

# A Blockchain-Powered Framework for Tele-ultrasound Data Integration: Supporting Deep Learning for Primary Care Physicians

Xiaoli He

XXXXXXXXXX

Kaiju Yang

XXXXXXXXXX

Cuo Yi

XXXXXXXXXX

Jian Li

XXXXXXXXXX

Xue Li

XXXXXXXXXX

Guoping Wang

Shapingba Hospital, Chongqing University (Shapingba District People's Hospital, Chongqing)

Rong Chen

3.Shapingba District Community Health Service Center,Chongqing

Luoying Zhang

XXXXXXXXXX

Yan Zhang

XXXXXXXXXX

Zhebo Qin

The First Affiliated Hospital (Southwest Hospital) of Army Medical University

Xi Yang

yangxi\_210@126.com

XXXXXXXXXX

---

## Research Article

**Keywords:** Tele-ultrasound, Primary Care, Quality Improvement, Continuing Medical Education, Real-World Data, Retrospective Cohort Study

**Posted Date:** May 25th, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-9449663/v1>

**License:**  This work is licensed under a Creative Commons Attribution 4.0 International License.  
[Read Full License](#)

**Additional Declarations:** No competing interests reported.

---

# Abstract

## Background

Tele-ultrasound platforms are increasingly implemented to support primary care institutions, yet real-world evidence linking platform engagement to tangible improvements in diagnostic quality is scarce. This study aimed to quantify the association between the intensity of tele-ultrasound platform usage and the diagnostic quality of primary care institutions.

## Methods

We conducted a retrospective institutional cohort study of 23 primary care institutions over three quarters. Institutions were categorized into high-intensity and low-intensity usage groups based on cumulative platform logins. The primary outcomes were institutional mean report scores and image scores. Paired-samples and independent-samples t-tests were used to analyze temporal changes and group differences.

## Results

A significant improvement in mean report scores was observed from the first to the third quarter (99.45 to 99.68,  $p = 0.031$ ). Critically, the high-intensity usage group demonstrated significantly higher report quality at the study's endpoint compared to the low-intensity group (mean score 99.82 vs. 99.56,  $p = 0.001$ ). In contrast, no significant temporal improvement ( $p = 0.311$ ) or difference between usage groups ( $p = 0.596$ ) was found for image quality scores.

## Conclusion

The efficacy of tele-ultrasound platforms in improving diagnostic quality is strongly associated with the depth of user engagement, particularly for cognitive skills such as reporting. Our findings suggest that to maximize the return on investment for these technologies, healthcare policies should focus not only on expanding access but also on fostering active and sustained user participation, potentially supplemented by hands-on training for psychomotor skills.

## 1. Introduction

Ensuring equitable access to high-quality healthcare in primary and rural settings remains a significant global challenge. Physicians in these areas often face professional isolation, limited resources, and insufficient opportunities for continuing medical education (CME), which can impede their ability to manage an increasingly complex patient demographic<sup>[1]</sup>. This issue is not confined to a single region; international studies, such as those from rural Japan, highlight systemic difficulties in supporting and

retaining a skilled primary care workforce <sup>[2]</sup>. The challenge extends beyond technical proficiency, encompassing non-technical attributes like "clinical courage"—a construct identified as crucial for sustained practice in underserved communities <sup>[3]</sup>. Consequently, developing robust, scalable, and effective educational and support systems for primary care physicians is a critical priority for health systems worldwide.

The advent of telemedicine has introduced powerful tools to mitigate these challenges, with tele-ultrasound (TUS) emerging as a particularly impactful solution. By enabling remote image acquisition, real-time guidance, and expert consultation, TUS platforms can directly address the diagnostic and educational needs of physicians in primary care <sup>[4]</sup>. This technological advance aligns with growing evidence that platform-based e-learning can be a highly effective modality for CME. For instance, a comprehensive evaluation of training for primary healthcare workers demonstrated that asynchronous e-learning led to significant improvements in knowledge scores, whereas traditional face-to-face training showed no comparable effect, suggesting a paradigm shift in how professional development is delivered <sup>[5]</sup>. To further enhance the capabilities of these platforms, advanced technologies are increasingly being integrated. Blockchain, for example, offers a promising framework for addressing the persistent problems of "data silos" and security vulnerabilities, which are critical concerns in multi-institutional medical data sharing environments <sup>[6]</sup>. Concurrently, artificial intelligence (AI) is being leveraged to augment diagnostic capabilities. Deep learning models have shown high accuracy in tasks such as the prediction of thyroid nodule malignancy <sup>[7]</sup>, the automated severity assessment of skin conditions like atopic dermatitis <sup>[8]</sup>, the complex segmentation of anatomical structures such as facet joints <sup>[9]</sup>, and the multi-modal evaluation of lymph node metastases <sup>[10, 11]</sup>.

