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Research

A Bio-Digital Expert System with Certainty Factor Reasoning for Early Kidney Disease Risk Assessment

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Abstract:
Introduction — Early identification of kidney disease risk is essential to prevent progression to severe renal impairment. However, uncertainty in symptom perception and limited access to transparent digital screening tools often hinder early assessment. This study proposes a bio-digital expert system incorporating enhanced Certainty Factor reasoning to support early kidney disease risk evaluation.
Methods — Early identification of kidney disease risk is essential to prevent progression to severe renal impairment. However, uncertainty in symptom perception and limited access to transparent digital screening tools often hinder early assessment. This study proposes a bio-digital expert system incorporating enhanced Certainty Factor reasoning to support early kidney disease risk evaluation.
Results — Evaluation across five structured scenarios demonstrated differentiated risk classifications consistent with symptom patterns and user confidence levels. The system produced graded outputs ranging from low to high risk, while minimal evidence scenarios correctly resulted in no significant risk classification.
Conclusion — The proposed system provides an interpretable, uncertainty-aware framework for early kidney disease risk assessment, emphasizing transparent digital decision support rather than clinical diagnosis.

Keywords: kidney disease risk assessment; certainty factor; bio-digital expert system; explainable artificial intelligence; decision support system

1. Introduction

Kidney disease represents a significant global health burden, affecting millions of individuals worldwide and often progressing silently until reaching advanced stages [1], [2], [3]. Chronic Kidney Disease (CKD), Acute Kidney Injury (AKI), glomerular disorders, and kidney stone-related complications can lead to severe morbidity, reduced quality of life, and increased healthcare costs [4], [5]. Early identification of kidney-related abnormalities is therefore crucial for timely intervention and prevention of irreversible renal damage [6]. However, many early-stage symptoms such as fatigue, mild edema, or changes in urination patterns are often nonspecific and frequently underestimated by individuals [7], [8].

In recent years, digital health technologies have emerged as promising tools to support early risk identification and self-assessment [9], [10]. Many contemporary approaches employ machine learning models trained on clinical datasets [9], [11], [12], [13]. While such methods may achieve strong predictive performance, they frequently operate as black-box systems with limited interpretability. In health-related applications—particularly those involving risk communication and preventive screening—transparency and explainability are essential to maintain user trust and ensure responsible artificial intelligence deployment [14], [15], [16].

Expert systems provide an alternative paradigm for intelligent decision support by explicitly modeling domain knowledge using structured rules and logical inference mechanisms [17], [18], [19]. Unlike data-intensive models, rule-based expert systems allow knowledge representation to be validated and audited by medical experts [20]. Nevertheless, traditional rule-based systems are typically deterministic and may not adequately represent uncertainty inherent in subjective symptom reporting.

To address this limitation, the Certainty Factor (CF) method—originally introduced in medical expert systems—enables uncertainty handling by associating confidence values with both expert knowledge and user-reported evidence [21]. Enhanced CF aggregation, such as MYCIN-style combination, allows multiple rules to contribute cumulatively to a risk assessment, resulting in graded outputs rather than binary decisions [22]. This study proposes a bio-digital expert system with enhanced Certainty Factor reasoning for early kidney disease risk assessment. The system integrates rule-based knowledge representation, MYCIN-style CF aggregation, explainability mechanisms, and graded risk classification to provide transparent and uncertainty-aware digital screening support.

2. Method

2.1 System Architecture

The proposed system is designed as a modular bio-digital expert system consisting of four principal components: (1) knowledge base, (2) enhanced Certainty Factor inference engine, (3) risk-level classification module, and (4) explanation facility. The system accepts user-reported symptom inputs along with confidence values ranging from 0 to 1. These inputs are processed by the inference engine, which evaluates rule activation and computes aggregated certainty values for each kidney-related condition.

The modular architecture ensures separation between knowledge representation and inference logic, allowing scalability and maintainability. The system was implemented in Python within the Google Colab environment to facilitate reproducibility and transparent computational procedures [23], [24], [25]. Figure 1 illustrates the overall system architecture and data flow of the proposed system.

