INSIGHTS-JOURNAL OF
HEALTH AND REHABILITATION

AI-POWERED ULTRASOUND INTERPRETATION FOR EARLY DETECTION OF KIDNEY ABNORMALITIES IN RURAL PATIENTS

Original Research

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Acknowledgement: The authors thank all participants and site staff for their cooperation.

Conflict of Interest: None   Grant Support & Financial Support: None

ABSTRACT

Background: Chronic kidney disease (CKD) often remains undiagnosed in its early stages, particularly in rural and underserved populations lacking access to nephrologists and diagnostic imaging. Ultrasonography is a first-line tool for kidney evaluation but is limited by operator dependence. Recent advancements in artificial intelligence (AI) have introduced opportunities for automated, standardized interpretation of ultrasound images, potentially improving early detection in low-resource settings.

Objective: To evaluate the effectiveness of AI-assisted ultrasound interpretation in detecting early renal abnormalities among underserved rural populations in Pakistan.

Methods: A cross-sectional study was conducted from January to June 2025 at private rural healthcare centers in Lahore, Faisalabad, and Multan. A total of 200 adult patients underwent renal ultrasonography using portable devices equipped with AI diagnostic software. Inclusion criteria were adults ≥18 years without prior CKD diagnosis. AI findings were compared with interpretations by experienced radiologists. Outcome measures included sensitivity, specificity, accuracy, and inter-observer agreement. Statistical analysis was performed using SPSS v26, and ROC curves were generated to evaluate diagnostic performance.

Results: AI-assisted ultrasound demonstrated a sensitivity of 92.3%, specificity of 89.1%, and accuracy of 90.7% in detecting early renal abnormalities, outperforming radiologist interpretation in certain lesion categories. The AI model showed particularly high performance in identifying increased cortical echogenicity and early hydronephrosis. Agreement between AI and radiologist findings reached 91%, with minimal discordance. The area under the ROC curve for AI was 94.2%, indicating excellent diagnostic capability.

Conclusion: AI-assisted ultrasound interpretation significantly improves early detection of renal abnormalities in rural populations, supporting its integration into primary care to reduce diagnostic disparities and enhance kidney health outcomes.

Keywords: Artificial Intelligence, Diagnostic Imaging, Kidney Diseases, Nephrology, Renal Ultrasonography, Rural Health, Screening, Telemedicine.

INTRODUCTION

Chronic kidney disease (CKD) represents a significant global health burden, affecting over 10% of the world's population and often progressing silently until reaching advanced, irreversible stages. Early identification of renal abnormalities is critical in preventing disease progression, yet access to diagnostic tools remains unequal—especially in rural and underserved regions, where specialized medical personnel and imaging infrastructure are scarce (1). Ultrasonography is considered the first-line imaging modality for evaluating renal morphology due to its non-invasiveness, affordability, and real-time imaging capabilities. However, the diagnostic accuracy of ultrasound is heavily dependent on operator expertise, which is often limited in rural settings (2).

Artificial intelligence (AI) has recently emerged as a transformative force in medical imaging. Leveraging deep learning and convolutional neural networks, AI algorithms can now detect, classify, and quantify abnormalities in ultrasound images with high precision and consistency. In the context of renal disease, AI-assisted ultrasound has shown exceptional promise in enhancing early diagnostic capabilities, even in the hands of non-specialist operators (3). A systematic review reported median diagnostic accuracy and area under the curve (AUC) values of 0.88 and 0.96, respectively, for AI models assessing renal abnormalities using ultrasound, underscoring their high potential as clinical tools (3). These models can assist in identifying a range of kidney conditions such as hydronephrosis, renal cysts, and cortical scarring, which are early indicators of progressive kidney disease (4).

For pediatric and adult patients alike, AI-based ultrasound interpretation has been tested with encouraging results. For example, in a large-scale validation study, AI-enabled systems distinguished between normal and abnormal pediatric kidney ultrasound images—including those with cysts, hyperechogenicity, and hydronephrosis—with overall accuracy reaching 92.9% (5). These technologies offer rapid, objective analysis and can dramatically reduce interobserver variability—an issue that commonly hampers ultrasound interpretation by less experienced clinicians (6). More importantly, such tools democratize access to quality diagnostics by equipping frontline healthcare workers in remote areas with decision-support systems that would otherwise require subspecialist input.

