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A Rule-Based Expert System for Pediatric Blood Draw Optimization: A Proof-of-Concept Study

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Abstract: Pediatric patients are particularly vulnerable to diagnostic blood loss due to limited circulating blood volume and frequent laboratory testing. This study presents a proof-of-concept expert system designed to optimize pediatric blood collection by integrating patient-specific blood-volume constraints with laboratory specimen requirements. A rule-based forward-chaining inference engine was developed in Python and implemented on a Raspberry Pi 3 Model B+ with a touchscreen interface. The knowledge base incorporated test-specific tube requirements, minimum and preferred analytical volumes, tube dead volume, whole-blood requirements, anticoagulant compatibility, and collection time points. The system calculated patient-specific total blood volume and maximum allowable blood draw using weight-based parameters. System performance was evaluated using 20 simulated pediatric cases involving endocrine test panels. The system identified lower-volume collection configurations within allowable blood-volume limits in 15 cases (75%), reducing volume by 0.36–19.63 mL. Five cases (25%) exceeded allowable limits, revealing conflicts between laboratory minimum-volume requirements and patient-specific constraints. Two cases incorporated extreme hematocrit values (~0.90) to stress-test system behavior. These findings demonstrate the computational feasibility of an explainable, rule-based approach to minimizing unnecessary pediatric blood collection while identifying infeasible testing configurations. However, the small, simulated cohort limits conclusions regarding clinical effectiveness and generalizability. Future work will incorporate formal optimization, dynamic specimen-yield modeling, expanded laboratory testing, and validation using real pediatric clinical data.

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

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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. 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.

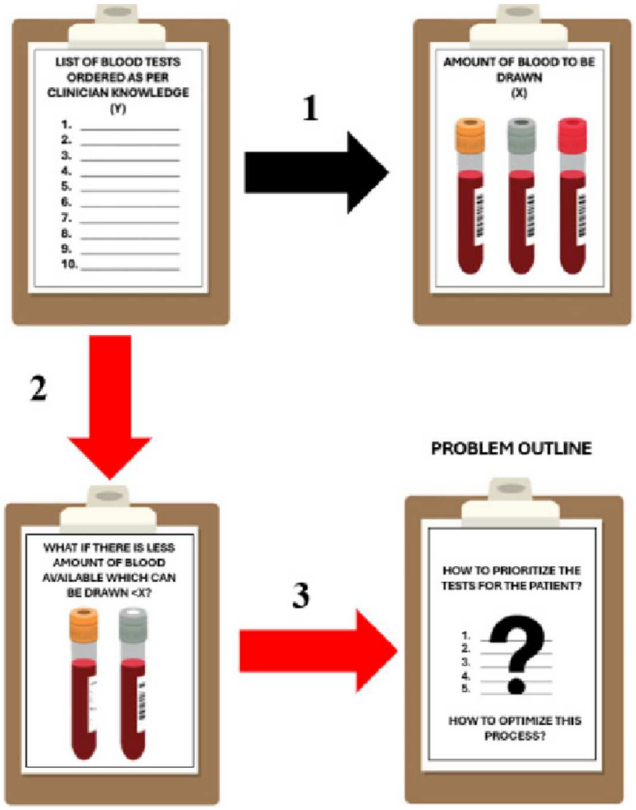
Few deployed tools address blood-draw volume specifically. The most directly comparable published system is a minimal-blood-volume clinical decision-support (MBV-CDS) tool implemented at a single-center neonatal intensive care unit, which calculates the minimum blood volume and container type required for a requested test combination by accounting for patient hematocrit and instrument-specific dead and minimum test volumes; a retrospective evaluation across 463 patients and 8,481 blood draws found that laboratory information system recommendations, and the volumes clinicians actually collected, both exceeded the tool's calculated minimum requirement, indicating a persistent opportunity for volume reduction even where an informatics tool exists [30]. This tool, however, is restricted to neonatal patients, calculates only a minimum required volume rather than jointly enforcing a patient-specific maximum allowable blood volume as a safety constraint, and is implemented as laboratory-information-system logic rather than a standalone rule-based expert system with dedicated point-of-care hardware. Beyond this example, the wider literature on reducing diagnostic blood loss centers on strategies such as smaller-volume collection tubes, closed blood-conservation sampling devices, and general computerized order-entry alerts, rather than on systems that jointly optimize tube selection against both minimum specimen and maximum patient-safety volume constraints. No publicly documented device, deployed system, or commercially available laboratory software currently performs a joint, patient-specific optimization for the general pediatric population outside the neonatal intensive care setting, motivating the framework proposed in this study.

