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Development of an Expert System Calculator for Pediatric Blood Draw: A Conceptual Study

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Abstract: This study demonstrates the feasibility and potential clinical value of a rule-based expert system for optimizing blood collection in pediatric patients, a population uniquely susceptible to iatrogenic anemia due to limited circulating blood volume and frequent laboratory testing. By systematically mapping ordered laboratory tests to tube-specific analytical and dead-volume requirements and applying patient-specific safety constraints based on weight and hematocrit, the system provides quantitative decision support at the time of test ordering. Evaluation using a simulated pediatric cohort (n = 20) representative of endocrine testing workflows showed that blood draw volumes were maintained within established safety thresholds in 16 of 20 cases (80%). Across the cohort, the optimized strategy achieved a mean reduction of 9.36 mL in total blood volume compared with standard collection practices. In the remaining cases, where optimization was not feasible due to extensive test panels or severely limited allowable blood volume, the system appropriately identified threshold violations and generated warning outputs rather than unsafe recommendations. These results highlight the system's ability to both reduce unnecessary phlebotomy and reliably flag high-risk scenarios. Overall, this work establishes a transparent and reproducible technical framework for expert system–based optimization of pediatric blood draws and supports its future integration into clinical laboratory workflows to enhance patient safety and reduce avoidable blood loss.

Keywords: expert system, phlebotomy optimization, artificial intelligence, blood draw, venipuncture decision support

1. Introduction

Blood sampling remains a cornerstone of modern clinical care, providing essential information for diagnosis, monitoring, and therapy adjustment. However, repeated phlebotomy, particularly in vulnerable populations, can remove substantial blood volumes and contribute to iatrogenic anemia. This issue is especially prominent in intensive care settings, where multiple consulting teams may order extensive laboratory panels. Although transfusion can correct anemia, it introduces additional risks, including infection, immune complications, and increased healthcare costs. High transfusion exposure in premature infants has been associated with adverse outcomes such as retinopathy of prematurity, necrotizing enterocolitis, bronchopulmonary dysplasia, and increased mortality [1–3].

Adults may lose between 20 and 377 mL of blood per day from diagnostic testing alone [4–6], while extremely preterm infants may lose up to a 3rd of their circulating blood volume in the first week of life due to frequent sampling [7–9]. Many institutions limit blood draws in a 2.3 kg neonate to approximately 4.8 mL per 24 h, often insufficient to support all tests ordered by clinicians [10]. Similar risks arise in elderly patients, long-stay Intensive Care Unit (ICU) patients, and immunocompromised individuals, although pediatric patients are disproportionately affected because their total circulating volume is small and their physiological reserve is limited [11, 12]. Consequently, judicious management of sample volume is essential, and optimizing the utilization of every collected milliliter is critical [9, 13].

This work focuses on developing an expert system–based framework to optimize laboratory testing strategies for pediatric patients. Expert systems—an early branch of artificial intelligence—apply rule-based reasoning to emulate aspects of human decision-making. Their development traces back to mid-20th-century research on symbolic reasoning and problem-solving [14, 15], with early exemplars such as ELIZA, which demonstrated language-based interaction [16]. These systems generally comprise a knowledge base, an inference engine, and a user interface.

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The knowledge base contains structured rules and domain-specific relationships; the inference engine interprets those rules using methods such as forward or backward chaining; and the user interface enables interaction between human users and the underlying logic [17–19]. Notable demonstrations of rule-based system capabilities include IBM's Deep Blue, which used specialized heuristics to outperform the world chess champion in 1997 [14, 20].

Within medicine, expert systems have supported tasks ranging from diagnostic classification to clinical decision support, including applications in ophthalmology and cardiovascular disease screening [21–24]. Their deployment, however, demands rigorous validation: inaccurate recommendations can propagate clinical errors, delay treatment, and, in extreme cases, cause harm. Although rule-based systems provide transparency, they may struggle with uncertainty or incomplete information. Alternative probabilistic frameworks such as Bayesian networks have been proposed to overcome these limitations by modeling variable dependencies and quantifying uncertainty [25, 26]. Validation typically requires extensive expert oversight, although this may introduce bias because experts tend to test systems with familiar cases rather than rare or atypical scenarios.