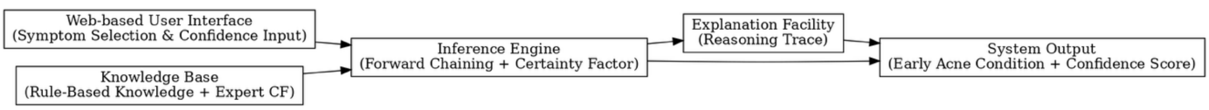

Fig. 1. Architecture of the proposed bio-digital expert system for early kidney disease risk assessment using enhanced Certainty Factor reasoning.

As illustrated in Fig. 1, the proposed system consists of a web-based user interface, a structured rule-based knowledge base, an enhanced Certainty Factor inference engine employing MYCIN-style aggregation, a graded risk classification module, and an explanation facility to ensure transparent decision support.

2.2 Knowledge Representation

Kidney-related knowledge is represented using structured rule-based models. Each rule contains a set of associated symptoms and an expert-defined Certainty Factor (CF_{expert}) representing the confidence level of medical relevance. Multiple rules may correspond to the same kidney-related condition, enabling cumulative evidence aggregation. Formally, each rule is expressed as Equation (1).

$$If\ (S_1 \wedge S_2 \wedge \cdots \wedge S_n)\ THEN\ D\left(CF_{expert}\right) \tag{1}$$

Symptoms include fatigue, edema, nocturnal urination, foamy urine, hematuria, hypertension, lower back pain, decreased urine output, and nausea [26], [27], [28]. The system models four kidney-related risk categories: Chronic Kidney Disease, Acute Kidney Injury, Kidney Stone Risk, and Glomerulonephritis Risk [26], [28].

2.3 Enhanced Certainty Factor Reasoning

For each activated rule, the rule-level certainty is computed using the following Equation (2).

$$CF_{rule} = CF_{expert} \times min(CF_{user}) \tag{2}$$

where CF_{user} represents the minimum confidence value among the user-reported symptoms involved in the rule [29], [30]. When multiple rules support the same condition, MYCIN-style aggregation is applied using Equation (3).

$$CF_{combined} = CF_1 + CF_2 \times (1 - CF_1) \tag{3}$$

This iterative combination allows accumulation of supporting evidence while preventing linear overestimation. The final CF value for each condition represents the aggregated confidence reflecting both expert knowledge and user-reported uncertainty [30]. Besides, Fig. 2 shows the explained enhanced CF reasoning.

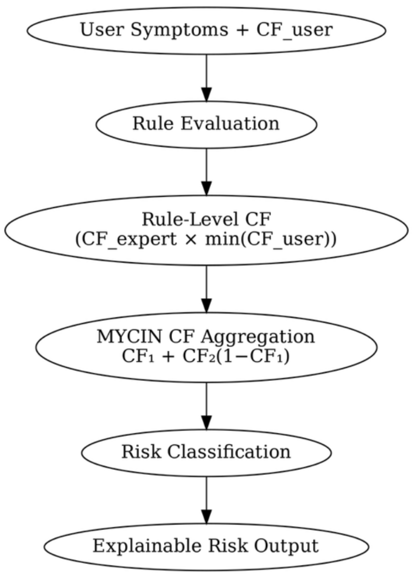

Fig. 2. Certainty Factor-based inference and explanation process.

Figure 2 presents the internal reasoning flow of the enhanced Certainty Factor mechanism, where rule-level certainty values are computed and subsequently combined using MYCIN-style aggregation to produce interpretable graded risk outputs.

2.4 Risk-Level Classification

The final aggregated Certainty Factor is mapped into graded risk categories, that explained in Table 1. This graded classification avoids deterministic diagnosis and ensures the system functions strictly as a risk assessment tool.

Table 1. Risk-level classification criteria

Classification	Criteria
High Risk	$CF \geq 0.7$
Moderate Risk	$0.4 \leq CF < 0.7$
Low Risk	$0 < CF < 0.4$
No Significant Risk	$CF = 0$

2.5 Explanation Facility

To ensure interpretability, the system records activated rules, contributing symptoms, expert CF values, rule-level CF contributions, and aggregated certainty values. The explanation trace allows users and domain experts to audit how specific symptom inputs influence final risk outcomes.