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 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

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

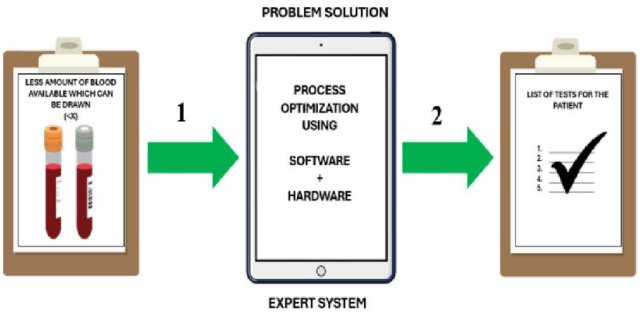


blood draws should not exceed 1–5% of total blood volume within a 24-h period or up to 10% over an 8-week period to prevent adverse effects such as anemia or hypovolemia [35, 36]. For children under 5 years of age, weighing between 5 and 40 lbs. (2.3–18.1 kg), this translates to maximum allowable draws 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 during preanalytical blood-collection planning. The system provides patient-specific decision support during blood-draw planning with real-time guidance to adapt test orders to each patient's maximum safe blood volume based on weight and hematocrit parameters, helps phlebotomists select 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

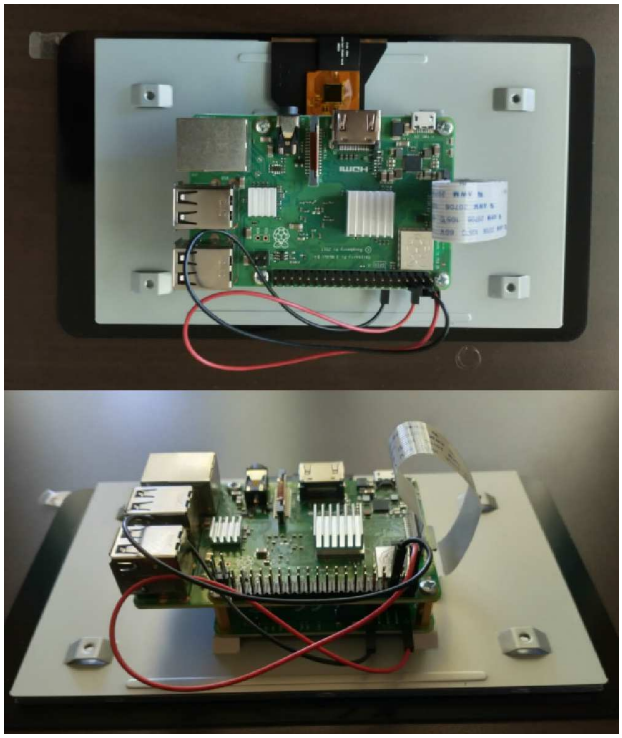
The device integrates a Raspberry Pi 3 Model B+, a 7-inch capacitive touchscreen, and a protective plastic enclosure. The Raspberry Pi is powered by a 64-bit Cortex-A53 processor with 1 GB of LPDDR2 RAM, and the software is stored on a 32 GB SD card. It supports multiple wireless communication standards, 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 whole paragraph 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 prototype system's total hardware cost 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 offline by default, eliminating

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



exposure to network-based attacks during standalone use. No patient-identifiable data are transmitted wirelessly, and data access is restricted to local interfaces. Future clinical validation attempts 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 [39].

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. The knowledge base was populated using published laboratory guidelines and tube-manufacturer specifications, with input from the co-author with clinical laboratory medicine expertise. This consultation informed rule content but did not constitute a formal, documented multi-reviewer validation process. Using a forward-chaining inference engine, the system generates optimized test lists for each tube by sequentially applying rules to patient-specific input until it achieves a target outcome. The system stores relevant test data in Excel files (a structured spreadsheet-based knowledge base) 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 collection volume exceeds the maximum allowable blood volume, the algorithm first evaluates opportunities to consolidate and reduce tube-associated dead volume. It then reduces specimen volumes toward their laboratory-defined minimum acceptable values where the preferred volume exceeds the minimum. Analytical specimen volumes are never reduced below the corresponding minimum requirements. If the resulting minimum-volume configuration remains above the maximum allowable blood volume, the system generates an explicit warning rather than violating laboratory specimen requirements. 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.

