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Research Article

Application of the Certainty Factor Method in Diagnosing the Risk Level of Coronary Heart Disease Based on Patient Clinical Parameters

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Abstract

Coronary Heart Disease (CHD) remains a global health challenge, yet health literacy gaps often make it difficult for the general public to understand clinical parameters and diagnostic uncertainty. In an effort to support social welfare and digital health accessibility, this study developed an expert system prototype that translates complex clinical data into easily understandable CHD risk levels (Low, Moderate, High). Utilizing the Certainty Factor (CF) method, the system is designed not as an independent clinical screening tool, but as a transparent, self-educational platform for non-specialist users. Evaluated on the extended UCI Heart Disease dataset (920 patient records), the CF approach successfully provided clear, explainable reasoning for its risk classifications. Although the initial algorithmic evaluation highlighted the limitations of static rules in handling the non-linear variability of medical data (achieving 46.30% accuracy), these findings emphasize that the primary value of digital health technology for the general public lies beyond mere computational accuracy. Instead, its significance is rooted in communication transparency, improving health information accessibility, and raising health awareness.

Keywords: Certainty Factor; Coronary Heart Disease; Expert System; Human–Computer Interaction; Risk Communication.

INTRODUCTION

Coronary Heart Disease (CHD) has a high mortality rate and poses a significant social challenge, particularly due to the health literacy gap among vulnerable communities in understanding their clinical parameters [1]. An essential challenge in digital health communication is that non-expert users often articulate physical complaints through ambiguous and subjective language, making it difficult for them to comprehend diagnostic uncertainty [2], [3]. Limited public access to understandable health information and specialists at primary healthcare facilities further exacerbates the rate of delayed detection, a problem significantly compounded by the prevailing health literacy gap among vulnerable communities [1], [4], [5]. Consequently, the development of a computerized expert system has become a matter of urgency not merely as a diagnostic tool, but as a medium for health education and community empowerment, serving as an interactive digital bridge to improve digital health accessibility and reduce fatalities caused by early detection errors [6], [7]. Supporting this initiative, research by Rohayani et al. [8] demonstrates that expert systems can effectively assist users in performing initial diagnoses of a problem based on the symptoms experienced and providing appropriate solutions.

Various computational approaches have been evaluated to address diagnostic and linguistic uncertainties in digital health communication, with the Certainty Factor (CF) method frequently implemented as a structured approach for this purpose [9], [10]. While not intended to serve as positioning it as a definitive clinical decision-making instrument, research conducted by Hetty Rohayani indicates that the CF method is practically useful in handling uncertainty within expert systems, particularly in processing subjective, symptom-based inputs from users [11]. To establish this foundation, recent studies have demonstrated the Certainty Factor (CF) method's capability to handle inexact reasoning in cardiovascular diagnostics. Specifically, Lubis et al. (2023) [12] and Fadhilah & Triayudi (2024) [13] highlighted CF's structural consistency over probabilistic models for symptom processing. In practical digital health applications, Elmi et al. [7] successfully integrated the CF method into an Android-based expert system, deriving diagnostic rules directly from medical expert validation rather than secondary datasets. Conversely, emphasizing the importance of established clinical parameters for screening, D. Setiawan et al. [14] utilized the Cleveland Heart Disease dataset to demonstrate the effectiveness of computational classification algorithms specifically Machine Learning models like Random Forest in predicting coronary heart disease risks. However, a critical synthesis of these studies reveals a shared limitation: they predominantly focus on optimizing algorithmic accuracy as a definitive medical calculator, often overlooking the Human-Computer Interaction (HCI) challenge of translating diagnostic uncertainty into understandable language for patients. Addressing this gap, the present study introduces a novel approach by utilizing CF not merely as a diagnostic tool, but explicitly as a transparent risk communication prototype for non-expert users. translator that converts the subjective degree of expert belief into accessible risk metrics [12]. This capability to process complex medical data based on patient clinical parameters has demonstrated utility in various cardiovascular disease applications [15], [16], [17].

