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AI-Based Smart Blood Management System: A Comprehensive Review of Data Sources, Machine Learning Methods, and IoT Integration

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Abstract. Blood cannot be manufactured, has a short shelf life and must be available at the right place and time, yet many blood banks still rely on manual records, telephone-based donor mobilisation and rule-of-thumb stock control, which contribute to shortages, expiry wastage and slow emergency response. Artificial intelligence (AI), combined with digital records, Internet of Things (IoT) sensing and blockchain-based traceability, is increasingly proposed to forecast demand, predict donor behaviour and optimise inventory. This paper presents a focused narrative review of peer-reviewed studies on AI in blood management, covering demand forecasting, donor prediction, inventory ordering and traceability. Three connected themes are examined: data sources and sensing technologies, learning methods (time-series models, classical machine learning, gradient boosting and deep learning), and IoT, cloud and blockchain integration. The literature reports that a hybrid forecasting and ordering strategy reduced hospital red-cell inventory by about 40 % and orders by 60 % against historical practice, that an integrated platform increased collected blood by 11 % and reduced wastage by 20 % in a pilot at one centre, and that random forests can identify returning donors with a Matthews correlation coefficient of 0.851. Simple time-series models often remain competitive with deep learning. However, most studies use single-centre or single-country data, retrospective validation and one blood component at a time, and few report multi-site field trials, complete blood-group coverage or long-term IoT operation. The review contributes a comparative analysis of representative studies, a proposed conceptual layered architecture that links data acquisition, edge and cloud AI, blockchain traceability and independent validation, and a prioritised agenda of research gaps and future directions.

Keywords: Blood Bank Management, Artificial Intelligence, Demand Forecasting, Machine Learning, Donor Prediction, Blockchain, Internet of Things, Inventory Optimization.

I. Introduction

Blood is a life-saving resource that cannot be manufactured and has a limited shelf life. According to the World Health Organization (WHO), a safe and adequate supply depends on regular voluntary donation, and donation by about 1% of the population can generally meet the basic requirements of a country [1]. Platelets can be stored for only about five days [3], so both shortage and overcollection are costly, and the blood supply chain is commonly framed as a trade-off between shortage and outdating [2], [16].

Many blood banks still work with registers, telephonebased donor calls and manual stock control, and information about stock and donors is often fragmented across centres. National portals such as e-RaktKosh in India aim to integrate blood bank information [12]. Reviews of the blood supply chain divide it into collection, production, inventory and distribution, each of which offers room for data-driven decisions [2], [3].

AI is now applied across this chain. Three developments converge: digital clinical and donor records that can be used to train models [4], [6]; machine learning (ML) and deep learning (DL) methods that map these data to demand, donor response and inventory decisions [5], [7], [8]; and IoT and blockchain connectivity that moves monitoring and traceability beyond a single laboratory [10], [11]. A recent systematic review of 338 studies in patient blood management found that recurrent and hybrid architectures were effective for blood supply forecasting [9]. This review examines these strands together, asks how mature the evidence is for real deployment, and proposes a conceptual architecture that addresses the weaknesses identified.

II. Review Methodology

A focused search was carried out through publisher and repository platforms (PubMed and PubMed Central, MDPI, BioMed Central, SAGE, Elsevier, Springer and arXiv) using combinations of the terms blood demand forecasting, blood bank management, donor prediction, blood inventory, machine learning, deep learning, blockchain and IoT, prioritising 2021–2026 publications. Studies were included when they reported a blood-specific AI task with a stated method and a quantitative outcome; reviews were used for context only.

The primary studies compared in Table I were each checked against a publisher, DOI or repository record. Well-established background sources [1], [2], [11], [13]– [16] are cited from the standard literature. Direct logged querying of Scopus and Web of Science was not carried out, so the review is narrative rather than systematic, and study counts are not reported.

