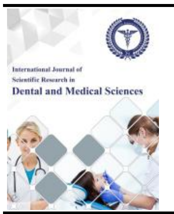

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Effect of Using Artificial Intelligence in the Prediction and Initial Assessment of Chronic Kidney Disease: A Systematic Review and Meta-analysis

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ABSTRACT

Background and aim: The present research aims to evaluate the effect of using artificial intelligence in the prediction and initial assessment of chronic kidney disease.

Material and methods: In the present study, the researchers searched the international databases Cochrane, Embase, and MEDLINE (PubMed and Ovid) for keywords related to the study objectives. Considering that recent data is significant with the advancement of artificial intelligence, the search was limited to the last five years, between January 2019 and January 2025. The effect size was used with the random-effects model and REML methods of 95% confidence intervals (CI). Meta-analysis was performed using Stata (as of version 17).

Results: The Area Under the Curve and accuracy of artificial intelligence in the prediction and initial assessment of chronic kidney disease was 90% (ES 0.90 95% CI; 0.28, 1.52) and 87% (ES 0.87 95% CI; 0.25, 1.49), respectively.

Conclusions: Based on the meta-analysis of the present study, artificial intelligence models could be highly effective in the early ancillary diagnosis of chronic kidney disease.

1. Introduction

Ten percent of the world's population now suffers from chronic kidney disease (CKD), a condition that is both very painful and fatal over time.[1] According to World Health Organization (WHO) projections, 2040 CKD will be the fifth most common chronic disease.[2] As the population ages and the prevalence of diabetes, hypertension, and obesity rises, the prevalence of CKD has increased in recent decades.[3] CKD cannot be diagnosed until irreversible kidney damage has occurred, which makes it even more deadly. When a patient discovers the condition, it becomes a time-consuming and exhausting process to have him tested, diagnose the condition based on potentially incorrect results, give him medication according to the stage of CKD he may be in, and provide all the care he needs to survive.[4, 5] The studies' results show no universally applicable markers to distinguish between healthy and sick people, which is why chronic kidney disease has become one of the worst diseases in the world. Researchers and doctors find it very difficult to accurately and quickly diagnose this condition, which can lead to an incorrect disease prognosis.[5-7] CKD is identified most commonly by screening with a blood chemical profile and urine testing or by discovering the condition as a side effect of another procedure.[8] Less frequently occurring symptoms include flank pain, nocturia, gross hematuria, and decreased urine production. People who have severe CKD may experience symptoms such as fatigue, low appetite, nausea, vomiting, metallic taste, unintended weight loss, pruritus, changes in mental state, dyspnea, or peripheral edema.[2, 9, 10] Artificial intelligence (AI) methods based on deep learning and machine learning have emerged as effective and valuable medical tools. They are opening new avenues for risk assessment, early diagnosis, and individualized treatment plans to help patients achieve better results.[11] AI has been used in multiple studies to maximize patient outcomes, enable prompt intervention, and predict the early onset of kidney disease.[12-14] AI can predict complications and identify at-risk patients, and doctors can monitor their health. On the other hand, AI can help patients by providing solutions for new preventive measures and personalized treatment plans.[13, 15] Considering the subject's importance in today's world and AI's daily advances, the present study tried to reach comprehensive results regarding the effect of using AI in predicting and initially assessing CKD.

2. Material and methods

Search strategy and Information sources

In the present study, the researchers searched the international databases Cochrane, Embase, and MEDLINE (PubMed and Ovid) for keywords related to the study objectives. Considering that the recent data is significant with the

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advancement of AI, the search was limited to the last five years, between January 2019 and January 2025. Google Scholar, Web of Science, Cochrane Central Register of Controlled Trials, EBSCO Information Services, ISI, Elsevier, and Scopus were also used to find relevant articles, and the 27-point PRISMA 2020 checklist was considered throughout the study.[16]

The Medical Subject Headings (MeSH) search strategy is as follows:

(((((((((("Artificial Intelligence"[Mesh]) OR "Intelligent Systems"[Mesh]) OR "Machine Learning"[Mesh]) OR "Deep Learning"[Mesh]) OR "Predictive Learning Models"[Mesh]) AND ("Renal Insufficiency, Chronic"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder"[Mesh] OR "Chronic Kidney Diseases of Uncertain Etiology"[Mesh])) OR ("Chronic Kidney Disease-Mineral and Bone Disorder/complications"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder/diagnosis"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder/diagnostic imaging"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder/drug therapy"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder/etiology"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder/mortality"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder/prevention and control"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder/surgery"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder/therapy"[Mesh] OR "Chronic Kidney Disease-Mineral and Bone Disorder/urine"[Mesh])) OR "Kidney Diseases"[Mesh]) AND "Data Accuracy"[Mesh]) OR "Diagnosis"[Mesh]) OR "Sensitivity and Specificity"[Mesh]) OR "Area Under Curve"[Mesh].