Comparatively, CF has been noted in broader diagnostic literature to offer a transparent representation of medical logic for inexact reasoning compared to Bayesian approaches [13],

[18]. The structural consistency of this algorithm has also been explored in mapping symptoms of other cardiovascular complications, such as arrhythmia, into comprehensible risk formats [19]. However, while CF provides a stable computational foundation to mitigate risks associated with delayed treatment-seeking behavior [9], this technical capability alone is insufficient. This limitation introduces a critical research gap in the realm of Human-Computer Interaction (HCI): the problem of effectively communicating these calculated risks to non-expert users. Even with a transparent algorithm like CF, if digital systems present diagnostic uncertainty using raw computational scores or complex medical terminology, it frequently results in linguistic ambiguity and dangerous misinterpretation.

Despite these computational advancements, a critical research gap remains in the realm of Human-Computer Interaction (HCI) and digital health: the problem of effectively communicating uncertain medical risks and diagnostic probabilities to non-expert users through digital interfaces [2], [3]. Although diagnostic expert systems have been widely explored, most studies focus purely on algorithmic accuracy, often neglecting patient understanding of digital diagnostic outputs. The application of the CF method specifically focused on classifying CHD risk levels based on direct weighting input from patients still requires optimization, particularly regarding how health screening interfaces communicate these risks to non-expert users [20]. When digital systems present diagnostic uncertainty using complex medical terminology or raw computational scores, it frequently results in linguistic ambiguity, triggering patient anxiety or dangerous misinterpretation.

Therefore, the objective of this study is to develop and computationally evaluate a rule-based expert system using the Certainty Factor algorithm as a user-centered risk communication prototype rather than a definitive medical calculator. Due to the absence of empirical usability testing with non-expert users at this stage, the novelty of this research is cautiously framed around the conceptual mapping of complex clinical parameters into linguistically simplified risk categories (low, moderate, high). The primary contribution of this study lies in providing a computational mechanism to bridge the health literacy gap, demonstrating how inexact medical reasoning can be translated into an understandable digital interface. Consequently, this research is expected to provide theoretical implications that digital health screening tools must prioritize transparent reasoning and linguistic clarity to empower vulnerable communities and prevent dangerous diagnostic misinterpretations.

METHODS

Research Design

The primary objective of this research is to develop a transparent digital health tool capable of translating complex clinical parameters into understandable Coronary Heart Disease (CHD) risk categories for non-expert users. To achieve this, the study adopts an applied quantitative computational approach utilizing a deterministic, rule-based Certainty Factor (CF) model [21], [22]. The methodological rationale for selecting the CF approach over predictive machine learning algorithms is its transparent handling of inexact reasoning. The CF model operates as a white-box system, providing explainable, step-by-step logic that is critical for health education and building user trust in digital health interfaces.

To ensure computational reproducibility, the entire framework was developed using Python (version 3.11.5) within the PyCharm IDE, relying on standard data science libraries, including Pandas (v2.1.1) for data manipulation and Scikit-learn (v1.3.0) exclusively for generating evaluation metrics. Because the CF model functions as a static, deterministic knowledge-based system rather than a trainable model, stochastic initializations, random seeds, and train-test data splitting were not applied. The computational workflow is executed through four sequential stages, focusing on the translation of medical data into user-readable diagnostic confidence levels.