Despite the widespread implementation of TUS platforms and their technological sophistication, a critical gap persists in the literature. The mere existence and accessibility of a platform do not inherently guarantee its effective use or a resultant improvement in clinical quality. While foundational reports from the study region, such as a 2019 survey, documented profound pre-platform deficiencies—with over 90% of physicians lacking formal consultation channels and only 13.6% of institutions implementing any form of quality control—subsequent quality assurance summaries from 2025 indicate that even with a functioning platform, inconsistencies in diagnostic quality remain. For instance, suboptimal image standardization persisted as one of the most frequent quality defects, occurring in 0.58% of all cases reviewed, suggesting a crucial distinction between platform availability and effective engagement. Most existing research focuses on the feasibility of implementation or the technical accuracy of AI models, but there is a paucity of real-world evidence quantitatively linking the intensity of platform usage with tangible improvements in the diagnostic quality of primary care institutions. It remains unclear whether deeper, more frequent engagement with such a platform translates into superior clinical performance, representing a significant unanswered question for healthcare administrators and policymakers investing in these technologies.

Therefore, this study was designed to address this knowledge gap by evaluating the real-world efficacy of a regional tele-ultrasound platform. Using a retrospective institutional cohort design, we aimed to achieve two primary objectives. First, we sought to determine if there was a significant improvement in the diagnostic quality of participating primary care institutions over time. Second, and most critically, we hypothesized that a higher intensity of platform usage—measured by metrics such as login frequency and engagement with educational modules—would be significantly associated with superior diagnostic quality scores. By analyzing the relationship between the depth of user engagement and objective quality outcomes, this study provides novel insights into the factors that drive the effectiveness of tele-ultrasound platforms in primary care settings.

## **2. Methods**

### **2.1. Study Design and Data Source**

This investigation was conducted as a retrospective, institutional-level cohort study. This design was selected as the most appropriate methodology for evaluating the real-world efficacy of a health service intervention using existing, longitudinal administrative data [12]. The study cohort comprised all 23 primary care institutions (e.g., community health service centers) actively participating in the Chongqing Shapingba District Tele-ultrasound Platform network. The flow of institutional selection for the study is presented in Fig. 1. This digital platform serves as a centralized hub for remote consultation, quality control (QC), and continuing medical education for primary care physicians within the district, facilitating the submission of ultrasound cases for review by senior radiologists at a central hospital.

We obtained a fully anonymized, aggregated dataset from the platform's administrative backend. The observation period for this study was defined as the first three quarters of the year 2025, providing a nine-month window to assess temporal changes and usage patterns. The inclusion criterion for the study was any primary care institution that actively submitted cases and had complete QC data for all three quarters. As all 23 active institutions met this criterion, no entities were excluded from the final analysis. The study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. Given that the research utilized pre-existing, fully anonymized, and aggregated data for the sole purpose of service evaluation and quality improvement, it was exempt from requiring formal institutional review board approval.

The selection process for the institutional cohort included in this study is detailed in Fig. 1.

### **2.2. The Tele-ultrasound Platform**

The intervention platform is an integrated tele-ultrasound solution designed to enhance the diagnostic capabilities of primary care physicians through remote quality control (QC), expert consultation, and continuous medical education. As illustrated in Fig. 2, the platform's architecture is composed of four key layers: (1) a data acquisition layer at the participating primary care institutions, where anonymized ultrasound images and reports are generated and securely uploaded from local workstations; (2) a

centralized cloud-based engine that integrates a blockchain-enabled security layer and an AI-powered analysis layer. The permissioned blockchain layer ensures data integrity and traceability, utilizing smart contracts to manage granular access control and creating an immutable audit trail for all data transactions. Concurrently, the AI engine employs a suite of deep learning models for automated image quality assessment, preliminary diagnostic assistance, and a recommendation system that provides personalized learning cases to users; (3) and an application layer that provides a web-based portal for end-users. This layer includes distinct modules for primary care physicians to submit cases and access educational resources, and for expert radiologists to perform remote reviews and provide structured feedback.