Selection criteria

The selection of articles was limited to the English language, and they were also selected based on the PICO strategy (Table 1).

Table 1. PICO approach.

Inclusion criteria	
PICO strategy	
Population (P)	CKD Patients
Intervention (I)	AI-based prediction approach
comparison (C)	Other prediction methods
Outcome (O)	Diagnostic accuracy
Exclusion criteria	
Criteria for exclusion	All diseases unrelated to CKD
	Physical- AI
	We excluded all studies except randomized clinical trials, cross-sectional studies, cohort studies, observational studies, and experimental studies.

The process of selection and data collection

Two blind and independent researchers reviewed the data of the selected studies, and the third researcher summarized them. The research team collected the data using a pre-designed form that included sections such as the first author's name, year of publication, study design, number of patients, gender, mean age, and comorbidities.

Statistical heterogeneity

Chi-square test ($\chi 2$) and I^2 to determine heterogeneity between studies. The value of I^2 checked in four levels (low heterogeneity: ≤25%; moderate: 25%-50%; substantial: 50%-75%; considerable: ≥ 75%.

Methodological quality

The prediction model risk of bias assessment tool (PROBAST) was used to evaluate the bias of prediction models.[17] PROBAST has four domains: assessment, outcomes, predictors, and participants. Based on how each item on the PROBAST checklist was answered, each domain was given a risk of bias rating (high, low, or unclear).

Data analysis

The diagnostic accuracy of AI was used as an effect size with a random-effects model and REML methods of 95% confidence intervals (CI). Meta-analysis was performed using Stata (as of version 17). Statistical significance was considered less than 0.05.

3. Results

Description of studies

Nine hundred sixteen articles were found in international databases during the initial search using related keywords. Two blind, independent researchers reviewed the articles and eliminated duplicates unrelated to the study topic. Abstracts of 746 studies were reviewed based on the inclusion criteria (613 articles were removed at this stage); the full texts of 133 articles were examined; only eighteen were included in the study because they were consistent with the objectives (Fig. 1).

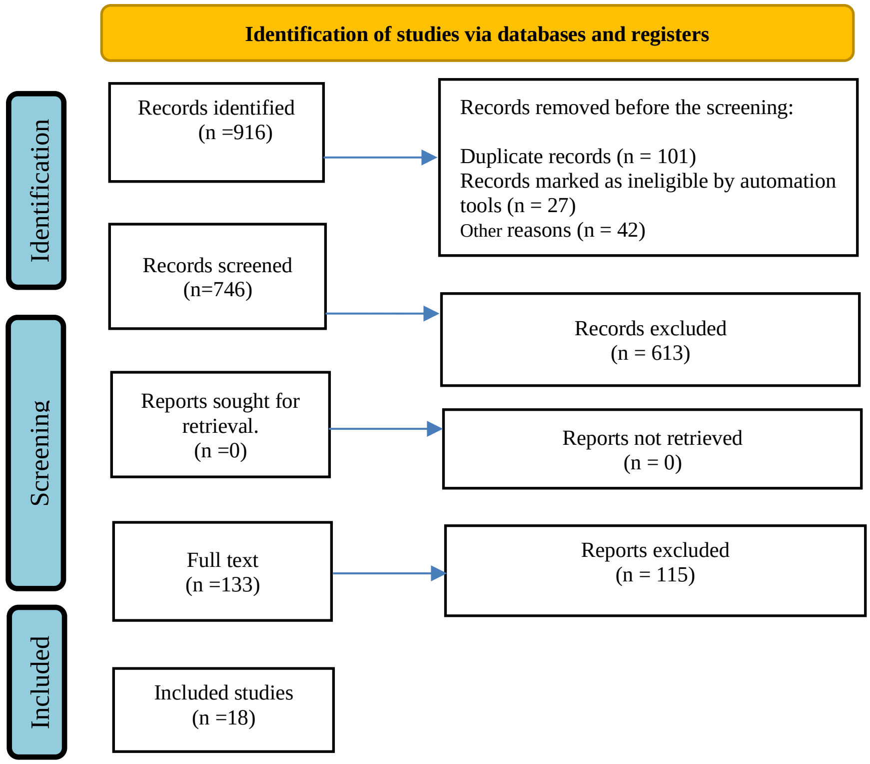

Fig. 1. PRISMA 2020 Checklist.