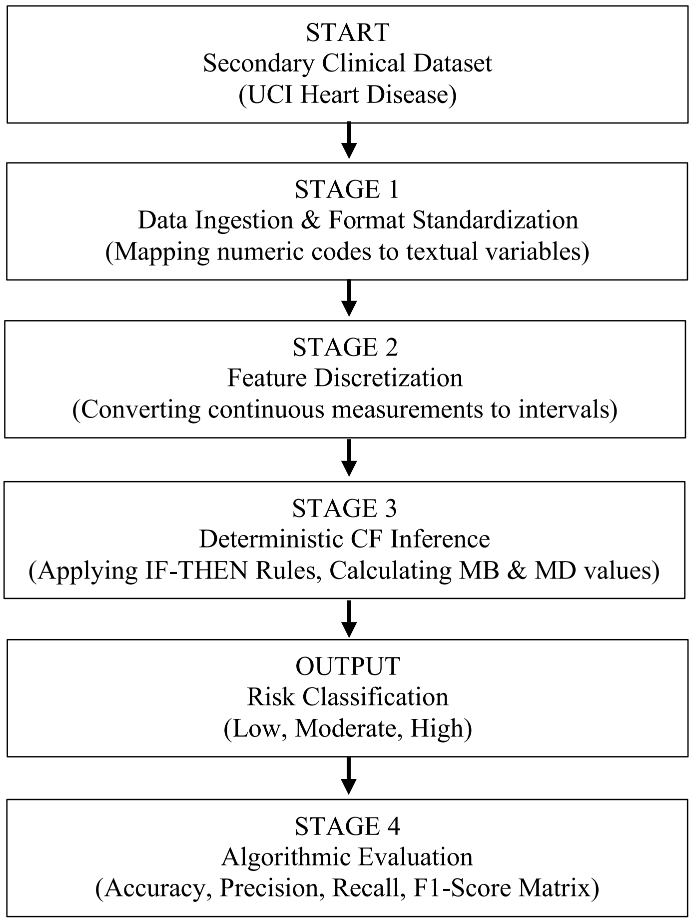

Figure 1. The Computational Workflow of the Certainty Factor Model

1. Data Ingestion and Format Standardization
   Loading the secondary dataset and mapping categorical numeric codes (e.g., chest pain types) into descriptive textual variables suitable for non-expert comprehension.
2. Feature Discretization
   Converting continuous physiological measurements (such as resting blood pressure and serum cholesterol) into categorical intervals based on established clinical guidelines.
3. Deterministic CF Inference
   Matching the discretized attributes against an IF-THEN rule base to aggregate the Measure of Belief (MB) and Measure of Disbelief (MD) weights, producing a final confidence percentage (0% - 100%).
4. Algorithmic Evaluation

Running the deterministic rules across the entire dataset to calculate overall accuracy, precision, recall, and F1-score via a confusion matrix.

Dataset Structure, Variables, and Class Distribution

The study utilized the extended UCI Heart Disease dataset obtained from Kaggle, which serves as a standard benchmark in cardiovascular expert system development [14]. The dataset consists of 920 instances (patient records) and 14 clinical variables. To ensure clarity and accessibility, the complete structure of the dataset encompassing demographic features, physiological measurements, and the target diagnostic variable is detailed in Table 1

Table 1. Clinical Variables in the Extended UCI Heart Disease Dataset

Variable Code	Description	Category
age	Age of the patient	Demographic
sex	Gender of the patient	Demographic
cp	Chest pain type	Physiological
trestbps	Resting blood pressure	Physiological
chol	Serum cholesterol in mg/dl	Physiological
fbs	Fasting blood sugar > 120 mg/dl	Physiological
restecg	Resting electrocardiographic results	Physiological
thalach	Maximum heart rate achieved	Physiological
exang	Exercise-induced angina	Physiological
oldpeak	ST depression induced by exercise relative to rest	Physiological
slope	Slope of the peak exercise ST segment	Physiological
ca	Number of major vessels (0-3) colored by fluoroscopy	Physiological
thai	Thalassemia condition	Physiological
Target	Presence of Coronary Heart Disease (CHD)	Target Variable

Furthermore, the target variable dictates the presence of CHD. As illustrated in Table 2, the class distribution of the dataset is detailed as follows, ensuring an equitable foundation for the deterministic rule base without severe class skew

Table 2. Dataset Class Distribution

Classification Status	Number of Instances	Percentage
Positive CHD	509	55.3%
Negative CHD	411	44.7%
Total	920	100.0%

Data Preprocessing and Missing-Value Treatment

An initial data inspection revealed that there were no missing values (0 nulls) in the dataset; therefore, no imputation techniques were required. Preprocessing was limited to standardizing the format of the categorical variables (e.g., mapping numeric codes of chest pain into descriptive text) to align with the system's rule-based logic, a crucial step to avoid prediction bias in large-scale secondary datasets [18], [23]. Any duplicate records or severe clinical outliers identified during the extraction process were filtered to ensure the integrity of the diagnostic reasoning. To ensure full transparency and reproducibility for the readers, Table 3 provides the complete coding protocol mapping each original categorical representation from the dataset into the system's operational clinical categories.

