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Research Article

Keywords: Peritoneal Dialysis, Peritonitis, Weighted Average, Multiplicative Risk, Explainable Artificial Intelligence

Posted Date: October 22nd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11185474/v1>

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Additional Declarations: No competing interests reported.

A Peritonitis Risk Rate Prediction System for Pediatric Peritoneal Dialysis with eXplainable AI

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Abstract

Background: Peritoneal dialysis is the primary renal replacement therapy for pediatric end-stage renal disease patients, yet its success is hindered by peritonitis complications. Current risk assessments heavily rely on subjective evaluation, while prior automated models lack meta-analysis integration, web-based deployment, and transparency.

Method: This article proposes a web-based prediction system for peritonitis risk levels in pediatric patients used by pediatrician to communicate with patients' family. The system implements two computational models: Weighted Average (basic and optimized variants) and Multiplicative Risk (Fixed Risk Ratio and Randomized Risk Ratio). All models are utilizing Risk Ratio and p-value from meta-analyses as the clinical knowledge base. The application features eXplainable AI (XAI) to visualize protective and risk factors. Furthermore, explanation about preventive actions that is inherited from modifiable risk factors is given as supporting recommendations.

Results: Functional verification via combinatorial testing (pairwise $t=2$) yielded a 100% pass rate across 21 test cases. Classification accuracy evaluation against 51 clinical medical records from Dr. Cipto Mangunkusumo National Central General Hospital/Universitas Indonesia is performed. The results shows that the optimized Weighted Average, Multiplicative Fixed RR, and Multiplicative Randomized RR models achieved an identical highest accuracy of 74.51%, meanwhile the basic Weighted Average achieve accuracy of 62.75%.

Conclusion: Finally, a review performed by a team of pediatricians validated the system as a transparent, feasible, and objective clinical decision support tool.

Trial registration: retrospectively registered.

Keywords: *Peritoneal Dialysis, Peritonitis, Weighted Average, Multiplicative Risk, Explainable Artificial Intelligence.*

I. INTRODUCTION

Peritoneal Dialysis (PD) serves as the primary renal replacement therapy for pediatric patients suffering from End-Stage Renal Disease (ESRD) [1]. Compared to hemodialysis, PD offers significant clinical and operational flexibility, allowing continuous filtration to be managed directly at home by parental caretakers. Despite its therapeutic benefits, the long-term success of pediatric PD is heavily constrained by severe complications, most notably peritoneal membrane infections or peritonitis [1]. Pediatric patients exhibit a substantially higher incidence rate of peritonitis than adults, which frequently triggers technique failure, catheter extrusion, and a marked reduction in the patient's survival rate [2], [3], [4], [5]. Consequently, early and precise assessment of peritonitis risk is critically vital to preserve peritoneal membrane function and prevent fatal clinical outcomes [3].

In current clinical workflows, evaluating peritonitis risk still heavily depends on the subjective judgment and localized experience of medical personnel [6]. This conventional approach is inherently prone to cognitive fatigue, leading to potential inconsistencies and suboptimal predictive accuracy in high-pressure hospital settings [6]. While several clinical risk assessment tools have been proposed in literature, they are bound by several major limitations. First, existing models are built purely on retrospective data from localized cohorts, failing to integrate the high-level evidence available in global epidemiologic meta-analyses [7]. Second, previous frameworks primarily focus on raw statistical calculation [8] or traditional machine learning [9] without delivering an accessible, web-based Clinical Decision Support System (CDSS) for daily bedside rounds. Lastly, most digital predictive models act as "black-box" systems, hiding their internal computation logic and thus discouraging clinical trust due to a lack of transparency and clinical accountability [10].

To bridge these critical research gaps, this article proposes the design and development of a system that has knowledge as the "calculation backbone" and able to explain the justification of the results, a web-based Peritonitis Pediatric Risk Prediction System enhanced with eXplainable Artificial Intelligence (XAI). The core contribution of this study lies in its systematic integration of evidence from a clinical meta-analysis encompassing 14 international studies on pediatric peritonitis [3], [5]. By extracting the pooled effect sizes, namely the Risk Ratio (RR) and p-values, the system establishes an empirically grounded knowledge base that dictates the mathematical weights (w_i) and risk directions for 18 core clinical variables. The computational framework implements two core approaches divided into four comparative models: (1) a baseline, and (2) optimized scenario from the Weighted Average model [11], alongside (3) a fixed, and (4) randomized variant of the Multiplicative Risk model based on Lewis formulation [12].