III. Data Sources and Sensing Technologies

1. Clinical and Operational Records

Demand models are only as good as the records behind them. Li et al. used a large clinical database from Hamilton, Ontario, covering 2008 to 2018, with clinical predictors for red blood cell (RBC) demand [4]. Kwon et al. combined open national data on blood inventory, supply and donation from Korea (2010–2021) with data from a single medical institution, and found that the department requesting blood was the most influential parameter [6]. In an Algerian case study, daily supply data covering 1,461 consecutive days (2017–2021) were taken from the National Blood Agency
[3].

2. Donor Records

Donor models use recency, frequency, total donations and time since first donation, together with donor attributes such as blood group, age and gender [3]. Kauten et al. built donor-retention models from the data of a regional blood centre in the United States [8].

3. IoT, Cold-Chain and Blockchain Sensing

The blood cold chain preserves blood from donor to transfusion site. Asokan summarised its typical problems and demonstrated a traceability solution that combines Ethereum smart contracts with IoT technology, enabling real-time information sharing among the entities involved and helping balance shortage against outdating [10]. A blockchain provides a tamper-evident shared ledger [11]. Evidence in this area is mostly demonstrations, and quantitative field validation of IoT-based blood monitoring remains scarce.

IV. Machine Learning and Deep Learning Methods

1. Time-Series Models Versus Machine Learning

Shih and Rajendran compared time-series methods with ML algorithms for forecasting the blood supply of the Taiwan Blood Services Foundation and found that exponential smoothing and ARIMA gave the lowest errors [5]. In the Algerian case study, autoregressive, ARMA and ARIMA models were most accurate in the first two months, after which their accuracy declined while ANN and support vector regression models improved gradually [3]. Li et al. combined statistical time-series modelling, ML and operations research into a hybrid forecast with a data-driven ordering strategy, which reduced hospital inventory by 40% and ordering by 60% relative to historical data [4].

2. Boosting and Deep Learning

Kwon et al. predicted monthly demand by blood type and component using XGBoost [14], LightGBM and CatBoost, with mean absolute error ranging from 14.67 for AB+ RBCs to 84.04 for A+ platelet concentrate, and improved the error range with an ensemble of the three [6]. MiriMoghaddam et al. compared a long short-term memory (LSTM) network [13] with a classical model for national blood product data and forecast supply and demand to 2027; the LSTM was judged better for the dominant products, and platelet demand was predicted to grow [7].

3. Donor Prediction

Random forests [15] have been used to model donor retention, reaching a Matthews correlation coefficient of 0.851 on data from a regional blood centre [8]. In Algeria, six classifiers were compared for predicting donor return; ANN and random forest reached recall of 95% and 94%, whereas logistic regression, SVM, decision tree and naive Bayes reached 62–65% [3].

4. Validation Practice

Most of the studies above validate retrospectively on data from one centre, region or country [3], [4], [6], [8]. The Korean model did not include RhD-negative blood types and its authors suggest adding them in future [6]. Reporting of external validation, multi-site testing and uncertainty is therefore limited, and accuracy values across studies are not directly comparable.

V. IoT, Cloud and Platform Integration

Ben Elmir et al. developed an information system with a centralised database and an AI/ML decision-support tool for forecasting blood demand, predicting donor behaviour and scheduling appointments [3]. A test version was run at one of the largest donation centres in Algiers from March to December 2021 without serious technical problems; compared with the average of the previous five years, collected blood volume rose by 11% and wastage fell by 20%, although the shortage rate could not be calculated [3]. On the traceability side, Asokan's smart-contract and IoT demonstration shows how entities can share data in real time [10]. Neither work reports long-term, multi-site operation, so the maturity of integrated deployments should be regarded as early-stage.

VI. Comparative Analysis

Table 1: summarises representative primary studies. Accuracy and savings are not directly comparable, because targets, datasets and validation schemes differ.