Table 3. Categorical Variables Mapping Protocol

Original Variable Name	Dataset Raw String Format	Clinical Meaning / Label	System's Operational Category
sex	Male Female	Male Patient Female Patient	Male Female
cp (Chest Pain Type)	typical angina atypical angina non-anginal asymptomatic	Typical Angina Pain Atypical Angina Pain Non-anginal Pain Asymptomatic	Angina Atypical Angina Non-anginal Pain Asymptomatic
fbs (Fasting Blood Sugar)	TRUE FALSE	Fasting Blood Sugar >1 mg/dL Fasting Blood Sugar ≤1 mg/dL	Elevated Fasting Sugar Normal Fasting Sugar
restecg (Resting ECG)	normal lv hypertrophy	Normal Electrocardiogram Left Ventricular Hypertrophy	Normal Hypertrophy
exang (Exercise Angina)	TRUE FALSE	Angina induced by exercise No exercise-induced angina	Angina Symptoms Present No Angina Symptoms
slope (ST Segment Slope)	upsloping flat downsloping	Peak exercise ST segm slope	Upsloping Flat Downsloping
thal (Thalassemia)	normal fixed defect reversible defect	Normal blood flow stat Fixed perfusion defect Reversible perfusion defect	Normal Fixed Defect Reversible Defect

Numerical Conversion and Rule Construction

To enable CF-based categorical reasoning, continuous numerical variables were discretized into rule-based categories using general clinical reference thresholds, which simplifies the reasoning process in expert systems [16]. The complete discretization logic for these physiological parameters is detailed in Table 4. These categorized parameters were then synthesized into an IF-THEN rule base [15].

Table 4. Discretization of Continuous Numerical Variables

Continuous Variable	Clinical Threshold	Categorical Label
Resting Blood Pressure (trestbps)	<120 mmHg	Normal
	120-139 mmHg	Elevated
	≥140 mmHg	High/Hypertension
Serum Cholesterol (chol)	<200 mg/dL	Normal
	200-239 mg/dL	Borderline
	≥240 mg/dL	High

Assignment of MB, MD Values, and Risk Thresholds

The Measure of Belief (MB) and Measure of Disbelief (MD) values for each rule were determined through the authors' synthesized expert judgment derived from a comprehensive review of existing cardiovascular literature, serving as an independent early detection screening framework [7]. The final Certainty Factor scores were mathematically converted into percentages (0% - 100%). The clinical risk thresholds were determined according to a logical severity distribution formulated by the authors:

1. Low Risk: Final CF score ≤ 40%
2. Moderate Risk: Final CF score between 40% and 70%
3. High Risk: Final CF score ≥ 70%

Algorithmic Evaluation Protocol

Since the Certainty Factor method is implemented as a static, deterministic knowledge-based system rather than a trainable machine learning model, the dataset was not split into separate training and testing subsets, and cross-validation was not applied. The system evaluated the predefined expert rules against the entire dataset to compute diagnostic accuracy, precision, recall, and F1-Score using a confusion matrix [20]. Furthermore, the model was not compared against baseline machine learning algorithms, as the primary objective was to evaluate the transparency of inexact reasoning via Python rather than merely optimizing predictive accuracy [9].

Computational Risk Communication (Journal Scope Integration)

Addressing the journal's scope on language and technology, this study approaches “interface language” from a computational perspective. The CF algorithm functions as a linguistic translator that processes complex, ambiguous physiological data and outputs diagnostic confidence as transparent risk labels (Low, Moderate, High). While this study successfully formulated the computational logic for transparent risk communication, empirical linguistic validation, readability metrics, and direct user comprehension testing with non-expert patients fall outside the scope of the current system design and remain a critical recommendation for future usability studies

RESULTS AND DISCUSSION

Results

Knowledge Base and Rule Representation

The system processes the medical data by matching patient parameters against a predefined knowledge base. To demonstrate the computational reasoning, the core rule base mapping clinical variables into expert weights (Measure of Belief / MB and Measure of Disbelief / MD) and risk interpretations is presented in Table 5.

Table 5. Comprehensive Expert System Knowledge Base (Sample Rules)

Clinical Variable	Category	MB	MD	CF (MB-MD)	Risk Interpretation	Reference
Chest Pain	Typical Angina	0.80	0.10	0.70	High	Literature
	Asymptomatic	0.30	0.60	-0.30	Low	Literature
Cholesterol	>240 mg/dL	0.70	0.20	0.50	Moderate	Literature
	< 200 mg/dL	0.20	0.50	-0.30	Low	Literature
Resting Blood Pressure	≥140 mmHg	0.60	0.20	0.40	Moderate	Literature
	< 120 mmHg	0.10	0.60	-0.50	Low	Literature
Max Heart Rate	< 120 bpm	0.50	0.30	0.20	Moderate	Literature

The Certainty Factor (CF) method sequentially combines these weights when multiple rules support the same hypothesis. For positive CF values, the combination follows the formula: $CF_{combine} = CF_1 + CF_2(1 - CF_1)$. The final score is converted into a percentage ($CF_{final} = CF_{combine} \times 100\%$) and categorized into Low Risk (≤ 40%), Moderate Risk (40–70%), or High Risk (≥ 70%).