Study characteristics

The characteristics of the studies are summarized in Table 2.

Bias assessments

As shown in Table 3, all studies were of high quality (low risk of bias).

Area under curve

The Area Under the Curve of AI in the prediction and initial assessment of chronic kidney disease was 90% (ES 0.90 95% CI; 0.28, 1.52), and the I^2 statistic was 0% (p=1.00), which showed low heterogeneity (Fig. 2).

Table 2. Baseline demographic characteristics of included studies.

No.	Study. Years	Study Design	Number of Patients	Gender		Rang/ Mean Age	Comorbidities
				Female	Male		
1	Hu et al., 2025[18]	ReC	555	204	351	<65<	Diabetes
2	Jawad et al., 2025[19]	Exp	780	NR	-----	>30	-----
3	Watanabe et al., 2025[20]	ReC	348	146	202	65.2	Diabetes
4	Tangri et al., 2024[21]	RCT	14464	5101	9363	63.2	-----
5	Isaza-Ruget et al., 2024[22]	Ob	1466	875	591	77	-----
6	Ghosh et al., 2024[23]	ReC	491	NR	-----	>20	-----
7	Khalid et al., 2023[24]	Exp	NR	NR	NR	NR	-----
8	Islam et al., 2023[25]	Exp	158	NR	NR	NR	-----
9	Liu et al., 2023[26]	ReC	3624	1590	2034	59.0	Diabetes
10	Ebiaredoh-Mienye et al., 2022[27]	Exp	400	NR	NR	2-90	-----

11	Dritsas et al., 2022[28]	Exp	400	NR	NR	NR	-----
12	Su et al., 2022[29]	ReC	858	NR	NR	80.8	-----
13	Dovgan et al., 2020[30]	ReC	8492	NR	NR	NR	-----
14	Song et al., 2020[31]	ReC	14039	NR	NR	NR	-----
15	Sabanayagam et al., 2020[32]	Exp	5188	2446	2742	58.4	Diabetes, hypertension
16	Navaneeth et al., 2020[33]	Exp	172	NR	NR	NR	-----
17	Xiao et al., 2019[34]	Exp	551	268	283	58.1	-----
18	Kuo et al., 2019[35]	Exp	1299	65	717	582	Diabetes

ReC: retrospective cohort study; Ob: Observational study; Exp: Experimental.

Table 3. Bias assessments of included studies according to PROBAST.

Study. Years	Risk of Bias				Overall
	Participants	Predictors	Outcomes	Assessment	
Hu et al., 2025[18]	★	★	★	★	Low
Jawad et al., 2025[19]	★	★	★	★	Low
Watanabe et al., 2025[20]	★	★	★	★	Low
Tangri et al., 2024[21]	★	★	★	★	Low
Isaza-Ruget et al., 2024[22]	★	★	★	★	Low
Ghosh et al., 2024[23]	★	★	★	★	Low
Khalid et al., 2023[24]	☆	★	★	★	Low
Islam et al., 2023[25]	★	★	★	★	Low
Liu et al., 2023[26]	★	★	★	★	Low
Ebiaredoh-Mienye et al., 2022[27]	★	★	★	★	Low
Dritsas et al., 2022[28]	★	★	★	★	Low
Su et al., 2022[29]	★	★	★	★	Low
Dovgan et al., 2020[30]	★	★	★	★	Low
Song et al., 2020[31]	★	★	★	☆	Low
Sabanayagam et al., 2020[32]	★	★	★	★	Low
Navaneeth et al., 2020[33]	★	★	★	★	Low
Xiao et al., 2019[34]	★	★	★	★	Low
Kuo et al., 2019[35]	★	★	★	★	Low

Black stars (★) to signify that a study satisfactorily meets a specific criterion.
White stars (☆) indicate that a criterion is not met.