Despite these advancements, real-world implementation of AI-assisted ultrasound in rural healthcare systems remains limited. Several barriers persist, including infrastructural constraints, lack of internet connectivity for cloud-based systems, and regulatory hurdles. A qualitative investigation into transferring AI ultrasound tools for hydronephrosis detection from Canada to South Africa revealed that while technical readiness was promising, contextual differences in patient demographics, clinical workflows, and sonographer experience significantly influenced adoption (1). Nevertheless, clinicians in rural settings expressed strong interest in AI-enabled tools, recognizing their potential to reduce diagnostic delays and improve care outcomes.

Further, AI is not only confined to image classification. It now encompasses tasks such as automated kidney segmentation, renal volume estimation, and even functional prediction models using ultrasound-derived features (7). These extended capabilities offer a comprehensive approach to early kidney disease screening that surpasses conventional methods. They are particularly crucial in regions where laboratory testing is either unavailable or delayed. AI-enhanced interpretation of sonographic features—such as cortical echogenicity, parenchymal thickness, and corticomedullary differentiation—can serve as early markers of CKD and correlate strongly with biochemical parameters like serum creatinine (8).

The intersection of artificial intelligence and ultrasound imaging presents an extraordinary opportunity to bridge diagnostic gaps in rural nephrology. By embedding intelligent algorithms into portable ultrasound systems, healthcare providers can detect renal abnormalities earlier and with greater confidence, potentially preventing thousands of cases of end-stage renal disease. Moreover, AI-integrated devices may serve not only as diagnostic tools but also as educational platforms, guiding novice users through scan acquisition and interpretation in real-time.

Given this transformative potential, the present cross-sectional study seeks to evaluate the effectiveness of AI-assisted ultrasound interpretation in detecting early renal abnormalities among patients in underserved rural communities. This study aims to contribute empirical evidence on diagnostic accuracy, user acceptability, and the feasibility of deploying such tools in resource-limited settings—ultimately offering insights that may help close long-standing disparities in kidney healthcare access and outcomes.

METHODS:

This study was conducted as a community-based cross-sectional survey with the objective of evaluating the effectiveness of AI-assisted ultrasound in detecting early renal abnormalities among underserved populations in rural areas of Lahore, Faisalabad, and Multan. Data collection was performed over a six-month period from January to June 2025 across selected private healthcare setups that routinely serve low-income populations. Each site was equipped with portable ultrasound systems integrated with AI diagnostic software for real-time image analysis. The study was ethically approved by the Institutional Review Board of the Central Research Ethics Committee (Reference No. CREC-2024-0592), and informed written consent was obtained from all participants or their legal guardians prior to enrollment.

The target population included adult patients aged 18 years and above, residing in rural or peri-urban regions of the selected cities, and visiting local clinics for routine health checkups or nonspecific abdominal complaints. Inclusion criteria involved patients with no prior diagnosis of chronic kidney disease (CKD) or structural renal anomalies and who were willing to undergo renal ultrasonography. Exclusion criteria encompassed individuals with known CKD, previous nephrectomy, congenital renal malformations, or pregnancy, as these conditions could confound diagnostic outcomes.

Sample size was calculated using an expected prevalence of undiagnosed renal abnormalities of 12% based on previous rural screening data, a 95% confidence level, and 5% margin of error. The estimated sample size was 163, but anticipating possible attrition, a final sample of 200 participants was targeted and achieved using stratified random sampling across the three locations.

Participants underwent standardized renal ultrasound examinations using portable devices equipped with AI modules based on convolutional neural networks. The embedded AI model, pre-trained and validated on diverse renal ultrasound datasets, automatically segmented the kidney structures and highlighted features suggestive of early pathology such as increased cortical echogenicity, reduced corticomedullary differentiation, or presence of cystic changes. A radiologist blinded to AI results concurrently reviewed the scans for manual diagnosis. The AI system employed a decision threshold calibrated to maximize sensitivity for early abnormalities, particularly early-stage fibrosis and hydronephrosis (9).

Outcome assessment was two-fold: first, the detection rate of renal abnormalities by AI as compared to expert manual interpretation, and second, the concordance between AI-based and radiologist-based findings. Primary outcome measures included sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) of the AI tool. To quantify the performance, a 2x2 contingency table was constructed and diagnostic test evaluation metrics were calculated accordingly. Secondary outcomes involved inter-observer agreement evaluated using Cohen's Kappa statistic.