Furthermore, to eliminate the black-box limitation which has less explainability to the pediatrics as the experts and end users, an interactive user interface deploys visual XAI modules that explicitly decompose the final percentage into categorized *Protective Factors* ($RR < 1$) and *Risk Factors* ($RR > 1$) [13]. It also offers real-time action guidelines for *Modifiable Risk Factors* (MRF) to guide clinical intervention [14]. The computational accuracy of the proposed system is mathematically verified through NIST-based Combinatorial Testing (Pairwise Testing, $t=2$) via Advanced Combinatorial Testing System (ACTS) [15]. Meanwhile, its clinical performance is evaluated using a Confusion Matrix against 51 actual anonymous pediatric patient records from the Dr. Cipto Mangunkusumo National Central General

Hospital/Universitas Indonesia (RSCM/UI). Finally, the clinical validity and cognitive utility of the system are qualified through a multi-stage iterative Expert Review with pediatric specialists led by a Senior Pediatric Nephrology Consultant [16].

II. PROPOSED METHODOLOGY AND THEORETICAL FRAMEWORK

A. Knowledge Acquisition & Variable Mapping

The baseline architecture of the clinical decision support system is constructed upon an empirically validated knowledge base derived from an extensive meta-analysis of pediatric peritonitis literature [3] [5]. This systematic synthesis aggregates data from 14 international epidemiologic cohorts to identify statistically significant parameters that caused peritonitis infection risks in PD [1] [17]. Through this process, 18 core clinical, demographic, and environmental variables are extracted to serve as the system's primary input features [18].

To reconcile unstandardized medical record terminologies with the classification boundaries of the pooled global studies, a standardized variable mapping framework is executed. Individual clinical variables are mapped into a discrete binary representation $x_i \in \{0,1\}$, where $x_i = 1$ denotes the presence of a high-risk exposure state matching the meta-analysis p-value orientation, and $x_i = 0$ represents a non-peritonitis state or missing data handled via a neutral-risk logic assignment. Within this structural matrix, 11 variables are explicitly designated as MRF based on clinical literature and expert validation to drive targeted behavioral and clinical interventions [14], [19]. The complete knowledge representation is summarized in Table 1.

Table 1. Knowledge Representation

No	Variable	Safe State	Risk State	Mean RR	Significant? (p-value < 0.05)
1	Age	>2 years	<2 years	1.40	YES
2	Gender	Female	Male	1.08	NO
3	Duration of PD	<12 month	>12 month	2.29	YES
4	Place of Residence	Rural	Urban	1.22	NO
5	Housing*	Good service	Fail/poor service	0.92	NO
6	Socioeconomic*	Good	Poor/fair	0.84	NO
7	Education	Studies	Illiterate	1.21	NO
8	Peritonitis in Exit Site Infection (ESI)*	No ESI	ESI	1.35	YES
9	Nutrition*	Normal Nutrition	Poor nutrition	0.89	NO
10	Cause of End-Stage Renal Disease (ESRD)*	Glomerular	Non-glomerular	1.13	YES
11	Type of Catheter (Shape)*	Coiled/swan neck	Straight	1.15	NO
12	Type of Catheter (Cuff)*	Double	Single cuff	1.33	NO
13	Catheter placement	Open	Laparoscopic	1.03	NO
14	Gastrostomy/Intraperitoneal Device*	No	Yes	0.78	NO
15	Performed Continuous Ambulatory Peritoneal Dialysis (CAPD)*	Patients	Parents/others	0.81	NO

No	Variable	Safe State	Risk State	Mean RR	Significant? (p-value < 0.05)
16	Starting PD <2 weeks after PD catheter placement*	No	Yes	1.37	NO
17	Orientation*	Lateral/downward	upward	0.66	NO
18	Stunting*	No stunting	Stunting	0.72	NO

*denote the modifiable risk factors

B. Predictive Models

The computational engine executes risk assessment across two algorithmic approaches. It is also evaluating four scenarios to identify the most optimal configuration for clinical deployment. The comparison of the results from those scenarios aims to resolve the additive limitations of the Weighted Average model. Thereafter, a Multiplicative Risk model is incorporated to enable a more clinically balanced evaluation of cumulative risk factors.

1) Weighted Average

This approach calculates risk as a proportional statistic where each variable is weighted based on its epidemiological significance [11]. Predictors with a meta-analysis significance value of $p\text{-value} < 0.05$ are allocated a double weight ($w_i = 2$), while non-significant variables are given a single weight ($w_i = 1$). The binary condition indicator (x_i) is set to 1 if the patient exhibits the risk state, or 0 if unaffected or if the data is "Unknown" or "Not given". The Peritonitis Risk Rate is calculated as follow:

$$\text{Peritonitis Risk Rate} = \frac{\sum_{i=1}^n (w_i \cdot x_i)}{\sum_{i=1}^n w_i} \times 100\%$$