The blood-draw planning problem was formulated as a constrained volume-minimization problem in which the primary objective is to minimize the total blood volume collected while satisfying patient-specific safety constraints and laboratory specimen requirements. The total collection volume is represented as:

$$V_{\text{draw}} = \sum_{i=1}^{N} V_{\text{analytical},i} + \sum_{j=1}^{M} V_{\text{dead},j}$$

where V_{draw} is the total blood volume collected, $V_{\text{analytical,i}}$ is the analytical specimen volume required for test *i, N* is the number of requested tests, $V_{\text{dead, }i}$ is the dead volume associated with collection tube *j*, and *M* is the number of tubes selected. The optimization objective is therefore $\min V_{\text{draw}}$.

The objective is subject to laboratory and patient-specific constraints. The primary patient safety constraint is

$$V_{\text{draw}} \leq \text{MBV}$$

where MBV is the maximum allowable blood volume calculated for the individual patient. For each requested test, the selected configuration must also satisfy

$$V_{\text{analytical},i} \geq V_{\text{minimum},i}$$

where $V_{\text{minimum,i}}$ is the minimum specimen volume established in the knowledge base for that test. Additional constraints require each test to be assigned to a compatible collection tube, preserve whole-blood requirements, remain compatible with the patient's anticoagulant status, and stay consistent with the designated collection time point. When multiple requested tests can be performed from the same acceptable tube, those tests may be consolidated to reduce the number of tubes and associated dead volume. The optimization variables are therefore the tube assignments and specimen volumes associated with each requested test denoted as

$$x_{ij} = \begin{cases} 1 & \text{if test } i \text{ is assigned to tube } j \\ 0 & \text{otherwise.} \end{cases}$$

In the current implementation, these variables are not determined using a general-purpose mathematical optimization solver. Instead, the system uses a deterministic forward-chaining heuristic to identify progressively lower-volume configurations. The inference engine first establishes the feasible tube assignments based on collection time, specimen type, anticoagulant compatibility, and whole-blood requirements. The system then consolidates compatible tests based on available tube configurations, preferring tube types used among the requested tests. The system then evaluates the resulting collection volume against the patient-specific MBV.

When the calculated collection volume exceeds MBV, the system applies the volume-reduction rules in a defined sequence. First, the system evaluates opportunities to consolidate tests and reduce tube-associated dead volume. If additional reduction is required, the system reduces analytical specimen volumes toward their laboratory-defined minimum acceptable values. Analytical volumes are not reduced below these minimum requirements. The optimization terminates when either a configuration satisfying all applicable constraints and $V_{\text{draw}} \leq \text{MBV}$ is identified, or when all permissible reductions have been exhausted. If the minimum feasible configuration remains above MBV, the system generates an explicit warning with the solution that the requested testing exceeds the accommodated blood-volume limit.

Accordingly, the current implementation is a rule-based constrained optimization heuristic. The formulation defines blood-volume minimization as the objective while treating patient safety and laboratory specimen requirements as constraints. This approach preserves the expert system's transparency and traceability, linking each tube assignment and volume adjustment to an explicit rule in the knowledge base. Future work could incorporate a formal mathematical optimization solver to evaluate the full feasible solution space and determine whether the current heuristic identifies globally minimal-volume solutions. The supplementary files show a process map of the expert system's minimization process.

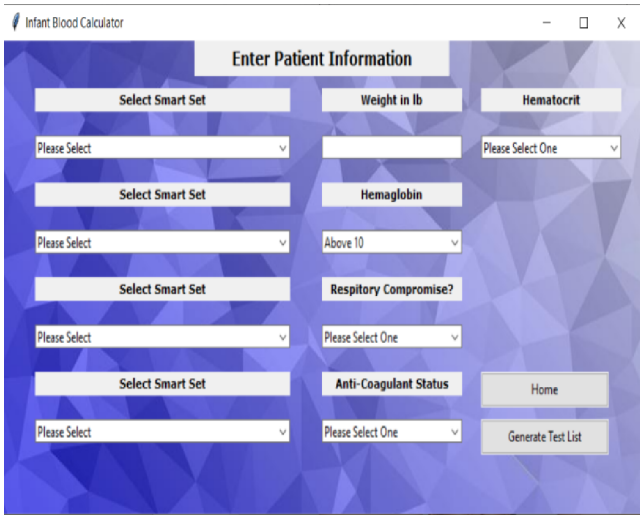
Steps of Expert System:

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. 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.