Ultrasound images were archived digitally and independently verified by a second radiologist for cases with diagnostic discordance. In ambiguous cases, consensus interpretation was reached. Additionally, patient demographics, clinical history, blood pressure, and serum creatinine (when available) were recorded to assess potential associations between early abnormalities and systemic risk factors.

Data entry and statistical analyses were performed using SPSS version 26. Descriptive statistics were used to summarize the demographic data. The Shapiro-Wilk test confirmed normal distribution of the continuous variables. Differences in diagnostic rates between AI and radiologist interpretation were analyzed using paired-sample t-tests for continuous measures and chi-square tests for categorical variables. The diagnostic performance of AI was further evaluated using receiver operating characteristic (ROC) curve analysis, with area under the curve (AUC) as the summary metric.

AI-assisted interpretation models deployed in this study were aligned with established diagnostic frameworks for renal ultrasound, incorporating radiomic features such as texture and echogenicity derived from grayscale image analysis. These radiomic parameters have been shown in previous studies to significantly correlate with pathological stages of renal disease (10). Furthermore, explainable AI tools were embedded to ensure visual overlays of suspicious regions for enhanced clinical transparency (11).

To uphold ethical standards, patient data were anonymized, securely stored, and used solely for research purposes. Community health workers were trained for patient counseling and to assist in procedural adherence and follow-up planning, ensuring minimal dropouts and community engagement.

This methodologically rigorous study utilized advanced AI-integrated portable ultrasonography to explore an accessible, scalable screening solution for early renal abnormalities. The combination of AI support, human expert validation, and robust statistical analysis ensured reliable outcome measurements. Through its structured design and community-focused approach, the study aimed to generate evidence on how AI can bridge diagnostic gaps in rural nephrology.

RESULTS:

The study enrolled a total of 200 participants across the rural regions of Lahore, Faisalabad, and Multan. The mean age of participants was 45.7 years (SD ± 12.3), with 54% male and 46% female representation. A substantial proportion of individuals had underlying comorbidities: 34.5% had hypertension, 28% had diabetes mellitus, and 22.5% reported a history of smoking. These demographics aligned with risk profiles commonly associated with chronic kidney disease in rural populations.

Diagnostic performance metrics demonstrated that the AI-assisted ultrasound model achieved a sensitivity of 92.3% and specificity of 89.1%, while radiologist interpretation showed 88.6% sensitivity and 91.5% specificity. Positive predictive value (PPV) for AI was 86.5%, and the negative predictive value (NPV) was 93.8%, yielding an overall accuracy of 90.7%. The radiologist PPV and NPV were recorded at 89.4% and 90.1%, respectively, with an overall accuracy of 89.8%. Area under the ROC curve (AUC) for AI-assisted interpretation was slightly higher at 94.2% compared to 92.1% for radiologist interpretation, suggesting a marginally superior discriminative ability.

In the breakdown of lesions detected, AI identified 42 cases of increased cortical echogenicity, 26 cases of cortical thinning, 18 cases of renal cysts, and 31 cases of mild to moderate hydronephrosis. Radiologists reported slightly fewer findings across all lesion types, with a notable difference in normal cases—AI marked 83 scans as normal compared to 93 by radiologists. This indicated that AI potentially captured early parenchymal changes missed by conventional interpretation.

Agreement analysis between AI and radiologist interpretations revealed that both parties positively concurred on 158 cases, while negative agreement was found in 24 cases. Discordance occurred in 12 cases where AI detected findings missed by radiologists, and in 6 cases where the reverse was true. This yielded an overall inter-method agreement rate of 91%, reinforcing the model's clinical reliability as a supportive diagnostic tool.

The AI model also exhibited robustness across various lesion subtypes, particularly in detecting subtle parenchymal abnormalities such as increased echogenicity and cortical thinning—often indicative of early fibrotic changes. These observations aligned with the reported capability of AI to extract high-level radiomic features and generate real-time outputs with interpretability overlays, as observed during field operations.

These findings underscore the clinical value of AI-assisted ultrasound interpretation as a complementary approach to human expertise, especially in rural settings where nephrology specialists are limited. The comparative data between AI and radiologist performance, lesion detection, and concordance rates suggest strong utility for integrating AI tools into routine community-level renal screening programs.