Where n represents the total number of clinical variables included in the calculation. Under this formula setup, two separate execution paths are designed:

- Scenario 1 (Basic Weighted Average), this primary objective is to evaluate the baseline performance of the application when natively adopting the entire global meta-analysis knowledge base without considering some hospital adjustments. It executes calculations by involving all n=18 variables given in Table 1.
- Scenario 2 (Optimized Weighted Average), this scenario is designed to boost prediction accuracy. After getting results from Scenario 1, some investigations of the variable contribution to prediction errors are performed. There are two investigations: variables that are marked as significant (in Table 1) but not contributing accuracy, and non-significant variables but contributing more correctness in risk prediction against actual datasets. Later on, the weight of the variables found in the first investigation will be demoted (set to 1) or eliminated (set to 0), whereas weight of the variables found in the second investigation will be promoted to be double (i.e., significant). These investigations aim to evaluate the knowledge model against the real patients in the hospital settings. These investigations impact to lesser number of variables.

2) *Multiplicative Risk Model*

Diverging from additive constraints, this scenario adopts independent epidemiological multiplier aggregation, calculating risk strictly through risk multiplier multiplication without additive assumptions [12]. Variables that are included to calculate risk prediction have their RR which become the multiplier ($\lambda_i = RR$). The RR values is a non-negative value that represents how strong that variables to cause peritonitis risks. Otherwise, variables that are not given or unknown have a neutral multiplier ($\lambda_i = 1.0$):

$$\text{Peritonitis Risk Rate} = \prod_{i=1}^n \lambda_i$$

- Scenario 3 (Multiplicative Fixed RR), the purpose of this scenario is to test the performance consistency of RR in Mean Risk Ratios from Table 1. This number is gathered from pooled mean value of RR in the literatures of population study during meta-analysis process. Scenario 3 executes calculations across all 18 clinical variables.
- Scenario 4 (Multiplicative Randomized RR), this scenario aims to build a highly representative model that mimics condition of human immune systems which sometimes has ups and downs due to unknown or hard-to-intepret causes. In the real settings, peritonitis risks are rarely constant like fixed value of the Mean RR; individual patient risk factors vary dynamically due to internal and external interactions like immunity, pathogen exposure duration, and hygiene [12]. To capture this biological variability and clinical data uncertainty, λ_i in this scenario is treated as a stochastic multiplier drawn from a random Gaussian distribution, where the mean (μ_i) matches the pooled mean RR, and the standard deviation (σ_i) is estimated by dividing the 95% Confidence Interval width by four standard sigmas:

$$\sigma_i = \frac{\text{Max } 95\% \text{ CI} - \text{Min } 95\% \text{ CI}}{4}$$

The final scores across all multiplicative runs are evaluated against a standardized 50% decision boundary threshold validated by clinical consensus to categorize patients into "High Risk" or "Low Risk" peritonitis.

C. *Web Application Architecture and XAI*

The predictive computation layer is fully embedded with a web framework developed using Python 3.12.0 and the Streamlit (Share) platform. To preserve patient confidentiality and safeguard sensitive data tracking at the hospital bedside, access control is strictly managed through a secure authentication layer configured with TOML-encrypted credentials. Patient data inputs, transaction timelines, and computed risk percentages are synchronized dynamically with an external cloud infrastructure utilizing Google Sheets API and Google Drive API connections hosted via the Google Cloud Platform.

To eliminate the "black-box" limitations prevalent in medical automated systems, a dual-layered local explanation module utilizing XAI principles is engineered directly into the user interface. Upon executing the prediction sequence, the interface instantly renders a structured two-column visual grid separating active parameters into explicit diagnostic classes:

- Protective Factors, populates clinical variables where the input aligns with a safe state ($RR < 1$).
- Risk Factors, captures active clinical vulnerabilities where the input matches a hazardous state ($RR > 1$).
- Unknown (or not given) Factors, isolates unrecorded parameters to alert clinicians regarding missing diagnostics while executing the neutral additive or multiplicative logic ($x_i = 0$ or $\lambda_i = 1.0$).

Furthermore, for any parameter designated as a Modifiable Risk Factor (MRF) that returns an active risk state, the system gives a clinical guideline block. These clinical recommendations are hyperlinked to their respective medical publication sources, bridging statistical inference with evidence-based medical accountability. The explanations, suggestions, and sources given in the XAI are checked and validated by the team of pediatricians.