Figure 5
The expert system graphical user interface



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, auditable representation of laboratory knowledge, enabling transparent rule execution and facilitating validation by laboratory personnel. During runtime, the expert system parsed these data programmatically to construct candidate tube combinations and evaluate volume constraints. When multiple rules produced conflicting tube assignments, the system resolved conflicts using a hierarchical precedence strategy. The system enforced patient safety constraints, including maximum allowable blood volume and anticoagulant compatibility, as hard constraints that could not be violated. The system next evaluated whole-blood requirements, followed by time-point compatibility. Among 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.

We evaluated system performance using descriptive statistics, 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, we did not perform inferential statistical testing.

2.4. Simulated Patient Cohort Generation

The simulated cohort was designed to evaluate the proposed expert system's computational behavior rather than serve as a clinically representative pediatric population. The primary purpose of the 20 cases was to test whether the rule-based framework could integrate patient-specific blood-volume constraints with laboratory specimen requirements and identify opportunities to reduce blood collection relative to standard practice. The structured nature of the simulation allowed evaluation of the effects of individual variables, including patient size, hematocrit, test-panel requirements, analytical volume, tube configuration, and dead volume, in a controlled environment.

Importantly, the simulation was not restricted to cases in which the optimization objective could be achieved. Feasible cases were accompanied by cases in which laboratory specimen requirements conflicted with the patient's maximum allowable blood-volume constraint. This was intentional because a clinically oriented optimization framework should identify an infeasible request rather than force a solution that violates a predefined safety threshold. Consequently, cases in which the optimized volume exceeded the maximum allowable volume should be interpreted as demonstrations of constraint handling and system warning behavior, rather than as clinically acceptable blood-draw

recommendations. The deliberate inclusion of edge cases also assesses the robustness of the rule-based inference process. The extreme hematocrit value in the dataset was introduced specifically to stress-test the system under an unusual input condition. Such a test does not establish that the corresponding physiological state is representative of pediatric patients; instead, it evaluates whether the computational framework remains operational and produces an interpretable result when presented with an extreme input. This distinction is important because the present study evaluates the behavior of a decision-support algorithm, not the prevalence or clinical distribution of the simulated patient characteristics. The results should therefore be interpreted primarily as evidence of algorithmic feasibility. The observed reduction in blood collection relative to standard practice demonstrates the potential of the encoded rules to identify lower-volume specimen configurations under the tested scenarios. At the same time, cases that remained above the maximum allowable blood-volume threshold demonstrate that optimization cannot always reconcile laboratory requirements with patient-specific blood-volume constraints. In such situations, the system should identify the conflict and alert the clinician rather than provide an apparently optimized volume that could be incorrectly interpreted as safe.

Because the cohort consisted of only 20 intentionally constructed cases, the observed blood-volume reductions and frequency of constraint violations cannot be generalized to the broader pediatric population. The simulation also does not establish whether reduced collection volume would translate into less iatrogenic anemia, fewer repeat blood collections, reduced transfusion requirements, or improved patient outcomes. Answering those questions requires validation with real pediatric patient data and comparison with actual clinical blood-draw practices. Accordingly, these results should be considered a proof-of-concept demonstration of the feasibility of integrating pediatric blood-volume constraints into a transparent, rule-based optimization framework, rather than evidence of clinical effectiveness.

3. Results

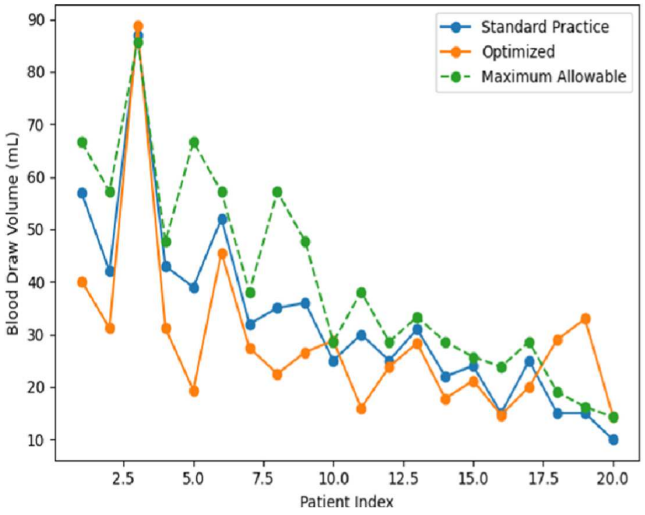
To test the device code output, we simulated 20 patients. The patients ranged in age from 1 to 10 and weighed between 6.80 kg and 40.85 kg, with an average of 19.25 kg. Hematocrit levels ranged from 0.2 to 0.9, with an average of 0.52. Each simulated child over age 6 was given 3 random predefined endocrine test panels. Patients under age 6 were given three or fewer predefined test panels at random. The output of the expert system is compared to the blood volume from the current practice and the maximum blood volume generated by the Blood V function to demonstrate blood savings and if the blood draw could be conducted per the standard and maximum blood draw guidelines (see Table 1 and Figure 6). Supplementary table provides full patient-level test panel and blood draw volume optimization data.