2.6 AI Disclosure

ChatGPT (OpenAI) was employed exclusively to support linguistic editing, grammatical refinement, and the structural arrangement of the manuscript. Its role was confined to enhancing clarity, coherence, and overall academic presentation, ensuring that the manuscript adhered to international scholarly writing standards [31]. The AI tool was not involved in the study design, development of the system architecture, construction of the knowledge base, formulation of the inference mechanism, Certainty Factor calculations, software implementation, experimental procedures, or the analysis and interpretation of the research findings [32], [33]. All research methodologies, computational processes, system development activities, and analytical evaluations were independently conceived, executed, and validated by the authors. The authors assume full responsibility for the accuracy, integrity, originality, and scientific soundness of the work presented in this manuscript [34], [35].

2.7 Ethical Clearance Statement

Ethical Approval — This research did not involve human participants, animal subjects, or any form of clinical intervention. The inputs utilized during system evaluation consisted solely of simulated test scenarios developed for validation purposes and did not include any identifiable personal or medical information. The proposed expert system is designed as an early risk assessment and decision-support tool rather than a clinical diagnostic instrument. Because the study was limited to computational modeling, rule-based reasoning, and simulated data, formal ethical clearance was not required. The system outputs are intended to promote consultation with qualified medical professionals and are not a substitute for clinical diagnosis or medical treatment.

3. Results

3.1 Multi-Scenario Evaluation

Five structured evaluation scenarios were constructed to simulate different symptom patterns. The aggregated results generated by the enhanced Certainty Factor inference engine are summarized in Table 2.

Table 2. System output across five evaluation scenarios

Test Case	Top Condition	Risk Level
Case 1 – CKD Pattern	Chronic Kidney Disease	Moderate Risk
Case 2 – AKI Pattern	Acute Kidney Injury	High Risk
Case 3 – Kidney Stone Pattern	Kidney Stone Risk	Moderate Risk
Case 4 – Glomerulonephritis Pattern	Glomerulonephritis Risk	Moderate/High Risk

Case 5 – Minimal Symptoms	No Significant Risk	No Significant Risk

The evaluation demonstrated that the system produces differentiated risk outputs across conditions. Case 1 activated Chronic Kidney Disease rules, resulting in a moderate risk classification with confidence values above 50%. Case 2 produced a high-risk classification for Acute Kidney Injury due to strong symptom alignment and high user confidence values. Case 3 and Case 4 generated moderate to high-risk outputs for Kidney Stone and Glomerulonephritis patterns, respectively. Case 5, representing minimal symptom input, resulted in no significant risk, demonstrating appropriate suppression of unsupported inference. The confidence values observed ranged from low (below 30%) to high (above 70%), reflecting variability in both rule strength and symptom certainty.

3.2 Explainability and Evidence Accumulation

The enhanced MYCIN-style aggregation enabled cumulative evidence modeling. In scenarios where multiple rules supported a condition, the combined Certainty Factor increased nonlinearly rather than linearly, preserving logical consistency. The explanation trace revealed which symptom combinations activated which rules and how each rule contributed to the final risk value.

This behavior demonstrates that the system does not rely on single-rule dominance but instead integrates distributed evidence. Such cumulative reasoning aligns with clinical intuition, where multiple symptom clusters strengthen suspicion of a condition.

3.3 Explainability and Reasoning Trace Output

Beyond numerical outputs, the system generates explicit reasoning traces for each valid diagnosis, thereby enhancing interpretability and transparency. For instance, in Case 1 (Acne Vulgaris), the system identifies “Inflamed red pimples” with a user confidence value of 0.8 and “Pus-filled pimples” with a user confidence value of 0.7 as the contributing symptoms that activate the corresponding rule. These contributing factors are explicitly displayed in the output, allowing users to trace how their reported symptoms influence the final confidence score. This explanation mechanism directly reflects the architectural design illustrated in Fig. 1 and the Certainty Factor reasoning flow presented in Fig. 2. By clearly linking symptom inputs, rule activation, and computed confidence values, the system ensures logical transparency. The integration of structured rule representation, Certainty Factor-based uncertainty modeling, ranked diagnostic outputs, and explicit reasoning traces confirms that the proposed system functions as a transparent and interpretable digital decision support tool rather than a black-box classification model. Last, the system’s interface shows in Fig. 3.