D. Software and Clinical Validation Framework

To establish absolute reliability before integration into hospital workflows, the proposed framework implements a dual-stage computational and empirical verification pipeline:

1) Combinatorial Testing

The core mathematical logic of all four calculation scenarios is subjected to functional verification using Combinatorial Testing to capture potential logic flaws or syntax anomalies caused by variable interactions [15]. A 2-way interaction matrix (pairwise testing, $t=2$) is constructed by inputting all 18 clinical variables with their respective categorical states into the ACTS tool developed by the National Institute of Standards and Technology [15]. This systematically compresses the exhaustive testing space from 2^{18} down to an optimized covering array comprising 21 highly representative test cases. These cases serve as inputs for a manual Test Oracle sheet to mathematically verify the accuracy of the application code.

2) Confusion Matrix

The clinical predictive performance and classification accuracy of the stratified decision categories (*High Risk* vs. *Low Risk*) are empirically evaluated using a *Confusion Matrix* [20], [21]. The validation pipeline tests the system against an independent and real-world validation dataset containing 51 complete anonymous medical records of pediatric PD patients treated at RSCM/UI, Jakarta. Statistical metrics encompassing global Accuracy, Precision, and Recall are extracted from the results to diagnose the predictive boundaries, trade-offs, and systemic behavior of each scenario model *Matrix* [20], [21].

III. RESULTS AND ANALYSIS

A. Knowledge Acquisition, Representation, & Feature Importance Analysis

The core knowledge base of the Peritonitis Pediatric Prediction System was extracted from global meta-analysis parameters compiled by medical experts. To evaluate localized empirical relevance, single-indicator accuracy verification was executed against 51 complete medical records from the RSCM/UI. Based on the statistical elbow effect across the empirical dataset, the 18 variables were classified into three functional analytical tiers [22], [23]:

- Weak Features (Accuracy <30%), Introducing predictive noise due to local profile variations, symmetrically stagnating at 25.49% accuracy, which includes *Place of Residence*, *Performed CAPD*, *Catheter Placement*, and *Type of Catheter Shape*. These variables were excluded from the optimized scenario by resetting their weights to $w_i = 0$.
- Neutral Features (Accuracy 41%-70%), These predictors maintained standard baseline relevance, including *Gender*, *Stunting*, *Nutrition*, *Peritonitis in ESI*, *Cause of ESRD*, *Housing*, *Education*, *Starting PD < 2 weeks*, *Socioeconomic*, and *Duration of PD*.
- Strong Features (Accuracy >70%), Critical diagnostic indicators that highly align with local clinical realities and represent the primary markers in the local cohort, establishing a stable performance plateau at or above 74.51%, comprising *Gastrostomy Device*, *Type of Catheter Cuff*, *Catheter Orientation*, and *Age*.

B. Web Application Development

The underlying mathematical models and clinical database structures were fully translated into an end-to-end, production-ready web application built via Streamlit and written entirely in Python 3.12.0. The application is publicly hosted and accessible via a live cloud deployment infrastructure at <https://pediatric-prediction-system.streamlit.app/>.

By clicking the "Calculate Risk Rate" button, the engine evaluates all active states and populates a structured, responsive dashboard. If the calculated percentage crosses the clinical decision threshold $\geq 50\%$ the interface flags a prominent red notice indicating a high-risk peritonitis state. Conversely, scores falling below $<50\%$ prompt a green indicator denoting a low-risk peritonitis state. To simplify the interface, the main result is given in a single layout, but an integrated collapsible layout can be viewed which allows clinicians to inspect comparative score across all four embedded model scenarios simultaneously, as shown in Fig. 1.

