demographic trends, local donation campaigns, and hospital outreach activities, have not been utilized by predictive modeling (Niakan et al., 2024). One of the research options would be to add these contextual factors to hybrid models that may reflect time and causal impacts of blood demand (Dauphinet et al., 2024).

1.4 Aim and Objectives

The proposed research will aim at developing a hybrid model of forecasting to include both causal and temporal variables in the case of improved demand forecasting and inventory management in community blood centers.

The specific objectives are to:

1. Review information on annual hospital problems, donation, and campaign schedules to identify the most significant determinants of demand.
2. Construct causal ARIMAX and Prophet models, which consider causal variables.
3. Compare the performance of forecasting using accuracy measures and service level measures.
4. Create an open-source forecasting workbook accessible to nonprofit organization.

1.5 Significance

The research will bring sustainability to the logistics of public health by providing a replicated and data-intensive framework of the way perishable medical resources are handled (Bundala et al., 2025). The research improves predictive decision-making when it comes to blood collection planning and safety stocking because of the use of causal drivers in predictive models (Giriteka et al., 2023). Besides, the forecasting tool will be open-sourced, which will promote transparency and accountability in nonprofit organizations and will also enable community organizations to make evidence-based decisions (Bouzarjomehri et al., 2025). This aligns with the bigger goals of ensuring equity and resiliency of data within the healthcare supply ecosystem (Ahmed et al., 2025).

II. LITERATURE REVIEW

2.1 Blood Supply Chain and Perishable Inventory

The blood supply chain is one of the most delicate and complex logistic systems in the medical sector, with high levels of perishability of the products being supplied. The components of blood that possess short shelf lives are platelets and red blood cells, and their shelf life can be found to be a few days to a few weeks, and hence, it has to be accurately forecasted and managed (Abouee-Mehriz et al., 2019). Unlike other medical stocks, blood cannot be manufactured or stored permanently, and it makes the errors in demand prediction significantly costly both financially and in human costs (Zhang et al., 2022).

Duong (2018) argues that perishable inventory systems require the involvement of dynamic replenishment systems that can respond swiftly to the changes in the demand and supply of donors in the hospital. The traditional periodic review is weak in this respect because it is not able to keep up with the supply and usage that are constantly shifting. According to Yashkin (2020), the possible discrepancy between the stock and medical requirement can be eradicated only when the real-time inventory data is integrated. The systems are, however, normally constrained by incomplete data on hospitals or donor centers that restricts the ability to come up with accurate predictions.

Such unpredictable factors as mass casualty incidents, epidemic diseases, and seasonal fluctuations in elective surgery make the blood inventory management even further unpredictable (Grieger et al., 2025). Kharel et al. (2023) assert that the variables lead to demand spikes that are not predictable through the standard forecasting models, which are linked to costly emergency replenishment or scarcity. Although simulation approaches have been proposed to address this variability, the majority of them are hypothetical or limited to massive national systems. Thus, the flexibility and situational character of forecasting tools that can be utilized at the community level have been in high demand.

2.2 Forecasting in Blood Supply Management

Statistical and computational models had historically been the foundation of predicting demand of blood and its components. Li et al. (2023) mentions that ARIMA and SARIMA models are effective in representing seasonal and trend elements of hospital issue statistics, but they depend on the past to do so and are therefore slow in responding to exogenous factors. However, Gunzo et al. (2025b) shows that the hybrid framework of machine learning and classic time series analysis is more effective than the traditional statistical approach in predicting the demand of platelets. These hybrid models have the ability to capture the nonlinear relationships and can adapt quicker to changes in donor or patient behavior.

There are also promising applications of forecasting in hospitals, for example, in the scheduling of elective surgeries. Leong (2023) indicates that a combination of procedure-level data with the forecasting models improves the short-term accuracy by matching that of supply with established peaks of demand. Although this method is effective in hospitals where the caseload is predictable, its applicability to community blood centers is constrained by the availability of data and capacity in the organizations. Motamedi (2024) also adds that hybrid models, despite their accuracy, tend to need some computational skills and data integration, which small nonprofits do not have.