Risk Categorization Outcomes

In alignment with the study's primary objective to translate complex clinical parameters into comprehensible risk metrics for non-expert users, the system categorized the final Certainty Factor (CF) scores of the 920 patient records into three distinct risk levels. The distribution of these classifications is presented in Table 6.

Table 6. Distribution of CF-Based Risk Classifications

Risk Category	CF Threshold	Number of Cases	Percentage
Low Risk	CF ≤ 40%	645	70.11%
Moderate Risk	40% < CF < 70%	196	21.30%
High Risk	CF ≥ 70%	79	8.59%
Total		920	100.0%

This distribution illustrates how the deterministic rule base interprets the dataset when mapped onto the predefined clinical severity thresholds, directly addressing the need for understandable digital health communication.

System Performance and Classification Outcomes

To compute the binary classification metrics (Accuracy, Precision, Recall, and F1-Score) from the system's three-tier risk output, a conversion rule was applied to align the risk categories with the dataset's binary target variable. Specifically, patients classified as "Low Risk" were mapped to the "Negative CHD" prediction. Conversely, patients classified as either "Moderate Risk" or "High Risk" were aggregated and mapped to the "Positive CHD" prediction. This binarization strategy reflects a conservative clinical screening approach, ensuring that any level of elevated risk is flagged for potential medical evaluation. The consolidated evaluation based on this mapping is presented in Table 7.

Table 7. Consolidated System Performance and Error Analysis

Target Class	Precision	Recall (Sensitivity)	F1-Score
Negative CHD	0.23	0.08	0.12
Positive CHD	0.51	0.77	0.61
Overall Accuracy	-	-	46.30%

Based on the objective findings, the proposed expert system achieved an overall accuracy of 46.30%. The model successfully identified a large proportion of positive cases (Recall = 0.77). However, the performance for the Negative CHD class was substantially lower (Precision = 0.23), reflecting a high volume of false-positive predictions.

Discussion

The algorithmic evaluation of the developed Certainty Factor (CF) expert system yielded an overall diagnostic accuracy of 46.30%. Based on the confusion matrix analysis, the system demonstrated high recall for positive CHD cases (0.77) but exceptionally low precision for negative cases (0.23), resulting in a substantial volume of false-positive predictions (377 cases). This performance profile reveals that the deterministic rule base operates under a highly conservative computational bias, frequently flagging healthy individuals as having elevated cardiac risks. When compared to recent cardiovascular diagnostic literature utilizing non-linear Machine Learning (ML) algorithms such as Random Forest, Support Vector Machines (SVM), or Multilayer Perceptrons [24], [25], [26], the static CF model exhibits significantly lower predictive accuracy. While those ML studies optimized classification performance by dynamically mapping multi-dimensional feature interactions, this study confirms and extends the understanding of CF's fundamental limitations when applied to non-linear biological data. A granular examination of the specific clinical variables explains why this diagnostic gap occurs in a static rule-based system: Chest Pain Type(cp**):** In the expert rule base, typical angina was assigned a high Measure of Belief (MB = 0.80,CF = 0.70), aligning with standard cardiology literature where exertional chest pain strongly signals ischemic heart disease [14]. However, in real-world clinical datasets, asymptomatic patients or those presenting atypical pain can still suffer from severe silent ischemia [13]. Because the static rule heavily penalizes asymptomatic presentation (CF = -0.30) without evaluating secondary indicators, the model risks misinterpreting complex atypical presentations, contrasting with the fluid probability adjustments found in dynamic Bayesian models [18].

Serum Cholesterol (chol): The system discretizes cholesterol into isolated threshold buckets (e.g., >240mg/dL and CF = 0.50). While this reflects general epidemiological risk thresholds [15], treating cholesterol as an independent additive factor induces severe classification skew. In clinical reality, elevated cholesterol in a young, non-smoking female carries vastly different diagnostic weight than in an elderly diabetic male [14]. The CF model's inability to adjust the weight of cholesterol based on age or gender compounding explains the surge in false positives. Resting Blood Pressure (trestbps) and Maximum Heart Rate (thalach): Hypertension (≥140 mmHg, CF= 0.40) and reduced exercise capacity (<120bpm, CF = 0.20) were integrated as moderate risk indicators. However, physiological responses during treadmill stress tests non-linearly interact with beta-blocker medications or baseline fitness levels [22]. Static CF rules treat these continuous measurements as isolated categorical steps, failing to capture the subtle physiological gradient that dynamic ML algorithms exploit to achieve high specificity [24].