## 2.3. Variable Definitions

All data were aggregated at the institutional level for each quarter to maintain anonymity and align with the study's focus on institutional performance.

**Outcome Variables:** The two primary outcome measures were the mean diagnostic quality scores for each institution per quarter. These composite scores, rated on a 0-100 scale, were meticulously defined and calculated by the platform's central QC team.

**Report Score:** This metric reflects the quality of the written diagnostic report. It is a composite score derived from a standardized rubric that assesses five key domains: (1) diagnostic accuracy against the final expert opinion; (2) completeness and standardization of terminology in describing sonographic findings; (3) logical consistency between the descriptive text and the final conclusion; (4) adherence to standardized reporting templates; and (5) overall clarity and conciseness. For instance, completeness was assessed by the inclusion of all relevant anatomical structures and required measurements according to protocol, while logical consistency evaluated the concordance between the sonographic descriptions and the final diagnostic conclusion.

**Image Score:** This metric evaluates the technical quality of the acquired ultrasound images. The score is based on a rubric assessing four domains: (1) adherence to standardized imaging protocols and acquisition of required anatomical planes; (2) optimization of technical parameters (e.g., gain, depth, focus); (3) appropriate and technically correct application of Doppler modalities where indicated; and (4) accuracy of measurements. Specifically, adherence to standardized protocols was determined by the successful acquisition of key anatomical planes (e.g., standard cardiac views), and parameter optimization was judged by the appropriate use of gain, time-gain compensation, and focal zones to produce a diagnostically informative image.

**Exposure Variable (Usage Intensity):** To quantify the level of institutional engagement with the platform, we defined usage intensity based on metrics logged by the system. The primary exposure variable was the cumulative number of user logins per institution over the entire three-quarter study period (Login\_Count). This metric was chosen as the primary indicator of engagement because it reflects a user's proactive intent to interact with the platform's resources. Compared to secondary metrics like

learning duration, which can be influenced by passive viewing, login frequency serves as a more direct and robust proxy for active and repeated participation. For the primary analysis, institutions were dichotomized based on the median value of their cumulative login counts into a High-Intensity Usage Group and a Low-Intensity Usage Group. This approach ensures two well-balanced groups for a robust statistical comparison. The cumulative learning duration (Learning\_Duration), measured in hours, was designated as a secondary metric for sensitivity analyses.

## 2.4. Statistical Analysis

All data processing and statistical analyses were performed using IBM SPSS Statistics for Windows, Version 28.0 (IBM Corp., Armonk, NY, USA).

Initially, descriptive statistics, including means, standard deviations (SD), and ranges, were calculated for all outcome and exposure variables to characterize the overall performance and usage patterns of the cohort.

To test our first hypothesis (H1) regarding temporal improvement, a Paired-Samples T-Test was employed. This test was chosen for its suitability in comparing the means of two related measurements from the same subjects (institutions) at two different time points. The null hypothesis ( $H_0$ ) was that the mean difference in scores between the first quarter (Q1, baseline) and the third quarter (Q3, endpoint) is zero. The alternative hypothesis ( $H_1$ ) was that the mean difference is not zero. The assumption of normality of the difference scores was assessed, and the test is known to be robust to minor deviations with a sample size of  $N = 23$ .

To test our second hypothesis (H2) concerning the association between engagement and quality, an Independent-Samples T-Test was utilized. This test is appropriate for comparing the means of a continuous variable between two independent groups. The null hypothesis ( $H_0$ ) was that the mean Q3 scores of the High-Intensity and Low-Intensity Usage groups are equal. The alternative hypothesis ( $H_1$ ) was that the means are not equal. Levene's test for equality of variances was performed to determine which t-statistic to report. A two-tailed p-value of  $< 0.05$  was considered statistically significant for all inferential tests.