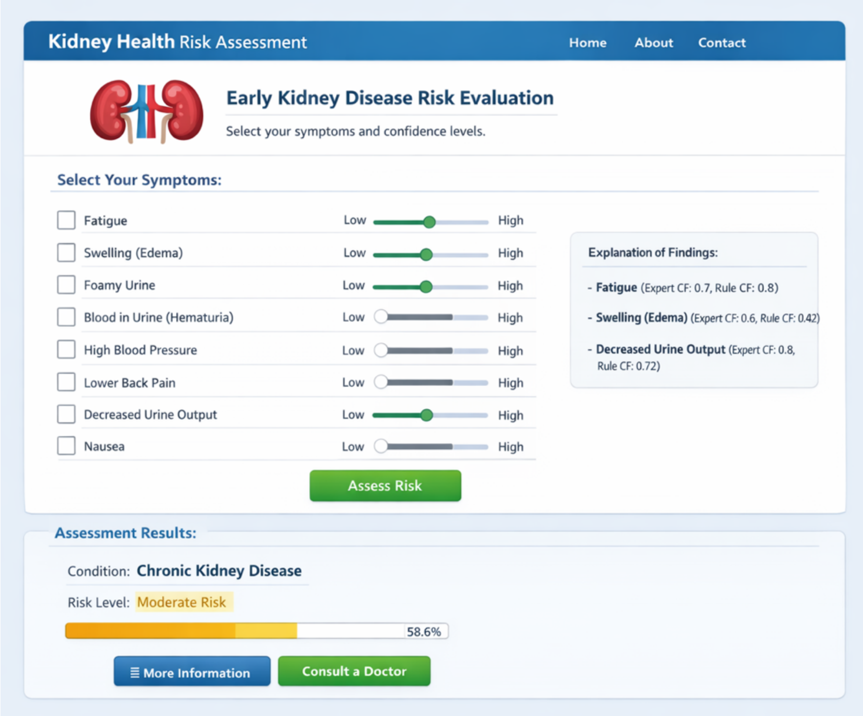

Fig. 3. The system's user interface.

4. Discussion

The proposed bio-digital expert system demonstrates that enhanced Certainty Factor reasoning can effectively support early kidney disease risk assessment under uncertainty. The multi-rule aggregation mechanism provides a mathematically consistent framework for integrating expert knowledge with subjective user input. Unlike deterministic rule systems, the use of MYCIN-style CF combination enables gradual confidence growth as supporting evidence accumulates [30], [36], [37].

The observed risk differentiation across evaluation scenarios confirms that the system is sensitive to both symptom patterns and user confidence levels [30]. High-confidence symptom clusters produced high-risk classifications, whereas incomplete or weak evidence resulted in low or no significant risk outputs [22], [38], [39]. This graded behavior is particularly important in kidney disease screening, where premature or overconfident classification could cause unnecessary alarm.

From an explainability perspective, the system provides transparent reasoning traces linking activated rules, symptom inputs, and aggregated certainty values. This transparency distinguishes the approach from black-box machine learning models and supports responsible digital health deployment. Users are informed that the output represents a risk assessment rather than a clinical diagnosis, reinforcing ethical safeguards.

Despite these strengths, limitations exist. The knowledge base is dependent on expert-defined rules and does not incorporate adaptive learning from real clinical datasets. The evaluation relied on structured test scenarios rather than patient-level clinical validation. Future work may integrate hybrid knowledge-data approaches or incorporate longitudinal symptom tracking for improved screening robustness. Overall, the proposed system contributes an interpretable, uncertainty-aware, and ethically framed digital screening tool aligned with bio-digital health principles and explainable artificial intelligence practices.

Conclusion

This study presented a bio-digital expert system employing enhanced Certainty Factor reasoning for early kidney disease risk assessment under uncertainty. By integrating structured rule-based knowledge representation with MYCIN-style Certainty Factor aggregation, the system enables cumulative evidence modeling and graded risk classification rather than deterministic diagnosis. Experimental evaluation across multiple structured scenarios demonstrated that the proposed approach produces differentiated risk levels consistent with symptom patterns and user-reported confidence values, while appropriately suppressing unsupported inferences in cases of minimal evidence. The inclusion of an explanation facility further enhances transparency by explicitly linking activated rules, contributing symptoms, and aggregated certainty values to final risk outputs. Importantly, the system is framed as a risk assessment and decision-support tool rather than a clinical diagnostic instrument, reinforcing responsible artificial intelligence deployment in digital health contexts. Overall, this research contributes an interpretable, uncertainty-aware, and ethically grounded framework for early kidney disease screening, aligning with bio-digital health principles and advancing explainable expert system applications in preventive healthcare.