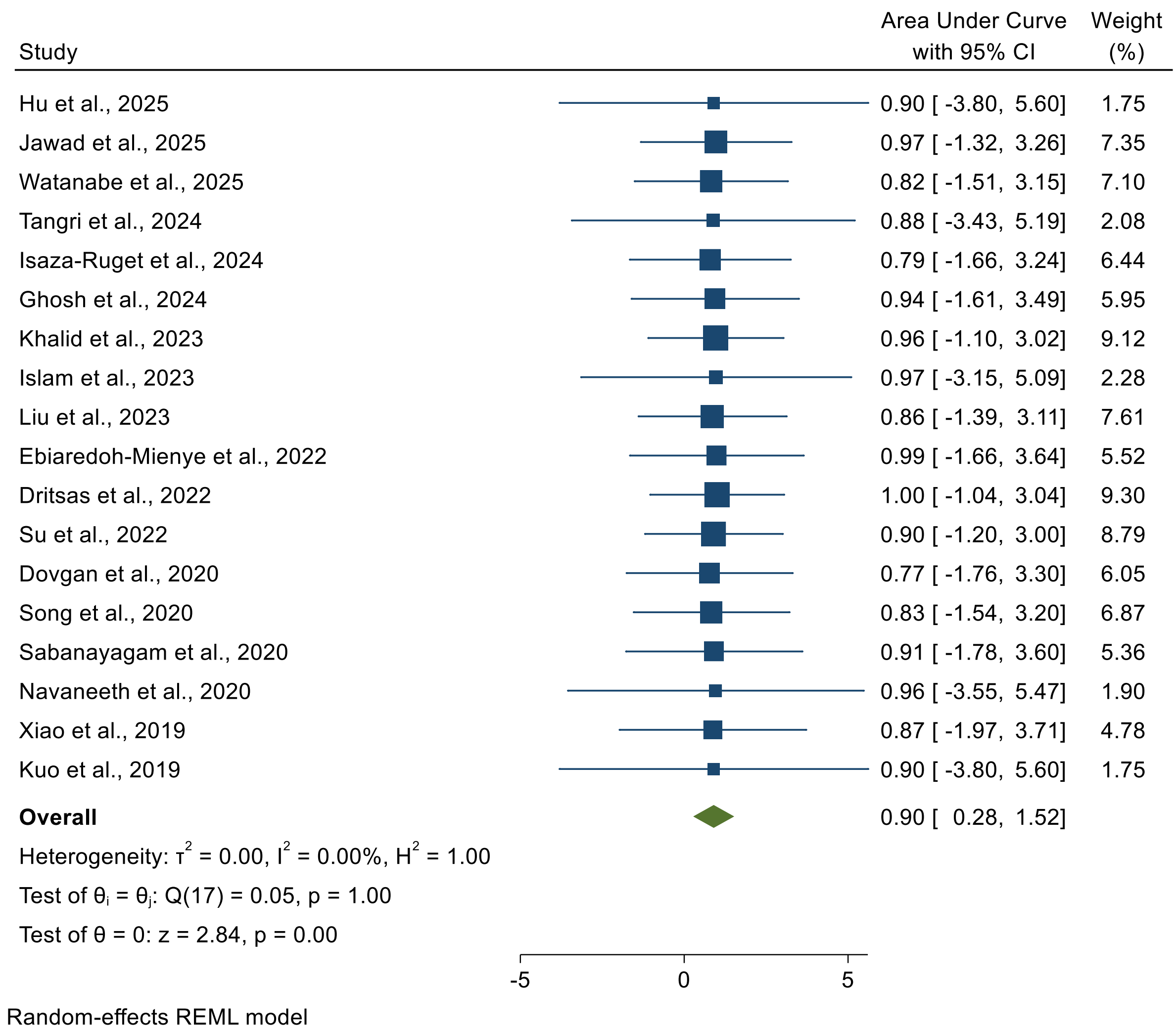

Fig. 2. The forest plot showed an Area Under Curve.

Accuracy

The accuracy of AI in the prediction and initial assessment of chronic kidney disease was 87% (ES 0.87 95% CI; 0.25, 1.49), and the I^2 statistic was 0% (p=1.00), which showed low heterogeneity (Fig. 3).