The expert system was evaluated using 20 simulated pediatric cases to determine whether the rule-based framework could reduce blood collection relative to standard practice while maintaining compliance with patient-specific maximum allowable blood-volume constraints. Most cases showed a reduction in required collection volume after optimization. However, five cases (Patients 3, 10, 18, 19, and 20) produced optimized volumes that exceeded their corresponding maximum allowable blood-volume thresholds. These cases represent infeasible optimization

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)	Within maximum blood draw volume
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)



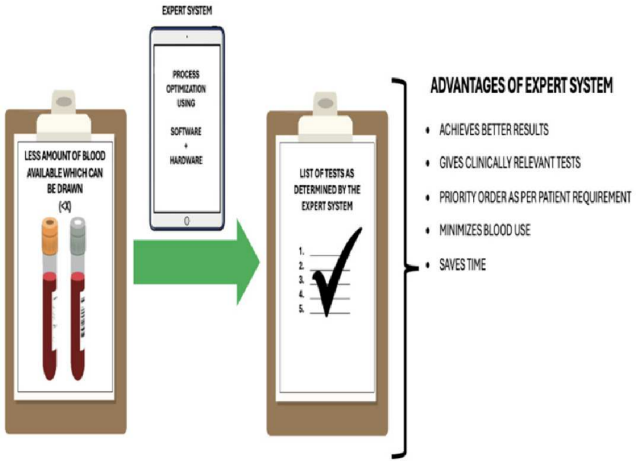
scenarios, in which the laboratory specimen requirements encoded in the knowledge base could not be satisfied within the predefined patient-specific blood-volume constraint. Thus, these cases should not be interpreted as successful clinical recommendations, but rather as instances in which the system identified a conflict between diagnostic requirements and the available blood-volume limit.

Importantly, the five cases did not necessarily arise from the same underlying condition. Patients 3 and 19 were deliberately constructed as edge cases with hematocrit values of approximately 0.90 to stress-test the inference engine under extreme physiological inputs. The extreme hematocrit condition exposes a limitation of the current model because it does not explicitly model the relationship between whole-blood volume and derived plasma or serum yield as a function of hematocrit. Consequently, although the system applied its prescribed volume-reduction rules, the resulting optimized collection volumes remained above the patient-specific maximum allowable thresholds. These cases therefore demonstrate the system's behavior under deliberately challenging hematocrit conditions rather than typical pediatric physiological scenarios.

Patients 10, 18, and 20 represent additional constraint-violation scenarios in which the laboratory requirements and patient-specific blood-volume limits could not be satisfied simultaneously under the current rule set. In these cases, the knowledge base's minimum specimen volumes and tube-specific requirements imposed a lower bound on the amount of blood that could be collected. Further reduction would have required violating the minimum specimen-volume requirements encoded for the requested tests. The system therefore identified the resulting conflict rather than forcing an arbitrarily lower collection volume.

These cases are important for interpreting the proposed system's behavior. The objective is not simply to minimize blood volume without regard to analytical requirements; rather, the system seeks to minimize collection volume subject to laboratory and patient-safety constraints (Figure 7). When no configuration satisfies all constraints simultaneously, the system should identify the conflict and generate a warning for clinical consideration. This is preferable to producing a lower volume that appears

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



mathematically optimized but may fail to provide sufficient specimen for the requested analyses or otherwise violate the predefined blood-volume constraint.