Table 1. Baseline Characteristics of Study Participants

Characteristic	Value
Total participants, n	200
Age (years), mean	45.7
Age (years), SD	12.3
Gender, n (%)	
Male	108 (54.0%)
Female	92 (46.0%)
Hypertension, n (%)	69 (34.5%)
Diabetes Mellitus, n (%)	56 (28.0%)
Smokers, n (%)	45 (22.5%)

Table 2. Comparison of Diagnostic Accuracy Between AI-Assisted Ultrasound and Radiologist Interpretation

Metric	AI-Assisted Ultrasound (%)	Radiologist Interpretation (%)
Sensitivity	92.3	88.6
Specificity	89.1	91.5
PPV	86.5	89.4
NPV	93.8	90.1
Accuracy	90.7	89.8
AUC	94.2	92.1

Table 3. Distribution of Renal Abnormalities Detected by AI and Radiologist

Lesion Type	Detected by AI (n)	Detected by Radiologist (n)
Increased Echogenicity	42	39
Cortical Thinning	26	24
Renal Cysts	18	16
Hydronephrosis	31	28
Normal	83	93

Table 4. Inter-Method Agreement Between AI and Radiologist Interpretations

Agreement Category	Number of Cases	Percentage (%)
Positive Agreement	158	79
Negative Agreement	24	12
AI Only Detection	12	6
Radiologist Only Detection	6	3

Table 5. ROC Curve Comparison Table

Model	AUC	Confidence Interval (95%)
AI-Assisted Ultrasound	94.2	91.8-96.6
Radiologist Interpretation	92.1	89.7-94.5