Sensitivity

The sensitivity of AI in the prediction and initial assessment of chronic kidney disease was 86% (ES 0.86 95% CI; 0.23, 1.48), and the I^2 statistic was 0% (p=1.00), which showed low heterogeneity (Fig. 4).

Specificity

The specificity of AI in the prediction and initial assessment of chronic kidney disease was 89% (ES 0.89 95% CI; 0.27, 1.51), and the I^2 statistic was 0% (p=1.00), which showed low heterogeneity (Fig. 5).

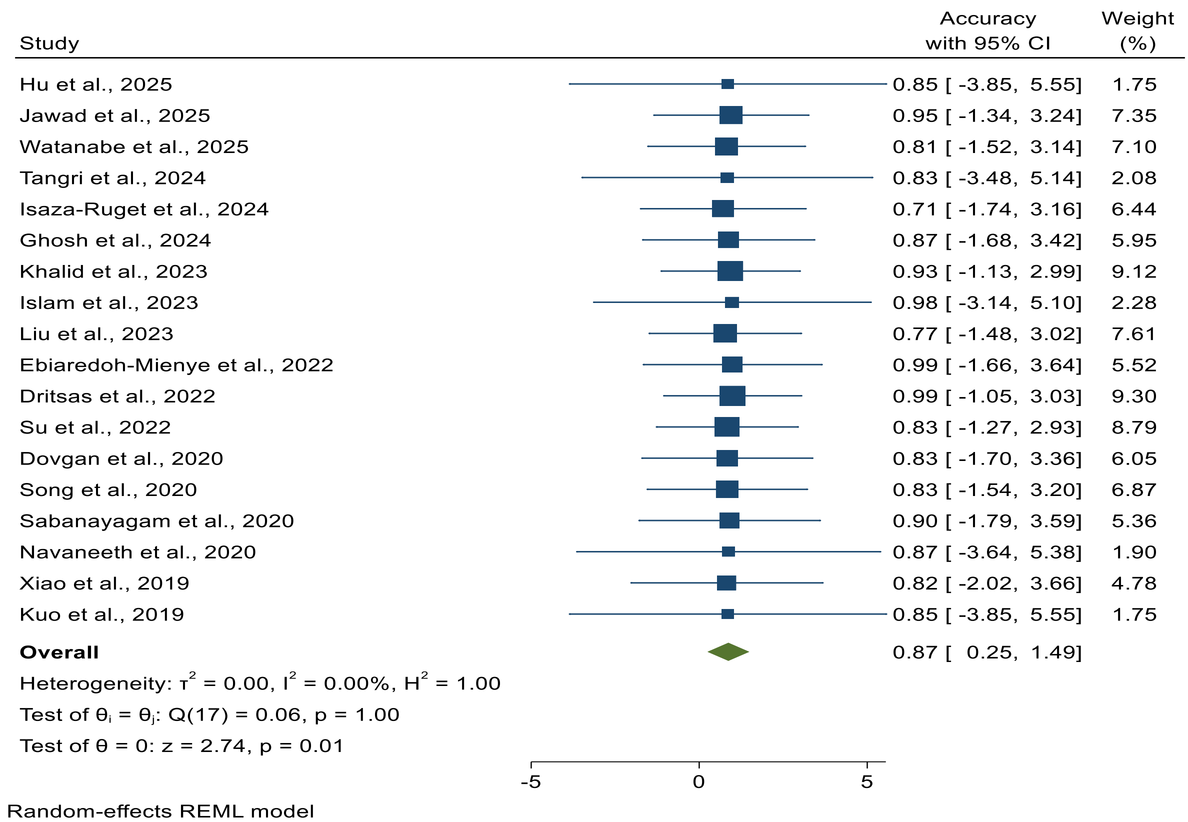

Fig. 3. The forest plot showed accuracy.