## 3. Results

### 3.1. Baseline Characteristics and Overall Performance

The study cohort consisted of 23 primary care institutions with complete data for the entire observation period from Q1 to Q3 2025. Based on the median of cumulative platform logins, the cohort was divided into a High-Intensity Usage Group ( $n = 11$ ) and a Low-Intensity Usage Group ( $n = 12$ ). At baseline (Q1 2025), the participating institutions exhibited a high and relatively consistent level of performance. The mean institutional Report Score for the entire cohort was 99.45 (SD = 0.53), and the mean Image Score was 99.59 (SD = 0.45). A comparison of the two usage groups at baseline revealed no statistically

significant differences in either mean Report Scores or mean Image Scores, indicating that the groups were well-matched at the start of the observation period (Table 1).

The primary longitudinal analysis assessed the change in mean quality scores from the beginning of the study (Q1) to the end (Q3). A statistically significant increase was observed in the quality of diagnostic reporting over this period. The mean institutional Report Score rose from 99.45 (SD = 0.53) in Q1 to 99.68 (SD = 0.23) in Q3. The Paired-Samples T-Test confirmed that this mean improvement of 0.23 points (95% Confidence Interval [CI], 0.02 to 0.45) was statistically significant ( $t(22) = 2.33$ ,  $p = 0.031$ ). This result indicates a significant enhancement in the quality of diagnostic reporting across the participating institutions over the nine-month interval.

In contrast, the change in the mean institutional Image Score did not reach statistical significance. Although a minor increase of 0.11 points was observed, from a mean of 99.59 (SD = 0.45) in Q1 to 99.70 (SD = 0.27) in Q3, this difference was not statistically significant (95% CI, -0.11 to 0.33;  $t(22) = 1.04$ ,  $p = 0.311$ ). This suggests that, within the study timeframe, there was no detectable improvement in the technical quality of image acquisition at the institutional level (Table 2).

## **3.2. Association Between Platform Usage Intensity and Diagnostic Quality**

The analysis of the endpoint data from Q3 revealed a pronounced and statistically significant association between usage intensity and reporting quality. The High-Intensity Usage Group achieved a mean Report Score of 99.82 (SD = 0.12), which was significantly higher than the mean score of 99.56 (SD = 0.24) observed in the Low-Intensity Usage Group. Levene's test indicated that the assumption of equal variances was violated ( $p = 0.002$ ); therefore, the t-statistic for unequal variances was reported, confirming this difference to be highly statistically significant ( $t(16.04) = 3.83$ ,  $p = 0.001$ ).

Conversely, no such association was found for the Image Score at the Q3 endpoint. The mean Image Score for the High-Intensity Group (99.73, SD = 0.29) was not significantly different from that of the Low-Intensity Group (99.67, SD = 0.26) ( $t(21) = 0.54$ ,  $p = 0.596$ ). This finding indicates that while deeper engagement with the platform is strongly correlated with superior reporting skills, it does not show a similar relationship with the technical quality of image acquisition (Table 3).

## **4. Discussion**

### **4.1. Summary and Interpretation of Key Findings**

This study provides novel, real-world evidence on the efficacy of a tele-ultrasound platform in enhancing the diagnostic quality of primary care institutions. Our primary finding is a clear and statistically significant improvement in the quality of diagnostic reporting over a three-quarter period, a result that is strongly correlated with the intensity of platform usage. Specifically, institutions that engaged more frequently with the platform demonstrated significantly higher report quality scores at the study's

endpoint. However, a second, equally important finding was the conspicuous absence of a similar improvement in the technical quality of image acquisition. Together, these results paint a nuanced picture: while the tele-ultrasound platform serves as a powerful tool for enhancing cognitive and knowledge-based skills, its impact on psychomotor skills may be limited within a similar timeframe.

## **4.2. Platform Engagement as a Determinant of Quality Improvement**

The strong, positive association between platform usage intensity and the quality of diagnostic reporting is the central finding of this investigation. This aligns robustly with a substantial body of literature demonstrating that well-designed continuing medical education (CME) programs can translate into tangible improvements in clinical practice. For instance, a study by Papadakis et al. on a CME e-learning program for European primary care practitioners found significant post-training improvements in knowledge, confidence, and self-reported clinical behaviors <sup>[12]</sup>. Our findings move beyond self-reported changes by linking platform engagement to objectively measured quality scores. This echoes the work of Clark et al., who demonstrated that a training program for managing child and adolescent mental health not only increased provider comfort but also led to a significant reduction in patient referrals, a direct change in clinical practice <sup>[13]</sup>.