The five constraint-violating cases also identify opportunities for future refinement. In particular, the current framework relies on predefined laboratory requirements, fixed minimum specimen volumes, tube dead volumes, and patient-specific blood-volume thresholds. Future iterations could incorporate more detailed hematocrit-dependent specimen-yield calculations, alternative tube configurations, test prioritization, and clinician-directed selection of lower-priority assays when the complete requested testing cannot be accommodated within the patient's allowable blood-volume limit.

Overall, the results demonstrate that the proposed framework can reduce blood collection relative to standard practice in the tested scenarios while also identifying cases in which the requested laboratory testing cannot be reconciled with the predefined blood-volume constraint. The five constraint-violating cases therefore provide useful information about the boundary conditions of the current rule set. Patients 3 and 19 demonstrate the value of deliberate edge-case testing by revealing system behavior under extreme hematocrit inputs, whereas Patients 10, 18, and 20 demonstrate additional conflicts between laboratory specimen requirements and patient-specific blood-volume limits. These outcomes should be interpreted as evidence of algorithmic feasibility and constraint handling, not as evidence of clinical effectiveness or as an estimate of the frequency of such cases in the pediatric population.

4. Discussion

4.1. Principal Findings and Contribution

This study presents a proof-of-concept, rule-based expert system for optimizing pediatric blood collection by integrating patient-specific blood-volume constraints with laboratory-specific specimen requirements. The primary contribution is a dedicated decision-support and optimization layer that treats available blood volume as a constrained resource while simultaneously considering test-specific analytical volumes, minimum specimen requirements, tube compatibility, tube dead volume, collection time points, whole-blood requirements, and anticoagulant status. Unlike conventional laboratory information systems (LIS)

and electronic health records (EHRs), which primarily support test ordering, specimen tracking, laboratory processing, and result reporting, the proposed framework evaluates how a requested group of tests fits within a patient-specific blood-volume constraint. It is therefore intended as a complementary optimization component rather than a replacement for existing clinical infrastructure.

Evaluation of the 20 intentionally constructed simulated cases showed that 15 cases (75%) produced lower-volume collection configurations within the calculated maximum allowable blood-volume threshold, while five cases remained above the threshold. Across the 15 feasible cases, the system reduced the calculated collection volume by a total of 120.21 mL relative to standard practice, corresponding to a mean reduction of 8.01 mL per feasible case. Individual reductions ranged from 0.36 to 19.63 mL. However, the 75% feasibility rate and observed volume reductions should not be interpreted as clinical success rates or estimates of performance in the pediatric population. We intentionally constructed the cohort to evaluate algorithmic behavior and included both feasible cases and challenging boundary conditions. The results therefore establish computational feasibility rather than clinical effectiveness.

We selected the rule-based architecture because explainability matters in clinical decision support. Recommendations are generated through explicit laboratory and patient-specific rules that can be inspected and reviewed rather than through an opaque predictive model. This also gives laboratory personnel a foundation to modify and audit the knowledge base as specimen requirements change.

4.2. Constraint Handling and System Boundary Conditions

The five cases that exceeded the calculated maximum allowable blood volume are an important component of the proof-of-concept evaluation. Patients 3, 10, 18, 19, and 20 represent scenarios in which the current laboratory requirements could not be simultaneously satisfied with the patient-specific blood-volume constraint. Once the system reduced collection requirements to the minimum allowable specimen volumes, it could not reduce them further without violating the encoded laboratory requirements. The system therefore generated a warning rather than producing an apparently optimized volume that could result in an insufficient specimen.

Patients 3 and 19 were deliberately constructed with hematocrit values of approximately 0.90 to stress-test the inference framework under extreme input conditions. These values are not intended to represent typical pediatric physiology. They instead demonstrate an important limitation of the current model: the relationship between whole-blood volume and the amount of plasma or serum obtainable from that volume is not explicitly modeled as a function of hematocrit. Future versions should incorporate a validated hematocrit-dependent specimen-yield model so that the required whole-blood volume can be estimated more physiologically when plasma- or serum-based testing is required.

Patients 10, 18, and 20 represent a separate type of infeasibility in which minimum laboratory specimen requirements could not be reconciled with the calculated blood-volume limit. These cases demonstrate that blood-draw optimization cannot always produce a feasible solution. In such situations, the system should identify the conflict and provide information that allows the clinician to reconsider test priority, timing, or alternative specimen strategies rather than automatically eliminating a clinically necessary test.

The simulated cohort also contained intentionally nonrepresentative characteristics, including an extreme hematocrit range and a 10-year-old patient weighing 40.82 kg. Interpret these characteristics as computational test conditions rather than evidence of a clinically representative population. Future evaluation should therefore include both clinically representative datasets to estimate expected system behavior and deliberate edge-case datasets to evaluate robustness and failure handling.