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Reference

[1] WHO, “Noncommunicable diseases.” Accessed: Apr. 08, 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases

[2] K. Ahmed, M. K. Dubey, Kajal, S. Dubey, and D. K. Pandey, “Chronic kidney disease: causes, treatment, management, and future scope,” *Computational Intelligence for Genomics Data*, pp. 99–111, Jan. 2025, doi: 10.1016/B978-0-443-30080-6.00010-9.

[3] A. Francis *et al.*, “Chronic kidney disease and the global public health agenda: an international consensus,” *Nat. Rev. Nephrol.*, vol. 20, pp. 473–485, Apr. 2024, doi: 10.1038/s41581-024-00820-6.

[4] C. P. Kovesdy, “Epidemiology of chronic kidney disease: an update 2022,” *Kidney Int. Suppl. (2011).*, vol. 12, no. 1, pp. 7–11, Apr. 2022, doi: 10.1016/j.kisu.2021.11.003.

[5] E. Daina, M. Cortinovis, and G. Remuzzi, “Kidney diseases,” *Immunol. Rev.*, vol. 313, no. 1, pp. 239–261, Jan. 2023, doi: 10.1111/imr.13167.

[6] R. R. Al-Hakim and Y. Prokopchuk, “Predicting Internal Diseases in Humans Using Machine Learning: A Systematic Literature Review,” *Journal of Advanced Health Informatics Research (JAHIR)*, vol. 2, no. 1, pp. 50–63, 2024, doi: 10.59247/jahir.v2i1.195.

[7] S. Chattopadhyay, “Emerging microchemical sensors for real-time point-of-care detection of chronic kidney disease biomarkers,” *Microchemical Journal*, vol. 220, p. 116751, Jan. 2026, doi: 10.1016/j.microc.2025.116751.

[8] K. Kalantar-Zadeh *et al.*, “Patient-centred approaches for the management of unpleasant symptoms in kidney disease,” *Nat. Rev. Nephrol.*, vol. 18, pp. 185–198, Jan. 2022, doi: 10.1038/s41581-021-00518-z.

[9] R. Ardianto, D. Yusuf, R. B. B. Sumantri, D. Febrina, R. R. Al-Hakim, and A. S. S. Ariyanto, “Bioinformatics-driven deep learning for nail disease diagnosis: A novel approach to improve healthcare outcomes,” *BIO Web Conf.*, vol. 152, p. 01024, Jan. 2025, doi: 10.1051/BIOCONF/202515201024.

[10] P. S. Ganney, *Introduction to Bioinformatics and Clinical Scientific Computing*. Boca Raton, Florida (US): CRC Press, 2022.

[11] T. Tan, Y. Diao, X. Yu, L. Chen, and H. Fang, “Artificial intelligence in precision mRNA therapeutics: Towards genomic language models and multi-agent virtual humans,” *Acta Pharm. Sin. B*, Jan. 2026, doi: 10.1016/j.apsb.2025.12.044.

[12] O. P. Handayani, Purwono, I. A. Ashari, and R. Ardianto, “Systematic Literature Review: Penerapan Machine Learning dalam Diagnosis dan Prediksi Penyakit Diabetes,” *Komputa : Jurnal Ilmiah Komputer dan Informatika*, vol. 14, no. 2, pp. 108–118, Nov. 2025, doi: 10.34010/KOMPUTA.V14I2.16642.

[13] R. Al-Hakim, N. R. I. Ayu, and R. Ardianto, “De-identified Clinical Administrative Dataset for Metabolic Disease Risk Analysis from RSI Banjarnegara, Indonesia (1.0),” *[Data set] Rosyid Ridlo Al-Hakim*, Dec. 2025, doi: 10.5281/ZENODO.17942628.