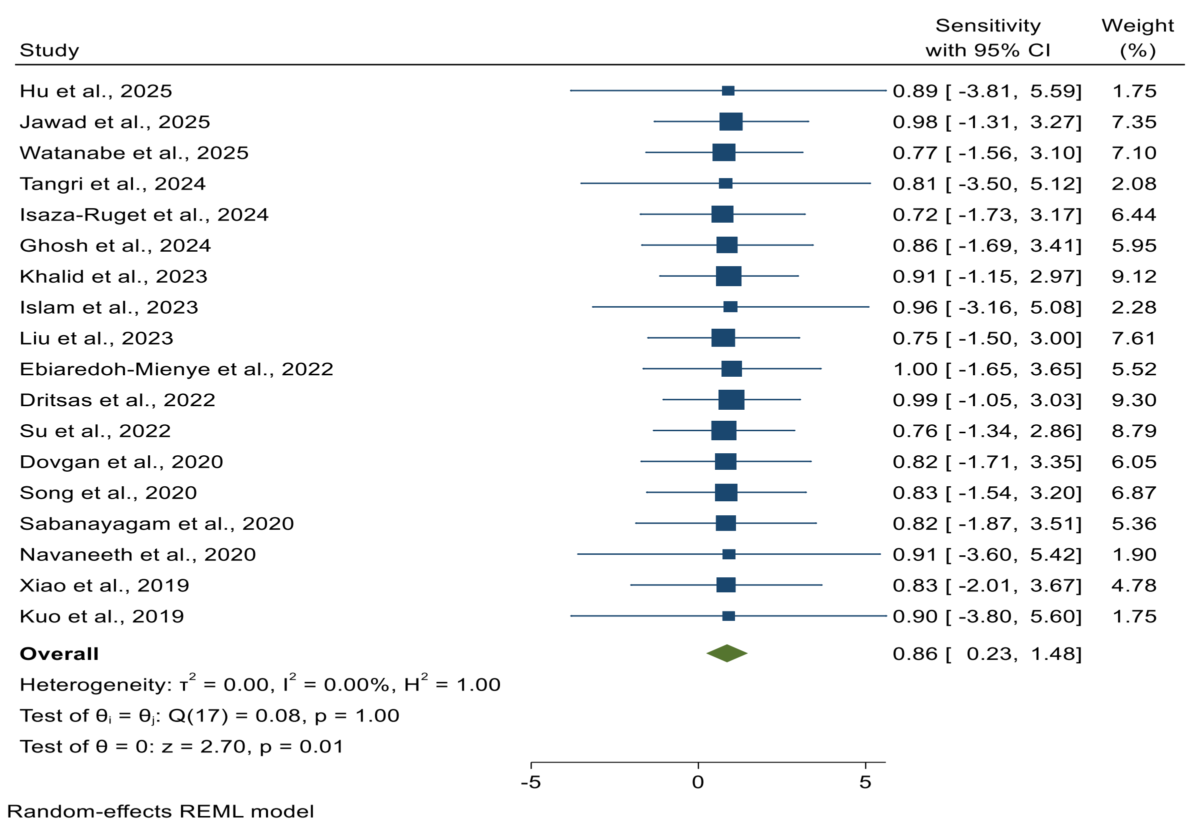

Fig. 4. The forest plot showed sensitivity.