4.3. Optimization Framework, Knowledge Base, and Physiological Constraints

The current inference engine uses forward chaining to sequentially separate tests by collection time, isolate whole-blood requirements, exclude incompatible tube types, identify compatible tube configurations, and evaluate the resulting collection volume against the maximum allowable blood volume. Although effective for the current prototype, this approach is a heuristic optimization strategy rather than a mathematically guaranteed global optimizer. Selecting the most frequently occurring compatible tube does not necessarily guarantee the globally minimum blood volume when multiple tests can be assigned to alternative tubes. Future development should therefore formalize the problem as a constrained optimization model that minimizes total collection volume subject to laboratory and patient-safety constraints. The optimization variables could represent test-to-tube assignments and tube activation, while constraints would enforce minimum analytical volumes, tube compatibility, whole-blood requirements, anticoagulant compatibility, collection time points, and the maximum allowable blood volume. Mixed-integer or constraint-programming approaches could then be compared with the current heuristic to determine whether additional reductions are achievable while preserving explainability.

The optimization objective should also eventually become multi-objective. Minimizing blood volume alone may produce a configuration that requires more tubes, more handling, or more collection events. Future formulations should therefore consider total blood volume, number of tubes, number of collection events, processing complexity, and clinician-defined test priority. Importantly, the system should support rather than replace clinical decision-making. If the system cannot accommodate all requested tests, it should present alternative configurations and allow the clinician to decide whether to defer or omit lower-priority testing. Clinician override should remain available and auditable. The blood-volume calculation itself represents another important limitation. The current framework uses weight-based estimates of total blood volume and applies a predefined fraction to establish the maximum allowable draw. These values represent estimated population-level constraints rather than direct measurements of circulating blood volume and may not adequately represent patients with severe dehydration, major fluid shifts, congenital heart disease, hematological disorders, or other conditions that alter physiological blood volume or reserve. Future implementations should allow institutionally validated blood-volume equations and clinical-context-specific thresholds to be configured rather than treating a single threshold as universally applicable.

The knowledge base is currently maintained in Excel because it provides a low-cost, accessible, and readily auditable format during prototype development. n this proof-of-concept study, rule content was informed by published laboratory guidelines, tube-manufacturer specifications, and consultation with a co-author with clinical laboratory medicine expertise, rather than

a formal, documented validation protocol (e.g., independent second-reviewer sign-off, a discrepancy-resolution procedure, or a versioned change log). We identify this as a limitation of the current implementation. However, a production clinical system would require formal knowledge governance, including laboratory expert verification, conflict resolution, version control, change tracking, and scheduled review. A controlled relational database or clinical knowledge repository would provide stronger mechanisms to prevent inconsistent entries and maintain historical versions of laboratory requirements. These measures are particularly important because changes in assay platforms, specimen requirements, and institutional laboratory policies could directly affect system recommendations.

4.4. Clinical Integration, Human Factors, and Validation Requirements

The present system should be viewed as a potential optimization layer that complements existing laboratory information system (LIS) and electronic health record (EHR) infrastructure rather than replacing those systems. The study did not directly benchmark the prototype against commercial laboratory software or institutional decision-support tools; therefore, it cannot establish superiority or equivalence. Future benchmarking should compare total collection volume, tube utilization, number of collection events, infeasible-order detection, execution time, and agreement with laboratory experts. Clinical integration will also require evaluation of human factors. Physicians, nurses, phlebotomists, and laboratory personnel must understand and act on system recommendations without introducing excessive alert burden. Future usability studies should therefore examine recommendation acceptance, override frequency, task completion time, alert frequency, and user understanding. The interface should clearly distinguish hard safety constraints from optimization preferences and provide a concise explanation for each recommendation. Clinicians should be able to override recommendations when clinical circumstances justify additional testing, with overrides recorded for auditability. The current offline prototype also provides only a preliminary cybersecurity architecture. Future networked versions would require authentication, authorization, encryption, audit logging, data-integrity controls, secure software updates, and institutional cybersecurity assessment before connection to hospital systems. Integration with an EHR or LIS would also require secure, standardized interfaces to retrieve patient characteristics and laboratory orders and transmit recommendations. These requirements should be addressed during a dedicated system-integration and validation phase rather than inferred from the security characteristics of the current standalone prototype. Most importantly, the system requires validation using progressively more realistic datasets. The next stage should involve retrospective evaluation using de-identified pediatric laboratory records, allowing comparison of recommended tube configurations and collection volumes with actual practice without influencing patient care. Relevant measures should include collected blood volume, number of tubes, repeat collections, insufficient specimens, and agreement with laboratory experts. Prospective testing could then evaluate whether the system changes blood collection practices and workflow. Longer-term outcomes, such as reductions in repeat phlebotomy or clinically relevant blood loss, should be investigated only after technical and workflow performance has been established.