Table 1: Comparison of Representative AI-Based Blood Management Studies

Author, year	Objective	Method	Major reported findings	Limitations
Shih and Rajendran, 2019 [5]	Forecast blood supply (Taiwan)	Time-series methods vs ML algorithms	Exponential smoothing and ARIMA gave lowest errors	One national blood service
Li et al., 2021 [4]	RBC demand and ordering	Hybrid forecast + inventory optimisation	Inventory −40 %, orders −60 % vs history; low shortage and expiry	One region (Hamilton); data 2008–2018
Kauten et al., 2022 [8]	Predict donor retention	Random forest	Matthews correlation coefficient 0.851	One regional blood centre
Ben Elmir et al., 2023 [3]	Demand, donor return, scheduling	ARIMA, ANN, SVR; ANN, RF classifiers	Collection +11 %, wastage −20 %; ANN/RF recall 95 %/94 %	One centre in Algeria; 2021 pilot; shortage not quantified

Kwon et al., 2024 [6]	Monthly blood demand by type	XGBoost, LightGBM, CatBoost, ensemble	MAE 14.67 (AB+ RBC) to 84.04 (A+ platelets)	Single institution; RhDnegative not modelled
Miri-Moghaddam et al., 2024 [7]	Five-year product supply and demand	LSTM vs classical model	LSTM better for dominant products; MAPE about 0.03–0.10	National aggregate data; no field trial
Asokan, 2022 [10]	Blood cold-chain traceability	Ethereum smart contract + IoT	Real-time information sharing demonstrated	Demonstration scenario only

Table 2: Conventional Vs. AI-Based

Parameter	Conventional	AI-Based
Demand estimate	Historical average	Predictive model [4], [6]
Donor contact	Mass phone calls	Targeted alerts [3], [8]
Expiry control	Manual register	Forecast-driven ordering [4]
Traceability	Paper records	Digital ledger [10]

Table II contrasts conventional practice with the AIbased approaches reviewed. The comparison is qualitative and based on the capabilities described in the cited studies.

VII. Proposed Conceptual Architecture

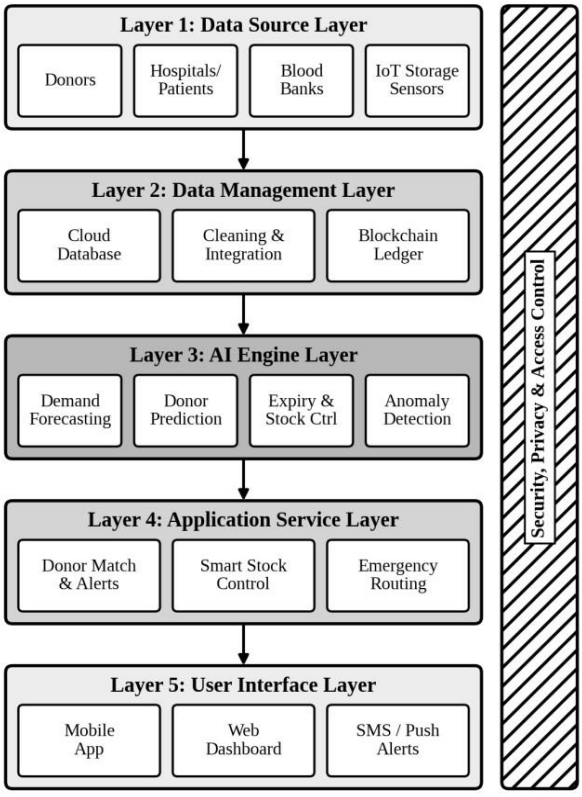


Fig.1. Proposed conceptual architecture of an AI-based smart blood management system (conceptual, not experimentally validated)

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Fig.1 presents a conceptual architecture derived from the reviewed systems [3], [4], [6], [10]. Donor, hospital, blood bank and IoT storage-sensor data are acquired (layer 1) and then cleaned and integrated in a cloud database, with unitlevel events written to a blockchain ledger (layer 2) [10], [11]. The AI engine performs demand forecasting, donor prediction, expiry and stock control, and anomaly detection (layer 3) [4]–[8]. Application services turn predictions into donor matching and alerts, stock transfers and emergency routing (layer 4), delivered through a mobile application, web dashboard and SMS or push notifications (layer 5). Encryption, authentication and audit trails protect all layers.