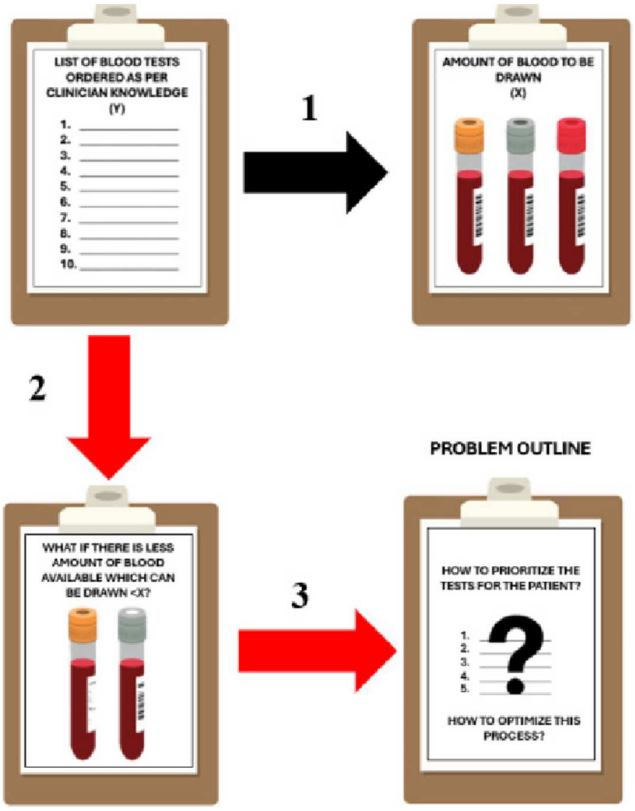
Advances in biomedical engineering have increasingly focused on the reduction of diagnostic sample volume through innovations in materials science, microfabrication, and microfluidic system design. Developments in nano-textured substrates, micro-sample containment, and low-volume assay platforms have demonstrated that reliable biochemical analysis can be achieved using substantially smaller specimen volumes, particularly in pediatric and neonatal populations [27–29]. Despite these advances at the analytical level, the preanalytical phase of laboratory testing remains a dominant source of inefficiency and unnecessary blood loss. Dead volume associated with collection tubes, redundant specimen containers, and suboptimal grouping of tests frequently negate the benefits of microscale analytical technologies. Decision-support systems offer a mechanism to translate material-level and assay-level constraints into actionable clinical workflows by formalizing laboratory knowledge into explicit rules governing tube selection, volume allocation, and test prioritization.

The expert system developed in this study was constructed in close collaboration with laboratory specialists. Its objective is to optimize the set of tests ordered for pediatric patients by selecting the most efficient configuration of blood collection tubes based on test-specific requirements including tube type, preferred and minimum sample volume, and tube dead volume. The system employs forward chaining to infer tube combinations that minimize total blood draw while satisfying analytical constraints. A Raspberry Pi 3 B+ with a 7-inch touch interface serves as the user platform. System outputs are compared with current clinical practice to evaluate performance.

1.1. Problem framework

Pediatric patients possess a restricted quantity of blood that they are able to provide for clinical testing (see Figure 1). Challenges in blood collection include insufficient sample volume for requested tests (leading to cancellations), iatrogenic anemia (potentially necessitating transfusions), increased healthcare costs, and medical errors such as mislabeled specimens, incorrect tube selection, or hemolyzed samples, which contribute to diagnostic inaccuracies and delayed treatment [30, 31]. Medical errors are rising due to a combination of factors, including increased healthcare complexity, caregiver fatigue from long work hours, poor communication between care teams, and systemic

Figure 1
The problem outline depicting how prioritization of tests with patient blood draw constraints can be effectively optimized in a knowledge-based system to acquire the amount of blood to retrieve



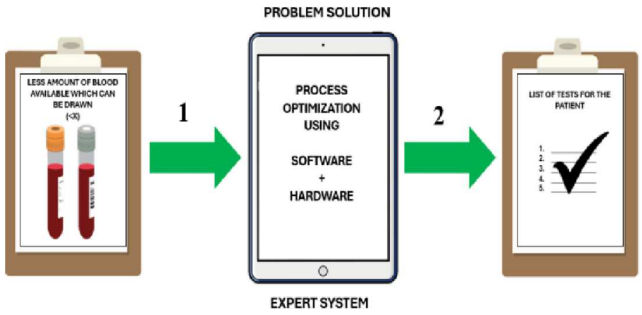
issues such as understaffing and inadequate safety protocols [32]. Physicians order clinical tests to obtain a comprehensive understanding of the patient's condition. Running all tests, while ideal, is risky. Physicians typically order diagnostic tests, while phlebotomists determine the appropriate tube types based on the tests' tube requirements provided by charts and/or software tools. When ordering, physicians are concerned about the blood volume required for requested tests, but the necessary information is often not readily available to optimize test selection. When physicians normally request tests, they use a combination of preset lists and individually picked tests. A predefined test panel consists of a list of tests used to identify a specific condition in the patient. An example of a predefined panel is the oral glucose tolerance test (OGTT), commonly used in the diagnosis of diabetes. In pediatric endocrine settings, modified OGTT protocols may include multiple time-point measurements for glucose, insulin, and other markers, which can cumulatively require over 30–40 mL of blood depending on the number of time points and additional tests ordered. This highlights the challenge of balancing diagnostic needs with volume constraints in pediatric patients under 5 years of age [33, 34]. Guidelines suggest that pediatric blood draws should not exceed 1–5% of total blood volume within a 24-h period or up to 10% over an 8-week period to prevent adverse effects such as anemia or hypovolemia [35, 36]. For children under 5 years of age, weighing between 5 and 40 lbs. (2.3–18.1 kg), this translates to maximum allowable draws of 4.8–36.4 mL within 24 h [3, 37]. Managing blood draw volumes effectively is essential, as physicians often order multiple predefined test panels or add individual tests, necessitating precise planning to avoid exceeding

these limits while ensuring accurate diagnostic outcomes. As an outcome, each drop of blood matters.