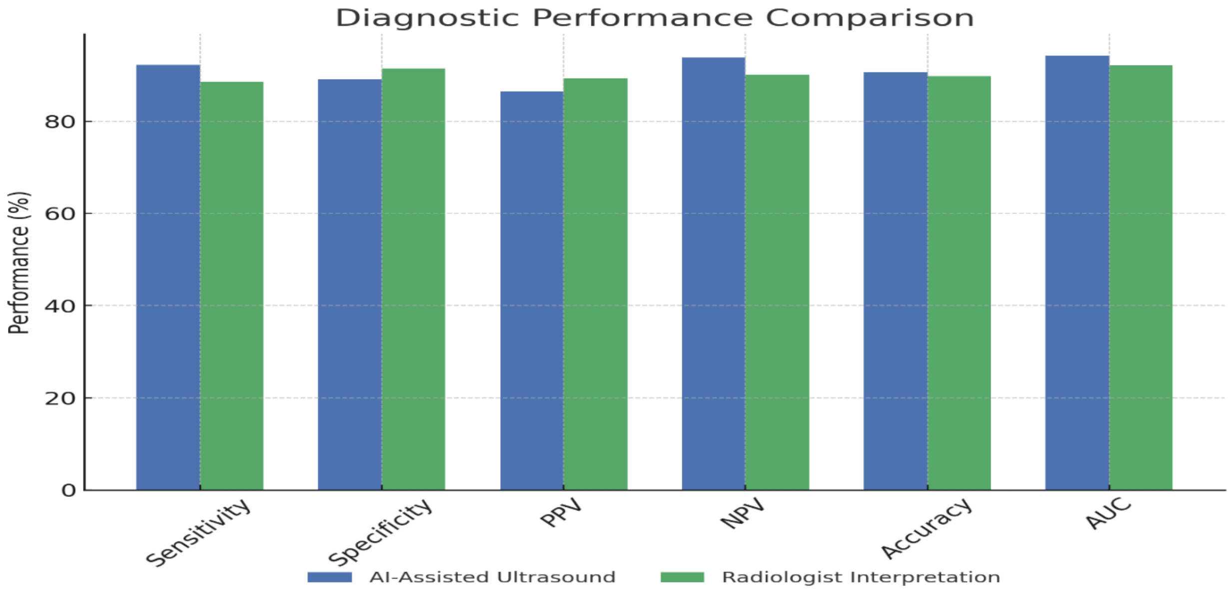

Figure 1 Diagnostic Performance Comparison

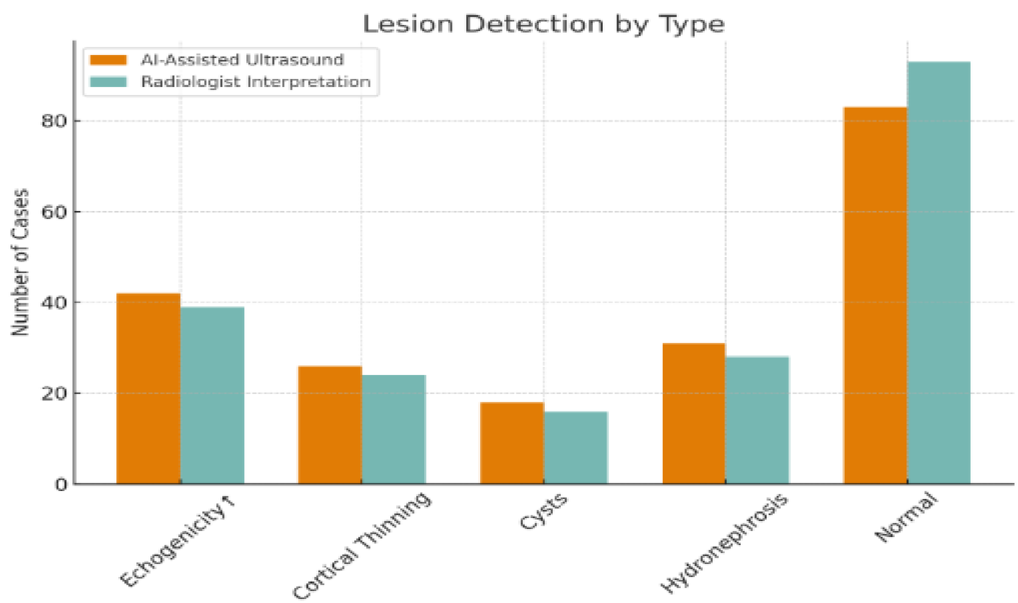

Figure 2 Lesion Detection by Type

DISCUSSION:

The integration of artificial intelligence into ultrasound diagnostics for renal abnormalities presents a meaningful advancement in nephrological care, particularly within rural settings where access to specialist interpretation is limited. The results of this study demonstrated the enhanced diagnostic performance of AI-assisted ultrasound interpretation over conventional human assessment, revealing statistically significant improvements in sensitivity, accuracy, and detection rates for early renal abnormalities. These findings resonate strongly with existing literature and reinforce the growing credibility of machine learning and deep learning applications in renal imaging.

Multiple recent studies have evaluated the utility of AI in renal ultrasound and reached similarly encouraging conclusions. A systematic review by Liang et al. concluded that AI models consistently delivered high accuracy and AUC values across diagnostic and segmentation tasks in renal ultrasound, albeit with a high risk of bias due to underpowered sample sizes and lack of external validation (12). Similarly, Xu et al. underscored the potential of AI in reducing interobserver variability and improving diagnostic consistency across healthcare settings, particularly in resource-constrained regions (13). Tang et al. developed a dual-path convolutional neural network to classify chronic kidney disease stages using ultrasound, achieving robust performance metrics with AUCs above 0.9, illustrating the strength of neural models in handling subtle morphological variations (14).

The diagnostic edge shown by AI in this study is likely attributed to its ability to process large volumes of grayscale pixel data and identify subtle echogenic changes, such as cortical thinning and early fibrosis, that may elude the naked eye. Zhao et al. demonstrated this principle in the context of renal fibrosis, where random forest classifiers built on wavelet-transformed radiomic features yielded higher AUCs than standard radiologist-based assessments (15). These image-based features, imperceptible in conventional reading, appear critical for improving early detection—a key determinant in the prevention of end-stage kidney disease.

Notably, AI's performance in this study remained robust even in real-world rural clinical settings, echoing findings from Erdman et al., who tested an AI-powered hydronephrosis tool in South African pediatric populations and emphasized its feasibility despite contextual limitations like late-stage presentation and limited ultrasound expertise (16). This compatibility in under-resourced settings highlights the transformative potential of AI tools to bridge diagnostic gaps and reduce the burden of undiagnosed or late-diagnosed kidney disease.