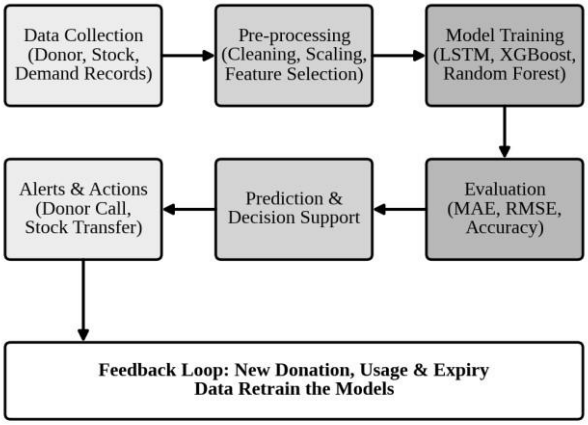


Fig.2. Conceptual workflow of the proposed system (conceptual, not experimentally validated)

As shown in Fig.2, donation, usage and expiry data are fed back and the models are retrained only after independent re-testing on a held-out period, which addresses the single-centre validation weakness noted in Section IV-D.

1. Demand Forecasting Module

Let D(t) be the units of a blood group issued in period t and X(t) a vector of external features such as day of week, season and hospital load. The next-period demand is modelled as

$$\hat{D}_{t+1} = f(D_t, D_{t-1}, \ldots, D_{t-n}, X_t) \quad (1)$$

where f is learned by an LSTM or boosting model, and accuracy is judged by mean absolute error (MAE) and root mean square error (RMSE) on a held-out period [6].

2. Donor Prediction Module

A classifier such as a random forest estimates the probability that a donor will respond, using recency, frequency, total donations and age. Eligible donors are ranked by this probability and only the top-ranked donors are notified [3], [8].

3. Expiry and Inventory Module

The module uses the forecast and the age of stored units to decide what to collect, transfer or issue first. Its performance is measured by the wastage rate

$$W_r = \frac{N_{exp}}{N_{tot}} \times 100\% \quad (2)$$

where N(exp) is the number of expired units and N(tot) the total units handled in the period. Lower wastage without higher unmet demand indicates better stock control.

VIII. Research Gaps and Future Directions

Gaps supported by the reviewed evidence. (i) Singlecentre or single-country datasets: the reviewed models were built on data from one institution, region or country [3], [4], [6], [8]. (ii) Limited field validation: the integrated platform was piloted at one centre [3], and IoT-based traceability was shown mainly by demonstration [10]. (iii) Inconsistent advantage of complex models: time-series methods remained competitive with ML [3], [5], and LSTM and classical models performed similarly on several products [7]. (iv) Incomplete blood-group coverage: RhD-negative types were not modelled in the Korean study [6]. (v) Few studies combine demand, donor and traceability modules in one validated system, and shortage outcomes are rarely quantified [3]

Directions requiring investigation. Priorities include multi-centre, multi-season datasets with complete bloodgroup and component coverage; prospective field trials of integrated platforms; IoT cold-chain monitoring with realtime anomaly detection; reporting of grouped or external validation and forecast uncertainty; privacy-preserving learning across blood banks; and data governance for shared blood-supply data

IX. Conclusion

AI-based blood management has progressed from statistical forecasting to hybrid ordering strategies, boosting and LSTM demand models, donor-retention classifiers and blockchain-enabled traceability. Reported benefits are encouraging, including about 40% lower inventory and 60% fewer orders [4] and 11% higher collection with 20% lower wastage in a pilot [3], but the evidence base is dominated by single-centre, retrospective studies. Simple models often match complex ones. Reliable deployment will need larger and more diverse data, prospective multisite trials, independent validation and continuous model maintenance, as reflected in the proposed conceptual architecture.

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