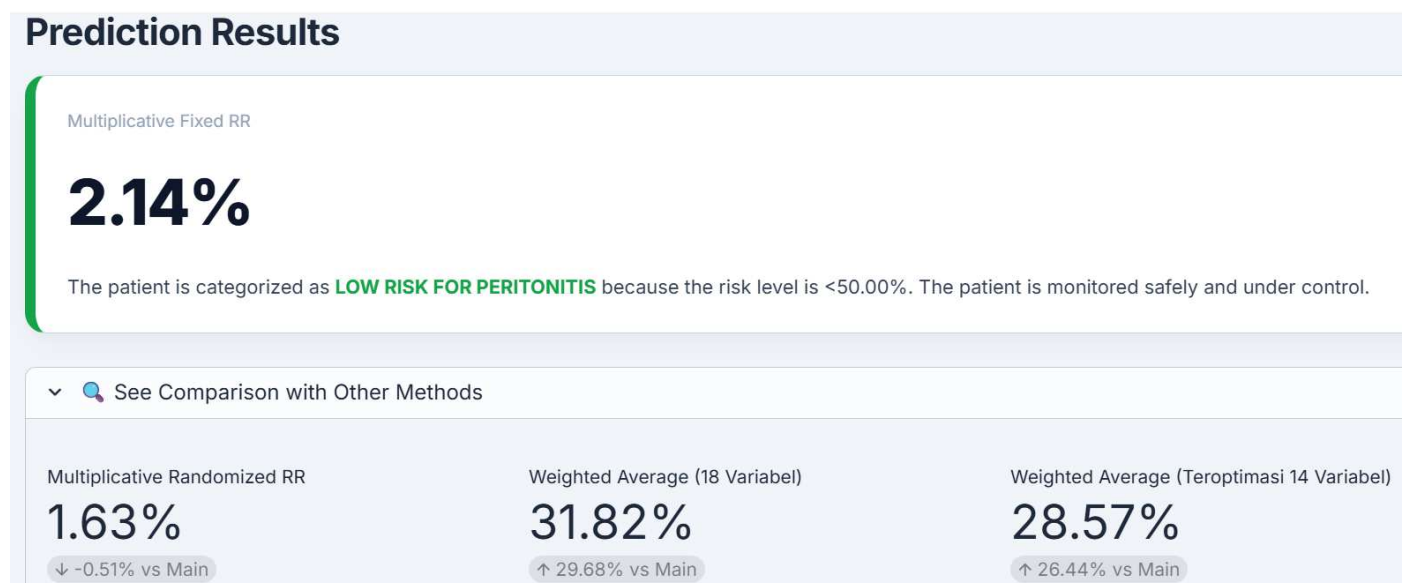


Fig. 1. The prediction result section of the web app

The main result, the Multiplicative Fixed RR, is chosen from four scenarios since the research question is about engineering the knowledge (risk ratios) gathered from existing literatures about risk of peritonitis in peritoneal dialysis and implementing it into a useable system by pediatrician. Thus, it has the more relevant value than the other scenario. However, the other three scenarios explain about the worse and worst probabilities that could happen in the real world. For example, by reading the prediction result in Fig. 1, it shows that the main result is 2.14% which is way less than the threshold (50%); it gives a good news that the patient is less likely to develop peritonitis risk. Furthermore, by accommodating the weighted average (14 or 18 variables), the risk prediction values is 28-31% (which falls into the same low-risk category). Thus, the pediatrician can inform the patients (family) that the risk is fairly low based on the inputted variables, and peritoneal dialysis is safe to use as a hemodialysis treatment.

To eliminate the traditional "black-box" paradigm, the system renders a transparent local explanation interface driven by XAI principles. Complete knowledge used by XAI can be accessed in <https://its.id/XAItable>. The interface that incorporates the knowledge is shown in Fig. 2.