[14] S. Sharma, L. Sharma, and T. K. Gandhi, “Integration of quantum artificial intelligence in disease diagnosis: A review of methods and applications,” *Comput. Methods Programs Biomed.*, vol. 274, p. 109175, Feb. 2026, doi: 10.1016/j.cmpb.2025.109175.

[15] W. Liu *et al.*, “Improving Kidney Outcomes in Patients With Nondiabetic Chronic Kidney Disease Through an Artificial Intelligence–Based Health Coaching Mobile App: Retrospective Cohort Study,” *JMIR Mhealth Uhealth*, vol. 11, Jan. 2023, doi: 10.2196/45531.

[16] Y. Zhao, D. He, L. Yang, J. Lu, and S. Lu, “Development of an artificial intelligence-based chronic kidney disease management platform for type 2 diabetes patients,” *Diabetes Res. Clin. Pract.*, vol. 230, p. 112562, Dec. 2025, doi: 10.1016/j.diabres.2025.112562.

[17] Z. Hu and X. Ma, “A novel neural network model fusion approach for improving medical named entity recognition in online health expert question-answering services,” *Expert Syst. Appl.*, vol. 223, p. 119880, Aug. 2023, doi: 10.1016/j.eswa.2023.119880.

[18] Y. Nataliani, H. D. Purnomo, I. K. Timotius, and P. Purwono, “DFU-MambaLiteUNet: A lightweight and efficient model for diabetic foot ulcer segmentation,” *Expert Syst. Appl.*, vol. 293, p. 128689, Dec. 2025, doi: 10.1016/j.eswa.2025.128689.

[19] R. R. Al-Hakim, R. A. P. Putra, A. Pangestu, I. Widhiarto, M. Yusro, and Y. Z. Arief, “Design of an Intelligent Military Recruitment Support System Based on Certainty Factor and Forward Chaining Inference,” in *2025 International Conference on Artificial Intelligence’s Future Implementations (ICAIFI)*, Yogyakarta, Indonesia: Institute of Electrical and Electronics Engineers (IEEE), Jan. 2026, pp. 81–87. doi: 10.1109/icaifi66942.2025.11326024.

[20] R. R. Al-Hakim *et al.*, “Rule-based ai system for early paediatric diabetes diagnosis using backward chaining and certainty factors,” *BIO Web Conf.*, vol. 152, p. 01020, Jan. 2025, doi: 10.1051/BIOCONF/202515201020.

[21] T. M. R. Gunung, A. D. Ningtyas, S. E. Sitepu, V. Rolanda, and A. Jinan, “Smart Skincare: Expert System Based on Certainty Factors for Skin Type Identification and Product Selection,” *Journal of Embedded Systems, Security and Intelligent Systems*, vol. 6, no. 4, pp. 595–604, Nov. 2025, doi: 10.59562/JESSI.V6I4.10015.

[22] S. Kusumadewi, L. Rosita, and E. G. Wahyuni, “Fuzzy linear regression based on a hybrid of fuzzy C-means and the fuzzy inference system for predicting serum iron levels in patients with chronic kidney disease,” *Expert Syst. Appl.*, vol. 227, p. 120314, Oct. 2023, doi: 10.1016/j.eswa.2023.120314.

[23] Dr. S. R. Sukhdeve and S. S. Sukhdeve, “Google Colaboratory,” in *Google Cloud Platform for Data Science*, Berkeley, CA (US): Apress, 2023, pp. 11–34. doi: 10.1007/978-1-4842-9688-2_2.

[24] J. C. Squire and A. E. English, “Introduction to Python,” in *Introduction to Python and Spice for Electrical and Computer Engineers*, London (UK): Elsevier, 2025, pp. 1–48. doi: 10.1016/B978-0-443-19007-0.00001-5.

[25] F. J. López-Flores, R. Ochoa-Barragán, A. Y. Raya-Tapia, C. Ramírez-Márquez, and J. M. Ponce-Ortega, "Machine learning with Python," in *Machine Learning Tools for Chemical Engineering: Methodologies and Applications*, London (UK): Elsevier, 2025, pp. 31–55. doi: 10.1016/B978-0-443-29058-9.00004-5.