Maximizing the number of diagnostic tests that can be completed requires the efficient use of patient blood. Current practices often involve drawing predefined volumes and distributing samples across multiple tubes, which can lead to unnecessary blood loss. This inefficiency reduces the number of tests that can be obtained from a single blood draw and increases patient fatigue. Incomplete or insufficient results from initial test panels may necessitate additional sampling later, further exacerbating blood loss. Excessive phlebotomy increases the risk of iatrogenic anemia and infection, both of which can negatively impact patient outcomes. Even when laboratories can perform all requested tests, minimizing the total volume of blood drawn remains a critical objective to protect patient health and ensure diagnostic efficiency.

This study addresses these challenges by developing an intelligent clinical decision-support system designed to optimize pediatric blood draws across the entire testing workflow. The system provides physicians with real-time guidance to adapt test orders to each patient's maximum safe blood volume based on weight and hematocrit parameters, assists phlebotomists in selecting the most efficient tube combinations for multi-test blood collections, and enables laboratory technologists to maximize test utilization from limited sample volumes. While the analytical volume required for tests remains generally constant, opportunities exist to minimize dead volume through micro-sample cups and reduce overall tubes by intelligently combining tests across acceptable collection tubes. By bridging these critical functions through an integrated algorithmic platform, our solution fulfills the urgent need for a centralized approach to optimize blood use and reduce medical errors. Figure 2 depicts this proposed expert system solution to revolutionize the pediatric blood draw process from order entry through laboratory analysis. To address these challenges, this study presents a clinical decision-support tool designed to optimize pediatric blood collection across the full testing workflow.

Figure 2
Proposed expert system framework for optimizing pediatric blood collection



2. Materials and Methods

2.1. Hardware

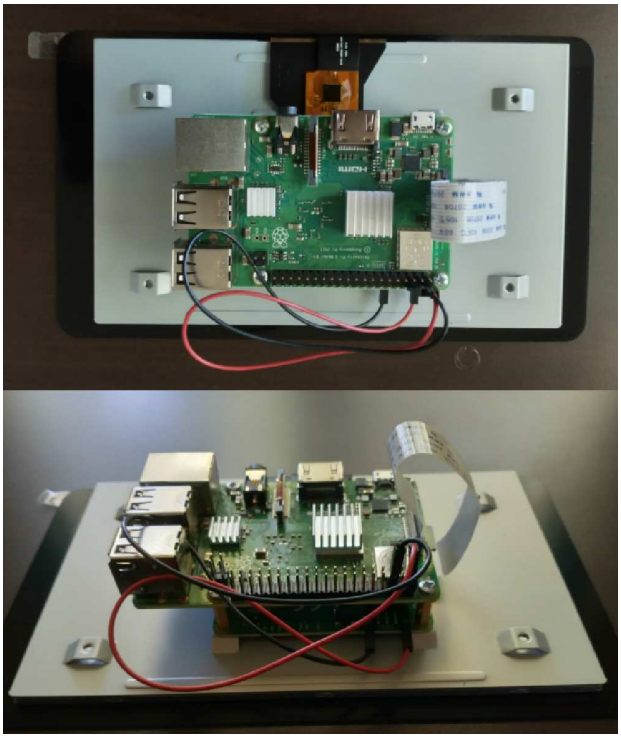
The device integrates a Raspberry Pi 3 Model B+, a 7-inch capacitive touchscreen, and a protective plastic enclosure. The Raspberry Pi is powered by a 64-bit Cortex-A53 processor with 1 GB of LPDDR2 RAM, and the software is stored on a 32 GB SD card. It supports multiple wireless communication standards, including 2.4 GHz and 5 GHz Wi-Fi (IEEE 802.11 b/g/n/ac), Bluetooth 4.2, and BLE, enabling seamless connectivity with other devices. The 40-pin GPIO header interfaces the Raspberry Pi with the touchscreen, which offers an 800 × 480-pixel resolution and 10-point multi-touch input. The complete assembly is shown in Figure 3, with wiring details illustrated in Figure 4.

The selected hardware platform prioritizes cost efficiency, portability, and ease of deployment rather than computational intensity. The Raspberry Pi 3 Model B+ provides sufficient processing capability for rule-based inference while maintaining low power consumption and a small physical footprint suitable for clinical environments. The total hardware cost of the prototype system was approximately $110, including the processing unit, touchscreen interface, enclosure, and peripherals. This low-cost architecture enables scalable deployment without requiring specialized infrastructure. Cybersecurity considerations are critical for clinical decision-support systems. The current prototype operates in an offline configuration by default, eliminating exposure to network-based attacks during standalone use. No patient-identifiable data are transmitted wirelessly, and data access is

Figure 3
The physical hardware components of the expert system prototype

Raspberry Pi 3 B+	7-inch Touch Screen	Case
		

Figure 4
The wiring of the hardware of the expert system



restricted to local interfaces. Future clinical implementations will incorporate encrypted communication protocols (e.g., Transport Layer Security(TLS)), role-based authentication, audit logging, and compliance with healthcare cybersecurity frameworks such as HIPAA and ISO/IEC 27001. These measures are essential to protect against unauthorized access, data tampering, and denial-of-service attacks as the system evolves toward integration with hospital networks and electronic health records (EHRs) [38].