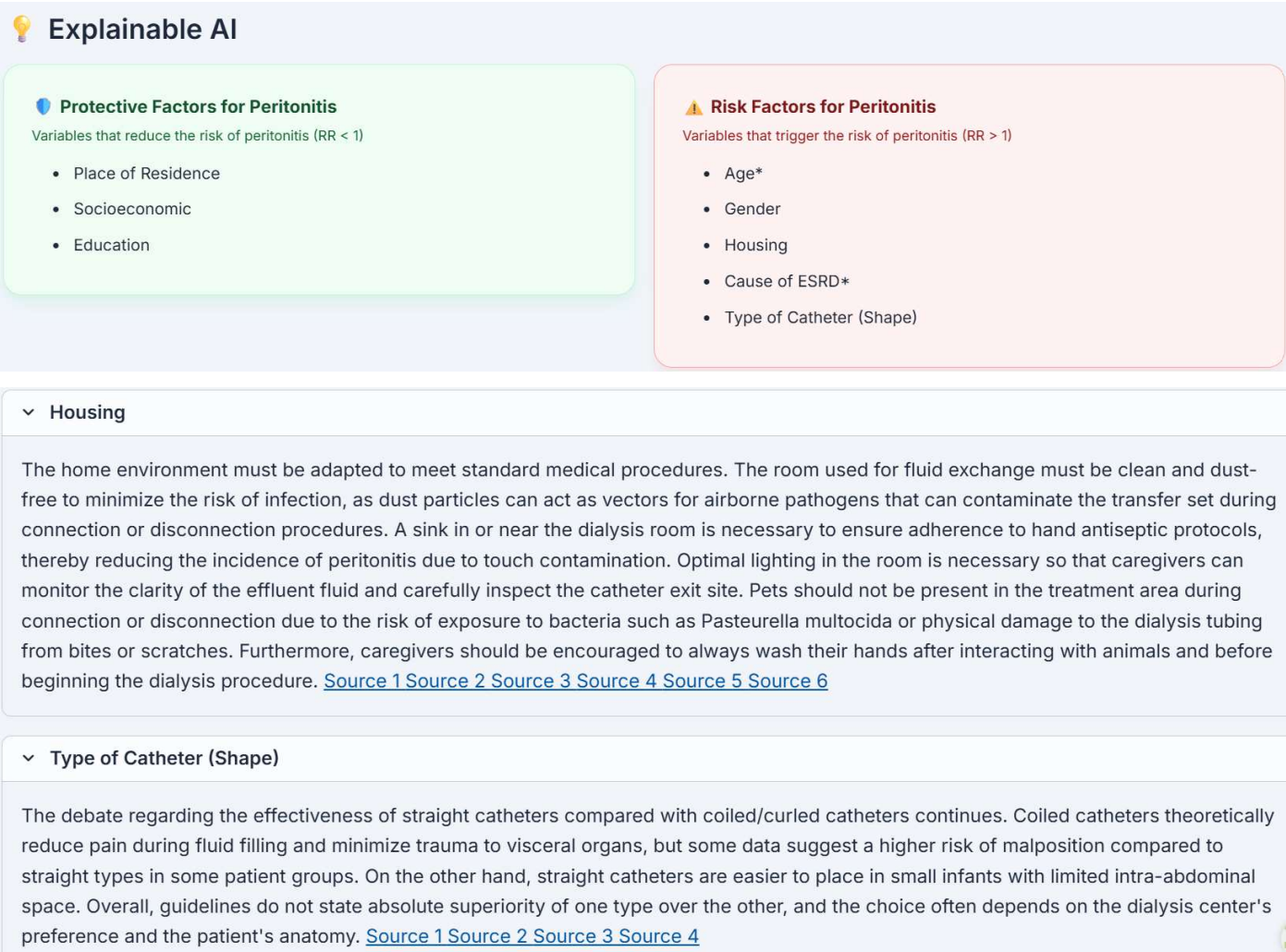


Fig. 2. The XAI section in the web app

The XAI cleanly separates active protective factors ($RR < 1$) and risk factors ($RR > 1$). Furthermore, for any active Modifiable Risk Factors, the system injects a dedicated recommendation module displaying real-time behavioral and clinical intervention guidelines hyperlinked directly to peer-reviewed source literature. Additionally, a dedicated document export button generates a physical, downloadable .csv medical report file detailing all parameter mappings, XAI outputs, and timestamp tokens to facilitate physical health record integration.

C. Combinatorial Testing

To mathematically guarantee that the core computation engine operates free of algorithmic logic flaws and syntax anomalies, a systematic functional software verification was conducted using Combinatorial Testin. The 18 binary clinical parameters were modeled inside the ACTS by defining each predictor with an enumerated domain containing three operational values: the high-risk state, the protective state, and the default "Unknown" state. Based on the local feature analysis, four identified "weak features" (*Place of Residence*, *Performed CAPD*, *Catheter Placement*, and *Type of Catheter Shape*) are eliminated by resetting their weights to $w_i = 0$. Conversely, three "strong features" (*Gastrostomy Device*, *Type of Catheter Cuff*, and *Catheter Orientation*) are boosted to $w_i = 2$. Therefore, This optimization selectively narrows the active computing space down to $n=14$ variables.

By setting the interaction strength parameter to $t = 2$ (*pairwise testing*), the combinatorial engine compressed the exhaustive search space from 2^{18} configurations down to a highly optimized covering array consisting of exactly 21 representative test cases. These 21 distinct test scenarios were systematically executed across the three algorithmic configurations, Scenario 1 (Weighted Average Baseline), Scenario 2 (Weighted Average Optimized), and Scenario 3 (Multiplicative Fixed RR). Scenario 4 (Multiplicative Randomized RR) was excluded from the matrix due to its stochastic, non-deterministic Gaussian distribution behavior. The outputs generated by the Streamlit application were systematically benchmarked against an independent, mathematically closed manual Test Oracle framework.

The experimental verification achieved success rate with 100% "passed" status across all test runs. This verification mathematically confirms that the application's source code perfectly translates the evidence-based rules embedded in the clinical knowledge base, establishing a reliable calculation baseline before deploying the tool for clinical rounds. The combinatorial testing result can be accessed in <https://its.id/CombTesting>.

D. Accuracy Results

Following functional validation, the clinical classification power of the system was evaluated using a *Confusion Matrix* against 51 real-world validation rows from the RSCM/UI patient registry. Statistical evaluation parameters, including Accuracy, Sensitivity, Specificity, and Precision were extracted across all four models.

Optimized Weighted Average and Multiplicative RR Models achieved an identical highest global accuracy rate of 74.51%. Conversely, Basic Weighted Average yielded the lowest global classification accuracy (62.75%) but demonstrated the highest clinical responsiveness with a Sensitivity of 30.77%, successfully capturing 4 true positive peritonitis events ($TP = 4$) and recording the lowest false negative rate ($FN = 9$).