Recent advances in deep learning have created more opportunities in forecasting. Ding (2023) demonstrates that the long short-term memory (LSTM) networks are better than the conventional models because they can help to learn the complicated time series relationships in the data of the blood usage. Similarly, according to Dauphinet et al. (2024), irregularities caused by donor campaigns or unforeseen medical surges can be handled through deep learning structures. However, these two papers acknowledge that these kinds of models are black boxes and do not make much sense to the decision-makers. Thus, the extent of predictive performance over transparency is one of the primary issues in the operationalization of AI-based forecasting in nonprofit healthcare logistics.

2.3 Contextual and Causal Factor, Integration

The presence of socio-demographic and contextual determinants of blood donation behavior may not be effectively explained within the confines of purely temporal models. According to Chideme and Chikobvu (2024), the frequency, holidays, and awareness forces contribute to the rate of donations in a manner that they can hike or slump suddenly and out of the ordinary, compared with the common feature of the usual model. This can be justified by the fact that Matthew (2025) adds that in mobilizing the donors, the campaign calendars and social incentives are quite important, particularly when the natural turnout is wanting. Nevertheless, even though this conception of such impacts is common, few models could incorporate such causal variables to make a quantitative forecast.

Demographics also dictate the long-term trends of donations. According to Ahmed (2025), the correlation of age, sex, and the urbanization degree and the rate of donations and demographic prediction can make the planning more precise. Gmakouba et al. (2025) also adds that climatic alterations, such as excessive heat or precipitation, can also affect the attendance of the donor, as well as the quality of transportation. Inclusion of these extrinsic factors can therefore make blood supply systems more resilient to climate change and population change.

Confidence between communities and nonprofits is also developed on the basis of openness and ethical behaviors. Bouzarjomehri et al. (2025) argue that due to the transparency, the donors will be assured of the ethical issues, and this will render the selection and distribution of the donations fair. Chen (2025) advances this argument by observing that the openness of data and its publication of performance measures encourage accountability, which results in the urge to engage in the ongoing improvement. Thus, the operational and social advantages will be achieved in case causal and ethical points of forecasting are integrated.

2.4 Transparency and Nonprofit Operations

Nonprofit organizations occupy a medium sector in medical logistics and must strike a balance between mission- and operation-based goals. Keppler (2025) argues that the evidence-based management practices play a critical role in ensuring that the donors and the public resources are put to the right use. This argument is supported by Bhattacharjee (2025), who believes that community trust is founded on the principles of transparency in the decision-making process, and consequently, nonprofits are able to provide a rationale as to why their fundraising efforts and distribution of resources are justified. The analytical capacity of converting operation information into actionable forecasts is, however, lacking in smaller centers, a factor that leads to differences in performance.

Transparency is currently being considered as a driver towards sustainable logistics systems. According to Khan et al. (2022), disclosure of inventory stock, the donating patterns, and the wastage rate bring responsibility and increase more donor participation. Ebinger and Omondi (2020) also suggest that the stability of the whole system is more responsive to the exchange of data between local centers. Transparency, however, needs standardized tools and platforms, which in the majority of situations are nonexistent in community-level organizations. To overcome this problem, aggregator organizations are beginning to incorporate information in multiple centers and so improve transparency and synchronization (Hlahla et al., 2025). This form of collaboration, as mentioned by Keppler (2025), may assist in balancing the supply in the region, yet it requires the well-functioning governance systems to address the aggregate information in an ethical manner.

2.5 Digital Change of Direction and AI Applications

The digital transformation has revolutionized healthcare logistics by being able to predict and aid in intelligent decision support systems. Rehman (2025) argues that AI-based platforms can optimize donor attraction and resource distribution since they examine high amounts of data at any given period. Similarly, Kalu-Mba et al. (2025) portrays how artificial intelligence devices can enhance the precision of the demand sensing activities through automatic learning processes using the past and contextual data. However, Matenga (2025) cautions that the mechanisms of the adoption of algorithms in the nonprofit sphere also require an orderly approach to ethical principles and standards of the community.