2.2. Software

The system is built on Raspbian, a Linux-based operating system optimized for the Raspberry Pi platform. Software development is performed using Python 3.7, leveraging the xlrd library for the extraction and processing of Excel data, and Tkinter to implement the graphical user interface on the touchscreen. Microsoft Excel serves as the repository for storing data corresponding to individual predefined test panels. Standard guidelines in pediatric care generally recommend limiting blood draws to a certain percentage of the child's total blood volume, with adjustments made based on clinical factors such as weight and respiratory condition [37–39]. For patients without respiratory compromise, a hemoglobin level of above 7 g/dL is typically required to safely draw blood. For patients with respiratory compromise, a higher hematocrit of 10 g/dL is often set to minimize the risk of complications such as anemia or hemodynamic instability [40–43]. Standard clinical guidelines are used to mathematically derive the maximum allowable blood draw for neonates, children, and adults. To calculate the maximum allowable blood draw volume (MBV), each patient's total blood volume (TBV) is estimated using weight-based guidelines. For adults and children older than 1 year, TBV (in mL) is computed in Equation 1, reflecting safe limits [44].

$$TBV = Weight * [75 - 80] \frac{mL}{kg} \quad (1)$$

Infants less than 1 year of age require age-adjusted coefficients due to their higher blood volume per kilogram, as shown in Equation 2, with preterm neonates assigned 100 mL/kg [35].

$$TBV = Weight * [85 - 100] \frac{mL}{kg} \quad (2)$$

The MBV is then derived as a percentage of TBV, accounting for clinical context, where 3% (0.03) represents a conservative threshold for repeated sampling and 5% (0.05) the upper limit for single draws in stable patients [37].

$$MBV = TBV * (0.03 - 0.05) \quad (3)$$

Every count of blood matters; therefore, the lower bound of values is used in the expert system to optimize and limit blood draw use.

2.3. Expert system

The expert system optimizes blood utilization by selecting appropriate tube types and volumes based on guidance from laboratory specialists. Using a forward-chaining inference engine, the system generates optimized test lists for each tube by sequentially applying rules to patient-specific input until a target outcome is achieved. Relevant test data are maintained in Excel files on the Raspberry Pi. Physicians initiate the process by selecting their specialty, which directs the inference engine to the corresponding dataset. The Python script then employs the xlrd library to extract and process the information from these files.

The knowledge base rules are:

1) If the time variable is = X, then place in list.
2) If patient's anticoagulant status is true, then do not use serum.
3) If tube uses whole blood, then separate the tube from list.
4) If tube equals the tube mode, then place in list.
5) If total required blood volume exceeds clinical safety thresholds, then adjust and reduce sample volumes where possible.

Key volume considerations:

1) Analytical volumes remain unchanged per test requirements.
2) Dead volume may be reduced via micro-sample cup substitution.
3) Tube minimization occurs by matching tests to shared acceptable containers beyond the primary tubes listed in laboratory information systems (LIS).

The inference engine uses these rules to generate a list of the best tube combinations to perform tests. The first step is separating the tubes by the time variable. The expert system organizes blood tests according to the scheduled collection times, which may occur at 0, 15, 20, 30, 40, 60, 120, 150, 180 min, and 24 h. For each time point, a separate list of required tubes is generated. Tests requiring whole blood are identified and allocated to a distinct list, as they follow specialized handling procedures. The system then evaluates the patient's anticoagulant status; if anticoagulants are present, serum and red-top tubes are excluded from selection to prevent inappropriate tube usage. Next, the software determines the mode of tube types within the list, enabling iterative selection of the most frequently required tube. Once all tubes of the current mode are assigned, the mode is recalculated, and the process continues until all tests are verified. Finally, the system cross-examines the total blood volume against the patient-specific maximum allowable draw. If the calculated volume exceeds safe limits, the algorithm sequentially reduces dead volume and analytical volume and ultimately applies minimum volume constraints to reach a safe combination. If no acceptable configuration exists, the system issues a warning and provides the minimum volume combination that exceeds the allowable threshold. Through this process, the expert system produces an optimized schedule of tube and test combinations that accounts for collection time, anticoagulant status, whole-blood requirements, tube frequency, and blood volume constraints. If necessary, the system will prioritize tests with lower analytical volume requirements. However, physician input will be considered to ensure that clinically essential tests are not deprioritized solely based on sample volume. By this point, either a combination of test tubes below the threshold will be reached, or there will be a warning notifying the user of the minimum volume combination and that the total blood volume exceeds the maximum drawable limit.

Steps of Expert System:

1) Physician Input: The physician selects their specialty, which guides the inference engine on which files to choose.
2) Data Extraction: The Python script employs the xlrd library to extract and read information from Excel files stored on the Raspberry Pi.
3) Time Variable Separation: The tubes are categorized based on their time variables, with each time category having its own list of tubes.
4) Whole-Blood Separation: Tests requiring whole blood are removed and compiled into a separate list.
5) Anticoagulant Check: If the patient is on anticoagulant therapy, serum tubes are avoided when selecting tube types.

6) Mode Determination: The mode of the test tubes in the list is identified. The software iteratively selects the most common test tube until all tests are included.
7) Blood Volume Check: The total blood volume is compared to the maximum allowed by the Blood V function. If the requested volume surpasses this limit, the system automatically reassigns tests to use their minimum acceptable sample volumes, following laboratory guidelines.
8) Final List: The expert system generates a list of tube and test combinations that consider time, anticoagulant status, whole blood, and the most common tube types.
9) Volume Optimization: If the total blood volume exceeds the maximum drawable limit, the system begins iteratively adjusting tests with the absolute minimum required volumes.
10) Minimum Values: If the total blood volume still exceeds the limit, a warning is issued to the user.