[26] F. S. Nazarova and S. S. Abdurakhimova, "Kidney and Urinary Tract and Their Diseases," *Western European Journal of Medicine and Medical Science*, vol. 2, no. 4, pp. 32–36, Apr. 2024.

[27] D. Fichandler and D. J. Malone, *Genitourinary Diseases and Disorders*, 2nd ed. London (UK): Routledge, 2024. doi: 10.4324/9781003522485-12.

[28] M. A. Alnabi and J. A. Al Mashikas, "Signs and symptoms of kidney disease in the critically ill pregnant patient," in *The Kidney of the Critically Ill Pregnant Woman*, New York (US): Academic Press, 2025, pp. 23–33. doi: 10.1016/B978-0-443-21473-8.00004-5.

[29] D. Heckerman, "Probabilistic Interpretations for Mycin's Certainty Factors," *Machine Intelligence and Pattern Recognition*, vol. 4, pp. 167–196, Jan. 1986, doi: 10.1016/B978-0-444-70058-2.50017-6.

[30] E. Hariadha, D. Nugraha, R. R. Al Hakim, A. Pangestu, M. Yusro, and M. H. Satria, "Using Certainty Factor for Symptoms Diagnosis of Thyroid Disorders," in *2022 International Conference on ICT for Smart Society (ICISS)*, Bandung (ID): IEEE, 2022, pp. 01–05. doi: 10.1109/ICISS55894.2022.9915219.

[31] S. S. Biswas, "ChatGPT for Research and Publication: A Step-by-Step Guide," *The Journal of Pediatric Pharmacology and Therapeutics*, vol. 28, no. 6, pp. 576–584, Oct. 2023, doi: 10.5863/1551-6776-28.6.576.

[32] O. M. Alyasiri, A. M. Salman, D. Akhtom, and S. Salisu, "ChatGPT revisited: Using ChatGPT-4 for finding references and editing language in medical scientific articles," *J. Stomatol. Oral Maxillofac. Surg.*, vol. 125, no. 5, p. 101842, Oct. 2024, doi: 10.1016/j.jormas.2024.101842.

[33] L. Lingard, "Writing with ChatGPT: An Illustration of its Capacity, Limitations & Implications for Academic Writers," *Perspect. Med. Educ.*, vol. 12, no. 1, p. 270, Jun. 2023, doi: 10.5334/pme.1072.

[34] A. A. Nafea, M. M. Al-Ani, M. A. Khalaf, and M. S. I. Alsumaidaie, "A Review of Using Chatgpt for Scientific Manuscript Writing," *Babylonian Journal of Artificial Intelligence*, vol. 2024, pp. 9–13, Jan. 2024, doi: 10.58496/BJAI/2024/002.

[35] J. Huang *et al.*, "A critical assessment of using ChatGPT for extracting structured data from clinical notes," *NPJ Digit. Med.*, vol. 7, pp. 106-, May 2024, doi: 10.1038/s41746-024-01079-8.

[36] A. Gunawan and F. Islami, "Implementing the Certainty Factor Method in a Dental Disease Expert System," *Journal Medical Informatics Technology*, vol. 2, no. 2, pp. 27–32, Jun. 2024, doi: 10.37034/MEDINFTECH.V2I2.33.

[37] R. R. Al-Hakim *et al.*, "Predict the thyroid abnormality particular disease likelihood of the symptoms' certainty factor value and its confidence level: A regression model analysis," *SISTEMASI: Jurnal Sistem Informasi*, vol. 12, no. 2, pp. 415–424, 2023, doi: 10.32520/stmsi.v12i2.2542.

[38] D. Cantarino, J. A. Acuna, M. Stevens, M. Heide, and J. L. Zayas-Castro, "Balancing equity and efficiency in kidney allocation: An online adaptive stochastic bi-objective approach," *Expert Syst. Appl.*, vol. 308, p. 131148, May 2026, doi: 10.1016/j.eswa.2026.131148.

[39] S. Mahmud *et al.*, "Automated grading of prenatal hydronephrosis severity from segmented kidney ultrasounds using deep learning," *Expert Syst. Appl.*, vol. 255, p. 124594, Dec. 2024, doi: 10.1016/j.eswa.2024.124594.