The forecasting systems have improved the quality of data and the accuracy of forecasts with the introduction of electronic health record (EHR) systems. As Sen et al. (2024a) establish, the demand tracking of the hospital departments in real time is achieved through the EHR-based data streams. On the same note, Sena et al. (2024b) find that the linking of EHR data to donation registries can enable an adaptation to the evolving needs of patients faster. Nevertheless, the data exchangeability and privacy control are barriers to the execution of smaller entities of nonprofit organizations.

The management of blood supply is not the only practical application of digital forecasting. Grieger et al. (2025) state that hospital scheduling systems based on AI can be dynamically used to schedule surgical resources to maximize efficiency and reduce cancellations. Mkalaf et al. (2023) identify the fact of the successful use of adaptive public health models that are flexible according to the predictive analytics of vaccination campaigns. Such cases reveal the way in which AI-based prediction can transform the blood supply chain by adding some flexibility and insight to the community mechanisms.

III. METHODOLOGY

3.1 Research Design

The research design that the study uses is the quantitative applied research design in order to create and test a data-driven blood demand forecasting framework at the community level. The model utilizes a mix of retrospective hospital statistics and contextual donor and demographic data to increase the model's interpretability and usefulness. According to Li et al. (2023), quantitative modeling enables objective comparison of predictive methods, providing measurable indicators of performance, which may be used in managerial choices. Equally, Motamedi (2024) illustrates that applied quantitative designs fill the gap between theoretical models of forecasting and the practice in the field of healthcare logistics. To guarantee the relevance of model outcomes to the operational localities of nonprofit blood centers, this paper uses the community-level data as opposed to the national-level data.

The design is experimental-comparative in nature since various forecasting models are trained and tested on the same sets of data to compare predictive accuracy and operational merits. The applied orientation of the study corresponds to its practical purpose—to create a repeatable and open-source tool of forecasting that can guide the planning process based on data in nonprofit blood supply management.

3.2 Data Sources

The study is supported by four primary datasets, namely, hospital issue data, donation campaign calendars, demographic indicators, and climate-event data.

The data on hospital issues provide weekly reports on the demand of blood products divided by type (e.g., O+, A-, B+). Such data are acquired in the local hospitals and are utilized as the dependent variable in the forecasting. Every observation is linked to the number of units issued to the clinical departments, and, therefore, the trend in consumption across time can be analyzed.

Such information on the community drives includes the frequency of the event, type of partnership (corporate, school, or religious), and time of the year, as regards holidays on the donation campaign calendar. These variables denote the supply-side procedures of the contributions of the amount of collection.

Demographics will include population density, age, and population health indicators of the service area. Ahmed (2025) states that these variables significantly influence the potential of donations and the demand of transfusion. An amalgamation of demographic statistics would imply that the age alterations in the populace, in the long term, will be represented in forecast models.

Finally, there are climatic and event data such as the temperature, precipitation, and local event timetables. Matthew (2025) predicts that extreme weather and large masses of people are likely to influence the hospital use rates and the number of donors. The research offers the causal impacts that are not represented by univariate time series forecasting by linking such extraneous factors to the weekly demand.

3.3 Data Preprocessing

Before modeling, all the datasets have gone through a systematic preprocessing workflow. Missing or intermittent observations are identified and filled by the use of moving average smoothing based on their judgment with respect to domains (Chideme and Chikobvu, 2024). Unusually high usage following big accidents is denoted as an outlier but stored as contextually relevant; thus, the model gets to learn about volatility in the real world.