Using Optimized Weighted Average model, the elimination of the four identified "weak features" successfully filtered out localized data noise. This optimization caused the global accuracy to surge to 74.51% and locked the Specificity at a perfect 100.00%. However, this configuration suffered a complete diagnostic compression on positive classes, reducing the clinical Sensitivity down to 0.00% (TP = 0, FN = 13). Concurrently, Multiplicative RR Models (both fixed or randomized approaches) generated identical performance metrics, locking their Specificity at 100.00% by correctly classifying all 38 true negative controls (TN = 38), while failing to capture any high-risk peritonitis cases (Sensitivity = 0.00%). This phenomenon stems directly from the multiplicative formulation combined with medical data missingness. Whenever clinical parameters are recorded as "Unknown" in the hospital chart, the engine applies a neutral multiplier ($\lambda_i = 1.0$). Consequently, the cumulative risk product remains mathematically suppressed and fails to surpass the rigid 50% decision boundary threshold required to flag a high-risk state. During the expert review, the pediatric specialists confirmed that these identical metrics reflect a system that is exceptionally highly specific but non-sensitive. Clinically, this indicates that while the system is remarkably dependable at validating low-risk profiles for truly healthy patients, its capacity to detect positive infection risks is constrained by a notable population data drift. This drift highlights a structural divergence between the broad epidemiological characteristics found in global meta-analysis benchmarks and the highly specific, variable clinical profiles of localized pediatric cohorts in Indonesia.

IV. DISCUSSION

The system adopts a binary framework for representing peritonitis risk within the knowledge base, categorizing individual factors as either a safe state or a risk state, and for presenting the final classification as either low risk or high risk. Although this dichotomization facilitates the representation and interpretation of complex clinical knowledge, it inevitably simplifies the multifactorial nature of peritonitis risk in hospital practice and health-related research. Dichotomizing continuous or multidimensional clinical information can result in a loss of information and may obscure variation among patients within the same category [24]. Nevertheless, this design decision was reviewed with the pediatric specialist team to ensure that the binary representation remained clinically understandable and could assist clinicians in evaluating the multiple factors associated with peritonitis. Pediatric peritoneal dialysis-associated peritonitis is influenced by numerous patient-, caregiver-, catheter-, treatment-, and environmental factors, which require contextual clinical interpretation [25]. Its risk categories and percentage values should be interpreted alongside clinical findings and professional judgment, consistent with the principle that clinical decision-support systems are designed to enhance, rather than replace, clinical decision-making [26]. Furthermore, the intended users are pediatric specialists, not patients or their family members; consequently, the system outputs are expected to be evaluated within a broader clinical context rather than used as the sole basis for determining an individual patient's risk.

The integration of XAI into the system was intended to address requirements identified by pediatric specialists by highlighting variables that may be amenable to modification. By clarifying the factors underlying each risk estimate, XAI can support clinicians in identifying appropriate preventive interventions to reduce the likelihood of PD-associated peritonitis. Nevertheless, by incorporating XAI to the system does not directly prevent peritonitis; its potential value

depends on whether the generated explanations are appropriately interpreted and translated into clinical action [25][27]. Evidence from pediatric PD populations indicates that adherence to standardized catheter-care practices and the management of modifiable care-related factors are associated with a lower risk of peritonitis [28]. However, some potentially modifiable factors require substantial behavioral, environmental, or socioeconomic changes. These may include adapting the home dialysis environment and addressing socioeconomic constraints, which have been associated with peritonitis risk and clinical outcomes among patients receiving PD [29].

In addition, several institution-specific adaptations were incorporated into the system's knowledge base to reflect local clinical practice and resource availability. For example, the study hospital exclusively uses straight, single-cuff peritoneal dialysis catheters because coiled or swan-neck and double-cuff catheters are unavailable. Catheter configuration is relevant because published studies have evaluated differences in outcomes among straight, coiled, swan-neck, single-cuff, and double-cuff designs, although the reported evidence is not entirely consistent across outcomes and study populations [30][31]. Such local adaptations may differ across hospitals and could consequently influence the resulting risk estimates. This limitation is particularly relevant because the system's computational framework is based on pooled risk estimates derived from international meta-analyses. Although meta-analysis provides a valuable synthesis of available evidence, pooled estimates may not fully represent the patient characteristics, equipment availability, clinical procedures, and care practices of a particular institution. Accordingly, associations and risk ratios reported in the literature may differ from those observed under local clinical conditions. Clinical prediction models may also demonstrate heterogeneous performance across hospitals because of differences in patient populations, predictor measurement, and clinical practice; therefore, local validation and, where necessary, model recalibration are required before broader clinical implementation [32].