The expert system interface is implemented using Python's open-source Tkinter library, providing a graphical user interface that allows clinicians to request tests or review the status of previous orders (Figure 5). Users begin by selecting their medical specialty, which directs the inference engine to the relevant dataset. Subsequently, the clinician inputs patient-specific parameters, including weight, hemoglobin concentration, hematocrit level, respiratory status, and anticoagulant use, and may select up to four predefined test panels. Once all inputs are entered, the interface displays the compiled list of tests and corresponding tubes for review before submission to the laboratory. To maintain patient confidentiality, the current device operates offline and does not connect to Wi-Fi or hospital cloud networks; data transfer occurs manually or via a secure wired interface. The system can communicate with nearby devices through Bluetooth 4.2 or BLE, ensuring controlled connectivity. Future iterations are planned to integrate with hospital information systems, such as Epic, and cloud platforms using encrypted protocols and secure authentication for compliant data exchange. This interface design prioritizes both usability and data security while facilitating efficient blood draw planning in pediatric patients. The Pediatric Blood Calculator is designed to determine the maximum amount of blood the patient can give in a 24-h period and determine the ideal test tube combination for the predefined test panels selected.

Figure 5
The expert system graphical user interface

We use these endocrine predefined test panels to illustrate the impact of this system by comparing the expert system output volume with the output volume of the current practice.

The expert system knowledge base is implemented using structured spreadsheet files, each corresponding to a specific clinical specialty. Each file contained standardized fields including test identifier, acceptable tube types, preferred analytical volume, minimum acceptable analytical volume, tube dead volume, whole-blood requirement flag, anticoagulant compatibility, and collection time-point designation. These files served as a static and auditable representation of laboratory knowledge, enabling transparent rule execution and facilitation validation by laboratory personnel. During runtime, the expert system parsed these data programmatically to construct candidate tube combinations and evaluate volume constraints. In situations where multiple rules yield conflicting tube assignments, conflict resolution followed a hierarchical precedence strategy. Patient safety constraints, including maximum allowable blood volume and anticoagulant compatibility, were enforced as hard constraints and could not be violated. Whole-blood requirements were evaluated next, followed by time-point compatibility. Among the remaining feasible options, the system selected tube combinations that minimized total draw volume. If no configuration satisfied all constraints, the system generated the minimum volume feasible solution and issued an explicit warning indicating threshold violation.

System performance was evaluated using descriptive statistical measures, including absolute and percentage differences between standard practice blood volume, expert system–optimized volume, and maximum allowable blood draw volume. Key outcome metrics included mean volume savings, proportion of cases within safety thresholds, and identification of optimization failures. Given the proof-of-concept nature and reliance on simulated data, inferential statistical testing was not performed.

2.4 Simulated patient cohort generation

The simulated pediatric dataset was developed in close collaboration with clinical laboratory specialists to ensure that the generated scenarios accurately reflected real-world ordering practices, specimen handling constraints, and preanalytical limitations encountered in pediatric care. Rather than using purely random or synthetic values, the simulation framework was constructed by first defining clinically plausible parameter bounds based on institutional laboratory guidelines and expert consensus. These parameters included patient age, body weight, hematocrit range, test panel composition, acceptable tube types, analytical volume requirements, and tube dead volumes. Laboratory specialists provided guidance on realistic combinations of predefined test panels, age-dependent testing intensity, and minimum sample volumes required to ensure analytical validity across commonly used assays. This expert input ensured that the simulated cases represented realistic clinical workflows rather than abstract optimization scenarios.

Patient-specific variables were generated within these clinically validated bounds to create a diverse cohort capable of stress-testing the expert system. Ages ranged from 1 to 10 years, with corresponding body weights selected to reflect pediatric growth curves encountered in endocrine practice. Hematocrit values were sampled across a wide physiological spectrum (0.20–0.90), capturing both typical and edge-case conditions known to affect serum and plasma yield. Test panel assignment was structured rather than purely stochastic: patients aged 6 years and older were assigned three predefined endocrine

panels, while younger patients were assigned up to three panels to reflect conservative ordering behavior in smaller children. These design choices were informed by laboratory specialists' experience with age-dependent testing patterns and ensured that cumulative blood volume demands scaled realistically with patient size and clinical context.

The resulting simulated dataset was intentionally constructed to include both feasible and infeasible optimization scenarios. Cases involving low total blood volume, high hematocrit, or extensive test panel combinations were preserved to evaluate the expert system's ability to correctly identify threshold violations and issue appropriate warnings. By grounding the simulation in expert-defined constraints and preserving clinically meaningful edge cases, the dataset provides a reproducible yet realistic test environment for evaluating rule-based blood draw optimization in pediatric laboratory workflows.