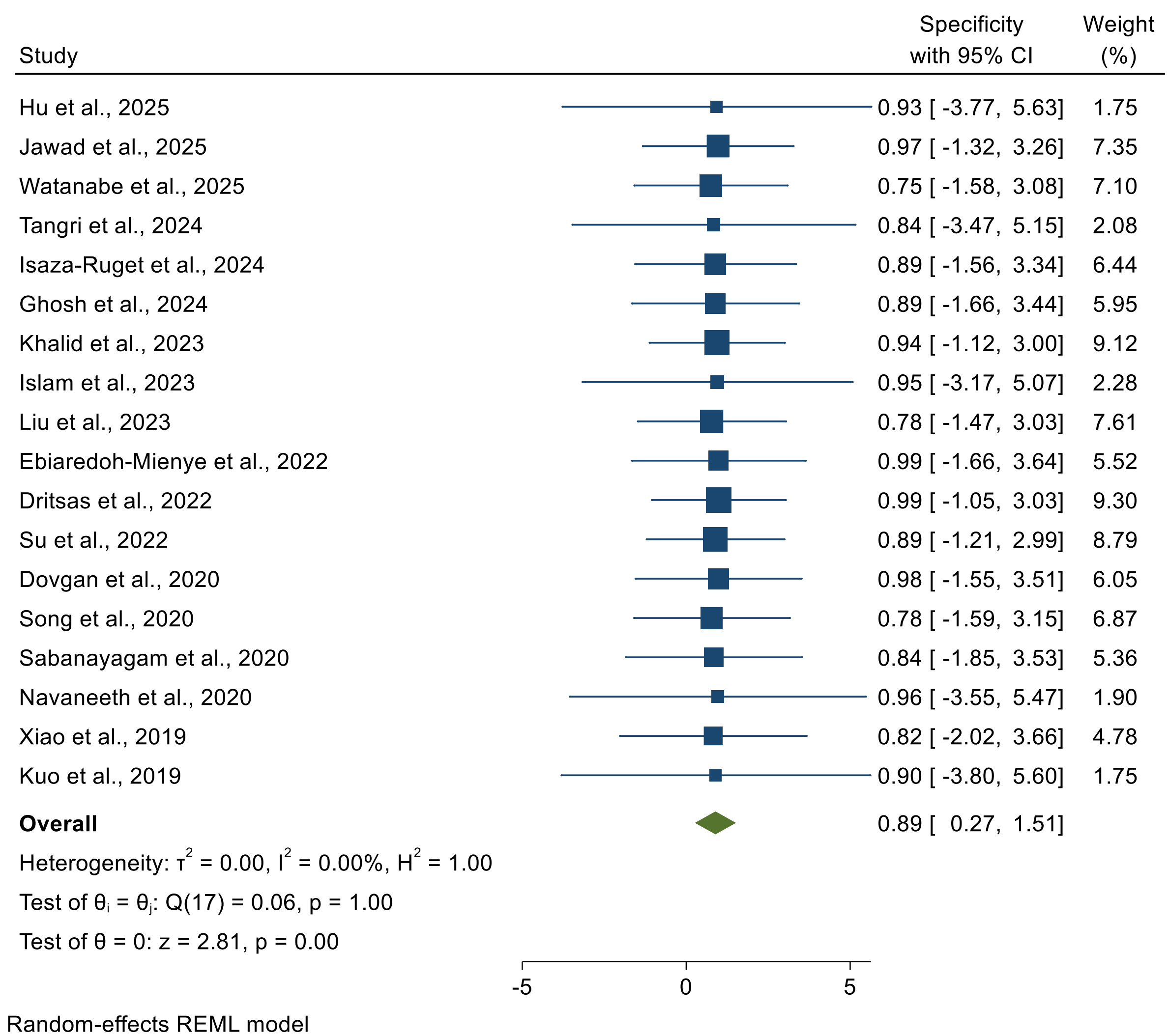

Fig. 5. forest plot showed specificity.

4. Discussion

Chronic kidney disease (CKD) is unquestionably one of the deadly conditions that is most difficult to diagnose with high precision and accuracy. In summary, developing an app to identify chronic illnesses will benefit those who have found it difficult to see a doctor and assist medical professionals in resolving urgent issues. One of the reasons for the difficulty in diagnosing CKD is that it is difficult to predict because it is not dependent on a single feature. Furthermore, common signs of CKD do not significantly aid in diagnosing the condition.[12] The selected studies in the present study have shown that when predictive models based on AI are used to predict CKD, clinical practice can be changed more accurately and effectively. Meta-analysis of the present study showed that the Area Under Curve, accuracy, sensitivity, and specificity of AI in the prediction and initial assessment of chronic kidney disease were 90%, 87%, 86%, and 89%, respectively. This advancement emphasizes how AI revolutionizes nephrology and can enhance patient outcomes and yield the best clinical judgments. The models' high sensitivity and specificity show that they accurately identify patients who have not experienced any progression of CKD.[36] The training data may not adequately represent certain clinical traits that are suggestive of progress, which results in imprecise predictions and, consequently, improper integration of progress. The ability to employ aggregate techniques to improve the models' detection of final information, careful data preparation, and wise selection are necessary to balance sensitivity and specificity. The current results demonstrate the high diagnostic accuracy of artificial intelligence-based predictive tools and align with previous research.[37, 38] Given that CKD is a condition in which several factors, including age, comorbidities, genetic predisposition, and environmental exposures, affect the course of the disease, this capability is invaluable. Conventional models that predict risk frequently perform less well because they cannot consider these intricate relationships.[39]

5. Conclusion

Based on the meta-analysis of the present study, AI models are a suitable option for predicting the progress of CKD because they are highly accurate. Therefore, AI could be highly effective in the early ancillary diagnosis of DKD. It was suggested that future modeling studies use machine learning models to improve the risk assessment model and data.

Conflict of Interest

The authors declared that there is no conflict of interest.

Acknowledgments

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