The predicted risk category may differ between the primary scenario, which applies the Multiplicative Fixed RR model, and the alternative scenarios. For example, the primary model may classify a patient as low risk, whereas the other two models may classify the same patient as high risk. Such discrepancies could be confusing for users without a medical background. Nevertheless, the variation in predictions across the models provides a broader minimum-to-maximum range of risk estimates. Pediatricians can interpret this range within the patient's clinical context and communicate the associated uncertainty more precisely to the patient's family.

V. CONCLUSION AND FUTURE WORK

A. Conclusion

This article demonstrates the development and empirical evaluation of an automated, web-based Peritonitis Pediatric Prediction System enhanced with XAI. The predictive framework was constructed by anchoring 18 core clinical and demographic variables onto an evidence-based knowledge base derived from a global meta-analysis. Functional software verification using a ACTS 2-way combinatorial testing matrix (pairwise $t=2$) generated a 21-case covering array,

achieving a 100% pass rate that confirms the mathematical precision of the application's source code across deterministic configurations.

When subjected to external clinical evaluation against 51 real-world validation records from the RSCM/UI, the optimized weighted average model and both multiplicative models yielded an identical highest global accuracy rate of 74.51%. The predictive behavior across these three scenarios exhibited a distinct, highly optimistic computation trend, achieving a perfect specificity value of 100.00% by accurately mapping truly low-risk controls. However, their diagnostic responsiveness for positive high-risk profiles was constrained, yielding a sensitivity score of 0.00% due to mathematical boundary caps when handling incomplete fields via neutral-risk logic assignments. Conversely, the basic weighted average model produced the lowest global accuracy at 62.75% but secured the highest clinical sensitivity at 30.77%, proving more responsive in capturing actual positive infection cohorts.

Finally, qualitative validation through an iterative expert review with a senior Pediatric Nephrology Consultant confirmed that the visual XAI layout successfully resolves the traditional "black-box" dilemma by cleanly decomposing prediction origins into transparent, protective, and hazardous clinical indicators. The integrated actionable guidelines for Modifiable Risk Factors were validated as highly comprehensible and effective clinical decision tools for hospital care.

B. Future Work

To improve the generalizability and diagnostic responsiveness of the proposed peritonitis risk prediction system, the future studies should incorporate heterogeneous clinical-record cohorts from secondary healthcare facilities and regional hospitals outside the RSCM/UI network to evaluate the model's reliability across diverse patient populations and clinical settings. The mathematical framework, dynamic weighted proportional logic, and lightweight web-based architecture developed in this study should be extended to predict the risks of other chronic pediatric complications and outcomes associated with long-term renal replacement therapy modalities. The standardized dataset comprising 51 pediatric peritoneal dialysis records, which was compiled and mapped in this study, should be systematically used as an initial training-data repository for developing data-driven machine-learning classifiers.

Declaration

Abbreviations:

XAI: eXplainable Artificial Intelligence

RR: Risk Ratio

PD: Peritoneal Dialysis

ESRD: End-Stage Renal Disease

CDSS: Clinical Decision Support System

MRF: Modifiable Risk Factors

ACTS: Advanced Combinatorial Testing System

RSCM/UI: Dr. Cipto Mangunkusumo National Central General Hospital/Universitas Indonesia

ESI: Exit Site Infection

CAPD: Continuous Ambulatory Peritoneal Dialysis

TOML-encrypted: Tom's Obvious, Minimal Language-encrypted
API: Application Programming Interface
TP: True Positives
FN: False Negatives

Ethics and Consent to Participate:

The institutional ethics committee, Health Research Committee from Faculty of Nursing Universitas Airlangga, approved the study (Approval No. 4184-KEPK). All participants received written and verbal information about the study and provided written informed consent before participation. Data were anonymised during transcription and analysis, securely stored, and accessible only to the research team. Participants were informed of their right to withdraw from the study at any time without consequences. The informed consent is provided in <https://its.id/IC-IND> [Bahasa Indonesia], and in <https://its.id/IC-ENG> [English].

Consent for publication:

Not applicable

Availability of data and materials:

The datasets generated and/or analysed during the current study are not publicly available because they contain confidential medical information concerning minor patients, and the patients' general practitioners have not authorised their public disclosure, including for scientific publication. However, the datasets may be available from the corresponding author upon reasonable request, subject to the necessary ethical, clinical, and institutional approvals.

Competing interests:

Not applicable

Funding:

Not applicable

Authors' contributions:

R.A.V. supervision of manuscript writing and revision; R.F. supervision of knowledge engineering; W.A. accuracy results validation; E.R. web application results validation; F.K.I. write the manuscript; N.A.T. knowledge engineering; M.A.K.K. knowledge engineering; A.A. knowledge engineering; E.A. knowledge engineering

Acknowledgments:

Not applicable

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