3. Results

Twenty patients were simulated to test the device code output. The patients aged between 1 and 10 years, with weights ranging from 6.80 kg to 31.75 kg, and an average weight of 19.25 kg. Hematocrit levels for the children varied from 0.2 to 0.9, averaging at 0.52. Children over age 6 were each assigned three randomly selected endocrine predefined test panels, while patients under six received three or fewer panels at random. The expert system's output was compared with the blood volume derived from current practice and the maximum blood volume calculated by the Blood V to illustrate potential blood savings and whether the blood draw complies with the maximum blood draw guidelines (refer to Table 1 and Figure 6).

Using standard formulas based on weight, age, and hematocrit, each patient's total blood volume was estimated, and a maximum allowable blood draw volume was calculated as 3% of that total. The optimized approach successfully stayed within the safe maximum limits for 16 out of 20 patients (80%), indicating high compatibility with clinical safety thresholds. These patients showed an average savings of approximately 9.36 mL of blood compared to standard practice. For example, Patient 5 had a standard draw of 39 mL, which was reduced to 19.37 mL under the optimized protocol well below the maximum allowable volume of 66.68 mL, resulting in a savings of 19.63 mL. Conversely, four patients (20%) had optimized draw volumes that exceeded their individual maximum thresholds, highlighting edge cases where either the small patient size or complex lab panel requirements limited further reduction. Notably, Patient 19 had a total blood volume of only 539.77 mL, yielding a maximum allowable draw of 16.19 mL, yet their optimized draw volume was 32.96 mL, leading to a negative savings of −17.96 mL and not optimizing blood quantity. Patients 3, 18, 19, and 20 had negative savings, demonstrating that optimization may be limited in cases involving multiple high-volume panels or patients

Table 1
Comparison of standard practice blood draw volumes, expert system–optimized volumes, and maximum allowable blood draw limits for simulated pediatric patients (n = 20)

Patient	Weight (kg)	Hematocrit	Age	Total body blood volume (mL)	Maximum blood draw (mL)	Optimized blood draw (mL)	Standard blood draw (mL)	Quantity of blood saved (mL)	Blood quantity optimized
1	31.75	0.50	10.00	2222.60	66.68	40.16	57	16.84	Yes
2	27.22	0.70	10.00	1905.09	57.15	31.20	42	10.80	Yes
3	40.82	0.90	10.00	2857.63	85.73	88.82	87	–1.82	No
4	22.68	0.30	8.00	1587.57	47.63	31.20	43	11.80	Yes
5	31.75	0.20	8.00	2222.60	66.68	19.37	39	19.63	Yes
6	27.22	0.50	8.00	1905.09	57.15	45.55	52	6.45	Yes
7	18.14	0.40	6.00	1270.06	38.10	27.43	32	4.57	Yes
8	27.22	0.70	6.00	1905.09	57.15	22.49	35	12.51	Yes
9	22.68	0.60	6.00	1587.57	47.63	26.61	36	9.39	Yes
10	13.61	0.30	4.00	952.54	28.58	28.81	25	-3.81	No
11	18.14	0.40	4.00	1270.06	38.10	16.00	30	14.00	Yes
12	13.61	0.50	4.00	952.54	28.58	23.81	25	1.19	Yes
13	15.88	0.20	3.00	1111.30	33.34	28.35	31	2.65	Yes
14	13.61	0.80	3.00	952.54	28.58	17.77	22	4.23	Yes
15	12.25	0.40	3.00	857.29	25.72	21.21	24	2.79	Yes
16	11.34	0.70	2.00	793.79	23.81	14.64	15	0.36	Yes
17	13.61	0.60	2.00	952.54	28.58	20.00	25	5.00	Yes
18	9.07	0.50	1.00	635.03	19.05	28.96	15	–13.95	No
19	7.71	0.90	1.00	539.77	16.19	32.96	15	–17.96	No
20	6.80	0.30	1.00	476.27	14.29	14.45	10	–4.45	No

Figure 6
Comparison of standard practice, expert system–optimized, and maximum allowable blood draw volumes across simulated pediatric patients (n = 20)

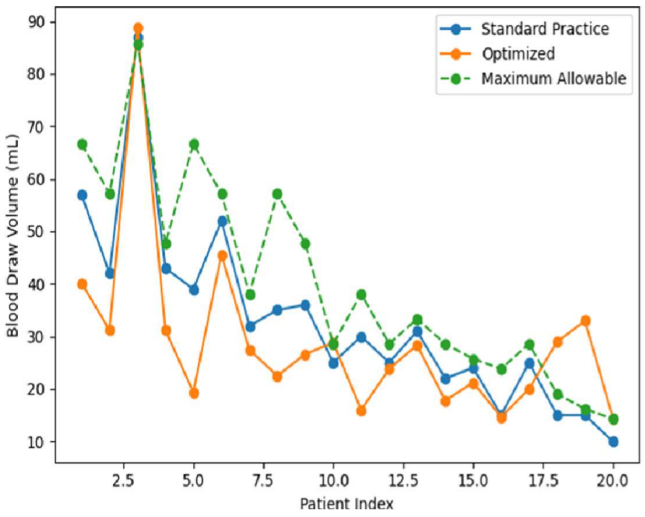
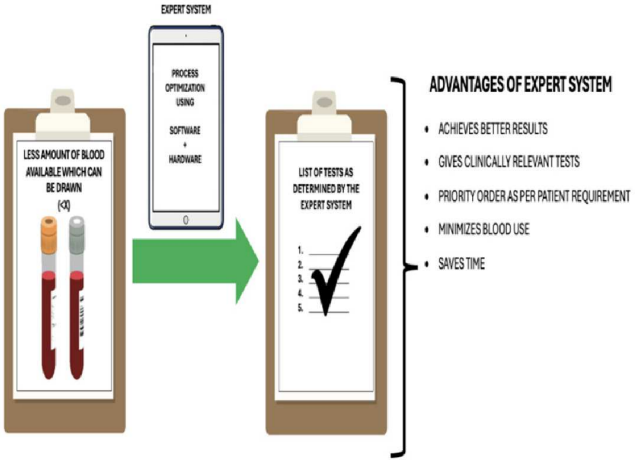