Despite these computational trade-offs, the implications of this study must be interpreted through the lens of Human-Computer Interaction (HCI) and digital health literacy rather than pure clinical automation [1]. Diagnostic studies by Veldasari et al. [27] caution that excessive false positives cause patient anxiety, whereas false negatives pose life-threatening risks of delayed treatment. Diverging from studies that focus solely on maximizing predictive metrics, this research aligns with and extends work by Manik et al. [20] and Wagner et al. [28] by emphasizing system transparency and auditability. The core strength of the CF model lies in its fully explainable inference engine. Unlike “black-box” machine learning models [24], [25], [26] whose inner weights remain opaque to non-experts, the proposed system acts as an accessible linguistic translator. It directly addresses the severe health literacy gaps identified in public health literature [4], [5] by converting intimidating numerical variables into intuitive risk categories (“Low”, “Moderate”, “High”) with step-by-step reasoning transparency. Consequently, the primary contribution of this work is establishing a transparent, user-centered risk communication prototype that empowers patients to seek timely professional medical evaluation without replacing clinical expertise.

CONCLUSION

This study aimed to develop a transparent digital health framework by utilizing the Certainty Factor (CF) method to translate complex Coronary Heart Disease (CHD) clinical parameters into accessible risk categories (Low, Moderate, High) for non-expert users. The algorithmic evaluation yielded a modest overall diagnostic accuracy of 46.30%. This outcome demonstrates that static, rule-based models struggle to capture the non-linear complexity of cardiovascular data, resulting in a highly conservative system prone to false-positive classifications. However, the primary computational contribution of this research lies in its explainable reasoning architecture. Rather than functioning as a definitive diagnostic instrument, the system serves as a transparent risk communication prototype that bridges the health literacy gap by converting intimidating medical variables into understandable metrics. Recognizing the inherent limitations of using a purely deterministic model for standalone clinical diagnosis, future research should integrate hybrid machine learning approaches to improve predictive accuracy while maintaining algorithmic transparency. Furthermore, empirical usability testing with vulnerable communities is strongly recommended to ensure the interface safely and effectively empowers patients without causing diagnostic misinterpretation.

LIMITATIONS

This study has several key limitations that affect the interpretation and generalizability of its findings. First, the Certainty Factor (CF) weights (Measure of Belief and Measure of Disbelief) were derived from literature rather than direct validation by practicing cardiologists, potentially limiting the clinical validity of the assigned risk thresholds. Second, the evaluation relies on a secondary dataset of 920 medical records which, while structurally uniform, lacks the broader demographic and lifestyle diversity required to generalize the findings to varied local healthcare settings. Third, the system's low accuracy rate (46.30%) underscores a fundamental limitation of static, rule-based CF models in capturing the non-linear complexity of cardiovascular data. Finally, the system was evaluated strictly within a computational simulation. Without empirical usability testing among non-expert users or direct integration into actual clinical practice, its real-world effectiveness and acceptance as a digital health communication tool remain unconfirmed.

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AUTHOR CONTRIBUTION

A. N. conceptualized the study, developed the research design, and led the overall research process, including data collection, statistical analysis, and primary manuscript drafting. H. R. contributed to instrument development, data management, supported data analysis and interpretation, provided theoretical and analytical guidance, and critically reviewed and revised the manuscript for important intellectual content. All authors have read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

CONFLICT OF INTEREST

"The authors declare no conflict of interest."

DECLARATION OF USE OF AI IN SCIENTIFIC WRITING

The author(s) used ChatGPT during the preparation of this work to enhance the grammatical clarity, improve sentence structure fluidity, and assist in refining the initial draft of the manuscript's background and discussion sections. The tool was utilized strictly for linguistic polishing and proofreading support, and it was not involved in data collection, computational analysis, or the generation of the core expert system logic. After utilizing the tool/service, the author(s) thoroughly reviewed and edited the content as necessary to ensure accurate technical alignment with the experimental results and assumed full responsibility for the publication's content.

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