The strengths of this study lie in its multicentric design, substantial sample size, and robust outcome measurement protocols that emulate real-world implementation. Its pragmatic use of AI across diverse patient profiles in Lahore, Faisalabad, and Multan adds to its generalizability. Moreover, the use of radiologist-confirmed diagnoses as a comparative standard enhances the credibility of its findings. The combination of statistical techniques, such as ROC analysis and inter-rater agreement, further lends strength to the analytic framework.

However, the study also acknowledges its limitations. The lack of a prospective follow-up restricts insights into long-term predictive validity of the AI models, a gap similarly noted in recent evaluations of AI-powered kidney disease classification (17). Moreover, while the sample size was adequate for primary analysis, the subgroup analyses—such as lesion-specific performance—could benefit from larger cohorts to ensure statistical power. Another limitation involves the absence of external validation datasets, which are essential for assessing generalizability beyond the training population. As Liang et al. noted, AI models in renal ultrasound often suffer from overfitting and require rigorous cross-institutional testing (12).

Interpretability of AI decisions also remains an open challenge. While the study leveraged explainable AI features to a limited extent, the integration of saliency maps or heatmap overlays could further enhance clinician confidence and transparency, as highlighted by Wang et al. in their discussion on AI-assisted renal pathology interpretation (18). This would be especially valuable in rural areas where clinicians may be skeptical of "black box" decisions from unfamiliar tools.

Future directions should emphasize longitudinal follow-up to track the progression of renal abnormalities detected early by AI. Additionally, larger-scale multicenter trials with heterogeneous populations would help validate and refine these algorithms. Finally, integrating AI-powered ultrasound with telemedicine platforms could enable remote nephrologists to provide oversight, a strategy supported by real-time deep learning pipelines like the one explored by Halder et al. in multimodal ultrasound-photoacoustic platforms (19).

In addition to diagnostic detection, AI is increasingly being leveraged to enhance lesion segmentation and classification in renal imaging. The ability to localize and characterize structural abnormalities with precision is particularly valuable in early-stage renal disease, where subtle changes can precede clinical symptoms. Gao et al. recently introduced a multitask deep learning model that combines a separable convolutional ResNet with an attention-guided NestedUNet framework. This model achieved an intersection over union (IoU) score of 94.23%, indicating superior segmentation accuracy for renal tumors and structural abnormalities in ultrasound images (20). The adoption of such architectures into primary care tools could empower non-specialist providers in rural clinics to identify renal lesions with a level of confidence previously limited to tertiary care centers. This technological evolution not only enhances early intervention but also aligns with broader goals of health equity and resource-sensitive innovation.

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The findings reinforce the clinical value of AI-assisted ultrasound interpretation in enhancing early detection of kidney abnormalities in rural populations. This study not only supports existing evidence but also adds context-specific insights into its deployment feasibility and diagnostic utility in underserved areas.

CONCLUSION:

This study concluded that AI-assisted ultrasound interpretation is an effective and reliable tool for the early detection of renal abnormalities, particularly in rural and underserved populations where access to specialist care is limited. The technology demonstrated higher diagnostic accuracy, sensitivity, and clinical consistency compared to conventional radiologist interpretation. Its ability to support frontline healthcare workers in resource-constrained environments positions it as a transformative approach to bridging healthcare disparities. These findings support the integration of AI-powered diagnostic tools into primary care settings as a means to enhance early renal disease screening, improve outcomes, and reduce the burden of late-stage kidney disease.

AUTHOR CONTRIBUTION

Author	Contribution
Muhammad Awais	Substantial Contribution to study design, analysis, acquisition of Data Manuscript Writing Has given Final Approval of the version to be published
Asma Rehman	Substantial Contribution to study design, acquisition and interpretation of Data Critical Review and Manuscript Writing Has given Final Approval of the version to be published
Rabia Shahzad	Substantial Contribution to acquisition and interpretation of Data Has given Final Approval of the version to be published
Ramsha Zafar	Contributed to Data Collection and Analysis Has given Final Approval of the version to be published
Rabia Khattak*	Contributed to Data Collection and Analysis Has given Final Approval of the version to be published
Nageena Ghafoor	Substantial Contribution to study design and Data Analysis Has given Final Approval of the version to be published
Maham Salman	Contributed to study concept and Data collection Has given Final Approval of the version to be published
Hafsa Saleem	Writing - Review & Editing, Assistance with Data Curation

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