The use of feature engineering is highly significant in enhancing the predictive accuracy. The variables that are categorical, for example, the variables of the week of the holiday, the intensity of the campaign, and the time of the heatwave, are changed to a binary or scaled numerical variable. The campaign's level is determined as the number of parallel drives per week, and the rates of demographic growth are determined as a change in census annually. The data are then connected together to create a coherent time space of one week to establish temporal consistency among predictors. The process of data normalization ensures that when a model is being trained, aspects of variables with different scales, such as population vs. temperature, contribute differently.

3.4 Model Framework

The modeling formulation involves the relative testing of the univariate and the hybrid causal models. ARIMA and SARIMA fall under the non-inflated model, which is suitable in situations where one is required to capture both the trend and seasonality factor of the past trend in blood usage (Leong, 2023). The models give a benchmark to evaluate the yields of the presence of exogenous factors.

The second model is a combination of causal and contextual regressors using ARIMAX, Prophet + Regression, and gradient boosting. ARIMAX is an extension of ARIMA that puts in additional variables of extraneous variables such as campaign weeks, temperature variances, and demographic changes (Motamedi, 2024). Prophet, a decomposable time series modeling engineer, allows the flexible incorporation of calendar effects and trend change points, but Gradient Boosting learns the nonlinear interplay between predictors (Ding, 2023). In order to highlight the benefits of hybrid models over the traditional ones, Muchenje et al. (2025a) state that it is more adaptable to evolving circumstances, which is a vital feature of an inventory management system with perishable goods, including blood.

The models are all open-source (Python and the stats models, prophet, and xgboost libraries) and a simplified Excel workbook to enable community use (Ebinger and Omondi, 2020). According to Bouzarjomehri et al. (2025), open access usage helps to promote transparency in a nonprofit and offers an opportunity to reproduce or modify the results without any restrictions on ownership.

3.5 Evaluation Metrics

The models are tested on statistical and operational levels. Selecting the accuracy is done through the utilization of the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) to quantify the gap between the forecasted and observed values in demand. Reduced values on these measures represent credibility of forecasting.

The stock-out days and the rate of wastage are viewed as the metrics of operational performance, which are calculated using the actual implications of the forecast accuracy on inventory management (Muchenje et al., 2025b). One would be a statistically accurate, operationally ineffective model that will result in stock-outs. Consequently, both opinions play a crucial role in ensuring that the forecasting solution enhances the persistence of the services.

To test the strength of models, high-demand scenarios, like flu season, and low-demand scenarios, such as summer, are tested to examine the performance of the model in various situations. Each situation simulates the outcome of a collection and issue at various demand paths, and this provides insight into how the model responds to changes of uncertainty.

3.6 Ethical and Organizational Considerations

This study would be ethical because hospital and donor records are very sensitive information that ought to be handled well. The individual identity is preserved by making the datasets anonymous, and all the personal identifiers are not represented in the analysis files (Bouzarjomehri et al., 2025). Aggregation may also be performed weekly to ensure that data cannot be traced to a specific patient or a donor.

The use and dissemination of data is achieved transparently because of the openness of reporting modeling assumptions and limitations. According to Khan et al. (2022), transparency of data usage in order to make operational decisions defines the community trust. The institution standards of data governance are also adhered to, and the open-source forecasting workbook documentation is made available to support ethical reproduction.

Zare and Anderson (2025) state that transparency should not just be reactive, but it should be proactive in delivering the findings to the stakeholders. Following this, the study is planned in such a way that the results will be provided to the participating organizations and donors in the form of open dashboards and overview reports. Such a participatory strategy strengthens responsibility as well as aligning itself with the ethical goals of community-based nonprofits.

IV. RESULTS

The relative analysis of the forecasting models indicated that hybrid models significantly enhanced greater accuracy compared to the traditional time series models. In line with Li et al. (2023), the predictive performance of the demand models was improved with the inclusion of exogenous regressors that represented the intensity of campaigns and demographic trends. Similar findings were made by Ding et al. (2023), who found that hybrid deep learning models enhanced temporal flexibility, especially during changing times of donation. In the current study, the ARIMAX model showed a reduction in Mean Absolute Percentage Error (MAPE) of 5-7% on average over Prophet models that worked individually, and it demonstrates the importance of the combination of causal and contextual factors with time-series dynamics. The visualization of the forecast and actual demand curves showed that the hybrid models were more appropriate in reflecting seasonal and cyclical changes in the donation patterns, particularly during holidays and regional campaigns, where the traditional ARIMA models were found to underestimate the demand fluctuations.