4.5. Limitations and Future Directions

Several limitations define the scope of the present findings. The evaluation consisted of only 20 simulated cases, was restricted to predefined endocrine test panels, and did not include real patient records, external validation, clinician usability testing, or direct comparison with existing clinical software. The simulated cohort was intentionally constructed to test computational behavior and included nonrepresentative edge cases. Consequently, the observed 75% feasibility rate and calculated blood-volume reductions cannot be generalized to the broader pediatric population or interpreted as evidence of clinical effectiveness. The current model also relies on estimated blood-volume thresholds, a spreadsheet-based knowledge base, and a heuristic inference strategy that does not guarantee a globally optimal solution. In addition, the model does not comprehensively account for specimen losses during collection, transport, processing, or analysis. These limitations identify the principal areas for future development rather than undermining the intended proof-of-concept objective.

The next stage should expand the system in four directions: (1) development of a larger and clinically representative validation dataset supplemented by deliberate edge-case testing; (2) formal mathematical and multi-objective optimization of tube and test configurations; (3) incorporation of dynamic hematocrit-dependent specimen-yield and longitudinal cumulative blood-loss models; and (4) retrospective, prospective, and ultimately multicenter clinical validation. Expansion beyond endocrine testing should include additional laboratory categories, while knowledge-base governance and secure interoperability should be established before clinical deployment.

Overall, the present study demonstrates that laboratory knowledge can be formalized into an explainable computational framework that treats pediatric blood volume as a constrained resource. The system is not intended to independently determine clinical testing or replace laboratory or physician judgment. Rather, it provides a foundation for decision support that can identify lower-volume collection strategies, expose infeasible testing configurations, and quantify the blood-volume implications of laboratory orders. Determining whether these computational capabilities translate into meaningful improvements in real-world pediatric blood conservation will require systematic clinical validation.

5. Conclusions

This study established a proof-of-concept, rule-based expert system for pediatric blood-draw planning that integrates patient-specific blood-volume constraints with laboratory-specific specimen, tube, and collection requirements. The primary objective was to determine whether laboratory knowledge could be formalized into an explainable computational framework that identifies lower-volume blood collection configurations while recognizing situations in which requested testing could not be accommodated within a patient's calculated blood-volume limit. Among the 20 intentionally constructed simulated cases, 15 cases (75%) produced lower-volume collection configurations that remained within the calculated maximum allowable blood-volume threshold, with blood-volume reductions ranging from 0.36 to 19.63 mL relative to standard practice. The remaining five cases exceeded the allowable threshold, demonstrating that the system could identify conflicts between minimum laboratory specimen requirements and patient-specific blood-volume constraints rather than force an infeasible collection configuration. These findings

support the intended proof-of-concept objective: patient-specific blood-volume limits can be incorporated with laboratory specimen requirements into a transparent, rule-based framework for blood-draw planning. The current implementation represents a constrained optimization heuristic rather than a mathematically guaranteed global optimizer, and the evaluation was limited to 20 simulated endocrine-testing scenarios. Therefore, the observed volume reductions and 75% feasibility rate should not be interpreted as evidence of clinical effectiveness or population-level performance. Future development should focus on formal mathematical and multi-objective optimization, hematocrit-dependent specimen-yield modeling, longitudinal accounting of cumulative blood loss, clinically guided test prioritization, expansion to additional laboratory disciplines, and formal governance of the laboratory knowledge base. Retrospective validation using real pediatric laboratory data, followed by prospective and multicenter evaluation, will be necessary to determine whether computational reductions in collection volume translate into meaningful improvements in blood conservation and clinical workflow. Ultimately, this work provides a foundation for an explainable decision-support approach in which the goal is not simply to minimize the amount of blood collected, but to maximize the diagnostic utility obtained from each specimen while maintaining predefined laboratory and patient-safety constraints.

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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