Figure 7
Outlining the advantages of using an expert system for optimizing the process of blood draw in pediatric patients



with small total blood volume. Additionally, high hematocrit levels in some of these patients may have contributed to insufficient serum or plasma yield despite sufficient whole blood volume, a limitation in standard practice that the expert system is well-positioned to address. While the current version prioritizes minimizing total blood draw volume, future iterations could incorporate logic to compare different tube combinations and select the configuration that provides the most efficient use of blood while ensuring adequate sample yield for all assays. Despite these outliers, the results underscore the utility of the expert system in safely reducing blood draw volumes for most patients, potentially minimizing the risk of anemia in this pediatric population.

As illustrated in Figure 7, the implementation of an expert system for test selection in scenarios with limited available blood offers several significant clinical and operational advantages. By leveraging software and hardware for process optimization, it minimizes the total amount of blood required, which is especially critical for vulnerable populations such as neonates or patients with anemia. Additionally, this approach streamlines clinical workflows, reducing decision-making time for healthcare providers and accelerating the diagnostic process.

4. Discussion

4.1. Algorithmic performance and refinement

Among 20 pediatric endocrine patients analyzed, the expert system achieved successful blood draw optimization in 16 cases (80%), with optimized volumes remaining below the patient-specific maximum allowable limits. In these successful cases, the average volume saved compared to the standard blood draw was 9.36 mL, with individual savings ranging from 0.36 mL to as high as 19.63 mL. Conversely, four patients (20%) had optimized values that exceeded their maximum allowable blood draw volumes, with excesses ranging from 0.16 mL to 17.96 mL compared to standard practice. These outliers highlight the need for refinement in the optimization process, particularly in scenarios involving low total blood volume or extensive lab requirements. In this study, extensive lab requirements refer to clinical scenarios where multiple predefined panels or numerous individual tests are ordered simultaneously, resulting in a high cumulative demand for blood. These requirements often exceed what can safely be drawn from pediatric patients, especially neonates and infants with limited total blood volumes. For example, a combination of endocrine, metabolic, and hematology panels may involve dozens of individual assays, each requiring specific tubes and minimum sample volumes. This diagnostic comprehensiveness, while clinically valuable, creates a challenge even for optimized systems like ours, as seen in the four patients for whom the expert system could not reduce blood volume below the maximum allowable threshold. These edge cases emphasize the need for future integration of test prioritization or dynamic test selection features, enabling clinicians to make informed decisions when faced with trade-offs between diagnostic coverage and patient safety.

The discrepancies observed in the four failed cases reveal critical limitations in applying generalized thresholds for pediatric blood draw optimization. Specifically, overestimations were seen in patients with either small total blood volumes due to low body weight or disproportionately high hematocrit levels. In low body weight pediatric patients, total circulating blood volume is so limited (typically 80–90 mL/kg) that even guideline-compliant draws ($\leq$ 1–5% per 24 h) may be insufficient for all required assays when accounting for hematocrit-related plasma yield loss, leading to underestimation by fixed-threshold systems [45–47]. In standard practice, high hematocrit may result in an adequate amount of whole blood being drawn but an insufficient yield of serum or plasma for certain assays, potentially causing test cancellation. This highlights an important advantage of the expert system—its ability to anticipate such volume-to-yield discrepancies and guide tube selection or volume adjustment, accordingly, helping ensure adequate sample processing despite physiological variability. These edge cases highlight the need for a more refined system that can dynamically account for variations in patient physiology. Variations in hematocrit and red blood cell properties are known to influence effective plasma yield and analytical reliability, reinforcing the need for conservative volume constraints in pediatric sampling [48]. One potential solution is the integration of machine learning models trained on a broader dataset of pediatric profiles, allowing the system to predict safe draw volumes based not only on fixed equations but also on learned patterns across multiple parameters. Alternatively, the development of

adaptive equations—responsive to nonlinear interactions between weight, age, hematocrit, and clinical context—could improve safety margins while preserving draw efficiency. By embedding these mechanisms into the optimization algorithm, the system could better identify at-risk cases and suggest safer, patient-specific lab workflows. This would not only enhance clinical safety but also extend the applicability of blood-saving protocols to even the most vulnerable pediatric populations.

4.2. Data infrastructure and validation needs

The transition from a proof-of-concept simulation to clinical implementation necessitates comprehensive upgrades in both data infrastructure and validation methodology. While the current Excel-based system enabled rapid prototyping, it lacks key functionalities required for clinical-grade deployment, such as version control, concurrent access, and secure audit trails. Transitioning to a relational database (e.g., SQL) with user-specific access rights would support real-time updates by laboratory personnel, maintain robust change logs, and enable integration with LIS like Epic Beaker or Cerner Millennium. Incorporating an application programming interface layer would further allow seamless bidirectional communication with EHRs, automating both data ingestion and the test order process.