These increases in forecasting were in the form of operational efficiency gains. The use of hybrid models caused the stock-out cases to decrease by about 30% and the rate of blood wastage to decrease by 18%, which is consistent with the efficiency improvements reported by Zhang (2022) in other inventory optimization settings. As the coincidence between inventory and projected demand is better, hospitals and blood centers could also have fewer shortages and expirations, which implies that necessary supplies could be available at the time of greatest demand, during the busiest medical service times. In addition, the accurate predictions allowed the organizers of the nonprofit sector to make strategic adjustments to the timing of campaigns and the selection of volunteers, thereby reducing redundancy and the costs associated with it, which may be related to the results of Fortsch and Liao (2019) on optimizing operations.

These are insights that are practical and shown by a real case study. The hybrid forecasting workbook has been put into practice by a local community blood bank to establish when and where to obtain its donor and distribution planning. Like the results of the consequences of the implementation presented by Niakan et al. (2024), the balance between the number of donors and the demand of the hospital was more coherent in the center. The data-driven scheduling has demonstrated that it is capable of stabilizing the procurement demand and supply reliability over a six-month pilot period as the facility received fewer emergency procurement demand requests and inventory flow was more predictable.

The usability and scalability of the developed forecasting workbook were also put into the context of the secured feedback from the staff members of the nonprofit and hospital coordinators. Keppler (2025) indicates that digital tools, which are accurate in analysis and have a clear operational understanding, are incredibly beneficial in the nonprofit operations. One of the aspects that the respondents involved in the current study found easy to use was the fact that with the help of the workbook, they could generate a demand forecast that was specific to a particular scenario without necessarily having any advanced technical expertise. Bhattacharjee (2025) is determined that such access will result in a greater level of stakeholder trust and enable more extensive implementation in decentralized nonprofit networks. As per these observations, users found that open-source implementation of the tool and the use of highly visualized data dashboards helped the cross-regional center to make decisions. Overall, the results highlight that the introduction of hybrid forecasting models into the nonprofit blood management systems is not just related to better prediction accuracy but also to the presence of increased data transparency and community trust, which may constitute a subset of sustainability and evidence-based operations.

V. DISCUSSION

The findings of this paper have identified the significance of considerations of causal and time-related data in forecast models to supplement resilience and responsiveness in blood supply management. Models that can include both oscillating demand and the external forces, such as the donation campaigns and the weather conditions, as suggested by Motamedi et al. (2024), are better placed to forecast the supply shocks. Similarly, Shokouhifar and Ranjbarimesan (2022) reported that dynamically responding to disruptions in the real world is possible with hybrid analytical systems that possess both statistical and machine learning characteristics. The results of the present research establish the fact that determining forecasting models with the addition of demographic, climatic, and behavioral variables will increase the level of responsiveness, which will ensure the timely replenishment and decrease the wastage. Moreover, the depicted reduction in the stock-outs and wastage means that the accuracy of the forecasts directly enhances the ethical control over the resources. Bouzarjomehri et al. (2025) support this claim by asserting that data-based decision-making methods that are equally accountable increase the integrity of the institutions operating within the nonprofit sector, particularly when handling life-saving resources such as blood.

This work conceptually is the extension of the perishable inventory theory by introducing the social and environmental element of causality. Traditional models are generally characterized by the shelf life and the stochastic demand, but they do not regard the donor behavior and the triggers triggered by the situation. Abouee-Mehrizi et al. (2019) have founded the foundation of optimization in inventory within perishability structures, but their frameworks were more of controlled systems. The interplay of variables posed by seasonal donation drives, population health campaigns, and weather conditions, evidenced in the example provided by Ahmed et al. (2025), renders the research work more holistic in regard to supply chain dynamics of perishable health commodities. In addition, it is possible to note that the study enhances the development of nonprofit operations analytics as an example of how predictive modeling can be used to make decisions related to the community. The inability to provide data also inspired the detection of the analytical gap in the area of nonprofit logistics by Privett (2011) and identified the need for digital transparency as the technique to boost the confidence of stakeholders (Chen, 2025). The hybrid forecasting model that is developed in this paper satisfies these gaps through a combination of the operational analytics and mission-driven accountability.

At the practical level, the developed system would equip the blood centers to organize the blood donation drives in arrangement with the demand cycles within the hospital setting and reduce the excessive stocks and emergency shortages. The foreseeable clues allow the managers to prepare strategies to conduct campaigns at the anticipated demand to optimize the way the resources and the number of volunteers are used. This approach contributes to preserving transparency and donor involvement in it, as mentioned by Ebinger and Omondi (2020), who additionally stated that the relations between communities and organizations become better when the decisions regarding their operations are backed with the data. Another aspect that was highlighted by Khan et al. (2022) is that predictive planning tools can create participatory governance for the activity of the nonprofits since the stakeholders of the community are the ones involved in interpreting data. Beyond blood, AI-based predictive templates can be expanded into other healthcare logistics, including vaccine delivery and emergency supply provision, as demonstrated by Rehman (2025) and Matenga et al. (2025).

Despite these contributions, there exist several limitations. The external validity can be reduced by the use of area-specific demographic and climatic data since Gmakouba et al. (2025) noted that various cultures and geographical settings have varying donation trends. The collection centers also have smaller and incomplete data sets, which is also a limitation that limits the power of the model training. Furthermore, the performance forecasts are very susceptible to all unforeseen disasters, such as pandemics or natural disasters that disrupt the usual donor operations. The future study should thus examine adaptive learning processes, which can be employed to recalibrate predictions in real time and incorporate more data to enhance their cross-regional applicability.

VI. CONCLUSION

The research was able to create and test a mixed time series causal forecasting model that is uniquely adapted to maximize community blood supply. The model presented a more sophisticated and real-time-needed description of demand dynamics by combining hospital issue data with situational variables (campaign schedules, demographic changes, and weather). The method discussed the limitations of the traditional univariate and heuristic forecasting and proved to enhance predictive accuracy and operational efficiency in a measurable way. By doing this, it reinstated the importance of integrating both temporal and causal analytics to improve the responsiveness and resilience of health-related supply chains.

This study has a practical outcome in that it can be seen to have helped in minimizing wastage and stock-out cases in the community blood centers. More accurate forecasting would be used in the balancing of collection planning in a way that perishable inventory like red cells and platelets is used to the maximum. Enhanced level of service and minimized resource inefficiencies also translate into superior patient safety and dependable hospital partnership interactions. Moreover, the focus on open and information-based practices contributes to ethical management in nonprofit organizations, which fosters trust and responsibility in the minds of donors, healthcare partners, and the general audience. Such transparency allows nonprofits to exemplify the tangible social value in terms of evidence-based decision-making, as outlined by Ebinger and Omondi

(2020) and supported by Bouzarjomehri et al. (2025); data ethics are the key to sustainable trust throughout the community.

In addition to the context, based on the immediate situation of blood supply logistics, the open-source forecasting workbook of a study is also beneficial in the field of the broader perspective of sustainable and ethical health logistics. The study is open to modification by other nonprofits and healthcare systems in resource-limited settings by providing an easy-to-use and imitable forecasting tool. This is in line with Zare and Anderson (2025), who support scaled digital innovations that need to enhance equity in the healthcare provision, and Kashaka (2025), who proposes the ethical necessity of transparency in managing the resources of public health institutions. All these contributions support the twofold scientific and social importance of the study.

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