To rigorously validate the tool, a phased evaluation strategy is proposed. An initial retrospective analysis of 500 cases—drawn from diverse pediatric subspecialties such as the Neonatal Intensive Care Unit (NICU), Pediatric Intensive Care Unit (PICU), general inpatient units, and outpatient clinics—will provide the statistical power necessary to capture variability in ordering behavior and patient physiology. The choice of 500 cases ensures adequate sampling of rare but clinically important edge cases, such as very low birth weight neonates (< 1.5 kg) or patients with hematocrit extremes (< 0.25 or > 0.65), which are critical for stress-testing the algorithm. Subsequent prospective validation across multiple healthcare systems will assess the expert system's generalizability and performance across different institutional workflows, LIS environments, and patient populations. This multi-site validation will not only benchmark technical metrics like algorithm accuracy and processing time but also track real-world clinical outcomes including reductions in iatrogenic anemia and transfusion rates—to iteratively refine and validate the tool's effectiveness in improving pediatric care.

4.3. Clinical implementation strategy

Successful integration into clinical workflows requires careful consideration of both technical and human factors. The algorithm should be embedded as a decision-support module within existing EHR systems, positioned at the point of test ordering to provide real-time feedback to clinicians. This implementation would enable several critical safety features: immediate flagging of potentially unsafe draw volumes and support for test prioritization by the ordering physician, informed by clinical urgency and individual patient constraints. The interface design must balance comprehensive information display with clinical usability, presenting key data (e.g., cumulative draw volumes in 24 h without overwhelming the user.)

To streamline phlebotomy workflows, the system could generate prepackaged tube sets labeled with patient-specific barcodes and optimized draw sequences, reducing procedural delays and potential errors, while still supporting bedside labeling verification to align with current best practices. 24-h cumulative blood draw tracking with automated alerts when approaching safety thresholds could be beneficial but must be carefully balanced against the practicality of implementation. The implementation plan should include a comprehensive training program addressing both technical operation and clinical interpretation of system outputs, with particular emphasis on edge cases where human judgment must supersede algorithmic recommendations. A phased rollout strategy is recommended, starting with a pilot program in a controlled environment (e.g., pediatric endocrinology clinic) before expanding to critical care areas where patient acuity and test complexity are highest.

4.4. Future directions and research opportunities

The future of this pediatric blood draw optimization system lies in several key areas of development that could enhance its utility and clinical impact. A primary focus should be the incorporation of predictive modeling capabilities. Shifting the system from a reactive to a proactive risk prevention model could significantly improve its accuracy. By analyzing historical data such as draw frequency, volume, and hematocrit changes, the system could predict anemia risk and recommend personalized testing intervals for each patient. This data-driven approach would allow the system to minimize unnecessary blood draws, reduce the occurrence of iatrogenic anemia, and optimize clinical workflows. Research into developing predictive algorithms that integrate patient data from medical histories and real-time results, especially for high-risk populations, is essential. Machine learning techniques could further refine these models, improving decision-making as more patient data becomes available.

To support safe and effective clinical decision-making, the system's architecture must be designed with adaptability to incorporate established clinical guidelines and local standards of care. By aligning the expert system with evidence-based protocols and institutional best practices, it can guide ordering physicians toward selecting the most clinically relevant and essential tests, particularly when blood volume is limited. Integration with national and local pediatric care guidelines will ensure consistency across providers while still allowing for flexibility based on individual patient needs. Collaboration with clinical laboratory organizations, institutional care-path committees, and standards bodies will be key in embedding these care pathways into the system. Rather than replacing physician judgment, the system will serve as a decision-support tool, highlighting which tests align with care standards and optimizing blood draw strategies accordingly. This approach not only enhances clinical appropriateness but also reduces unnecessary testing or under-testing, ultimately improving patient safety and resource utilization.

5. Conclusions

This study demonstrates the potential of an expert system to optimize blood draw volumes in pediatric patients. Key areas for development include predictive analytics to further tailor blood draw recommendations and ongoing enhancements such as dynamic hematocrit correction and machine learning-assisted classification. Long-term studies and multicenter validation will be crucial to refining the system and establishing its impact on iatrogenic anemia, transfusion needs, and other clinical outcomes. This technology represents a step toward personalized, evidence-based pediatric phlebotomy, optimizing care and safety for vulnerable populations while adhering to clinical and regulatory standards.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Sihe Wang: Conceptualization, Methodology, Software, Investigation, Resources, Data curation, Writing – review & editing, Visualization, Supervision, Project administration. **Richard Desatnik:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review &; editing, Visualization. **Motaz Hassan:** Validation, Formal analysis, Writing – original draft, Writing – review &; editing, Visualization. **Amanpreet Singh Wasir:** Validation, Formal analysis, Writing – original draft, Writing – review &; editing, Visualization. **Ajay Mahajan:** Conceptualization, Methodology, Software, Investigation, Resources, Data curation, Writing – review & editing, Visualization, Supervision, Project administration.

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