Furthermore, our results suggest a "dose-response" relationship, where higher engagement leads to better outcomes. This is consistent with studies like that of Sanchez-Ramirez et al., which found that participation in cardiology CME was associated with a higher likelihood of prescribing guideline-recommended therapies <sup>[14]</sup>, and the work of Papachristopoulos et al., which quantified a direct link between a physician's "education score" and their proactive management of mental health disorders <sup>[15]</sup>. While traditional training models, such as the rural generalist internships evaluated by O'Sullivan et al., provide foundational experience <sup>[16]</sup>, our study suggests that continuous, in-practice digital platforms offer a potent and measurable mechanism for ongoing quality improvement, particularly when actively utilized.

## **4.3. The Dichotomy of Cognitive vs. Psychomotor Skill Enhancement**

Perhaps the most thought-provoking result of our study is the observed dichotomy between the significant improvement in report quality and the non-significant change in image quality. We interpret this as evidence that the remote platform, in its current form, excels at delivering and reinforcing knowledge-based, cognitive skills. The process of writing a standardized, accurate, and logically consistent diagnostic report is a cognitive task that can be effectively learned and refined through access to templates, expert feedback, and a diverse library of cases.

Conversely, the act of acquiring a high-quality ultrasound image is a psychomotor skill, heavily dependent on hand-eye coordination, understanding of 3D anatomy, and the tactile feedback of probe manipulation. Our data suggest that passive, remote learning may be insufficient to substantially

improve these hands-on abilities. This finding does not diminish the platform's value but rather helps to define its optimal role. It highlights the potential need for a blended learning model, where the platform's strengths in cognitive training are supplemented by other methods, such as hands-on workshops or simulation training, to address the psychomotor component of ultrasound practice. This finding aligns with established theories of skill acquisition, which differentiate between declarative knowledge (knowing what), easily transmitted via text and visual examples on a digital platform, and procedural knowledge (knowing how), which often requires deliberate practice and direct kinesthetic feedback that is challenging to replicate in a purely remote learning environment.

## **4.4. Policy and Managerial Implications**

The findings of this study offer several actionable implications for healthcare administrators and policymakers responsible for deploying and managing telemedicine solutions. First, the strong association between usage intensity and quality outcomes suggests that the key performance indicators (KPIs) for such platforms should evolve beyond simple metrics of coverage or connectivity. Instead of focusing solely on the number of connected institutions, health systems should develop and monitor engagement-based metrics, such as active user rates, frequency of consultations, and completion of educational modules. This represents a strategic shift from evaluating platform access to measuring platform impact.

Second, the observed dichotomy between cognitive and psychomotor skill improvement underscores the need for a blended learning strategy. Our results advocate for a hybrid model where the remote platform serves as the primary tool for knowledge dissemination, case-based learning, and reporting standardization, while being supplemented by targeted, in-person workshops or simulation-based training for hands-on scanning techniques. Such a model would leverage the scalability of e-learning while addressing the unique requirements of procedural skill acquisition, creating a more comprehensive and effective educational ecosystem for primary care physicians.

## **4.5. Limitations of the Study**

This study has several limitations that must be acknowledged. First, the analysis was conducted at the institutional level, not the individual physician level. Therefore, our findings are subject to the potential for ecological fallacy, and the association observed at the institutional level may not directly translate to individual performance. Second, due to the retrospective nature of the study and the use of administrative data, we were unable to control for several potential confounding variables, such as staff turnover, the baseline experience level of the medical teams at each institution, or the influence of other concurrent educational initiatives. Third, the study was conducted within a single regional network, which may limit the generalizability of the findings to other healthcare systems with different organizational structures or resource levels. Finally, without a concurrent non-user control group, we cannot definitively attribute the observed improvements solely to the platform, as a general secular trend of quality improvement cannot be entirely ruled out, although the strong association with usage intensity mitigates this concern.

## 4.6.Future Directions and Technological Outlook

The findings of this study open several promising avenues for future research and platform development. To enhance the clinical utility and trustworthiness of integrated AI, future iterations should prioritize explainable AI (XAI). Methodologies such as the Class Activation Maps (CAMs) used by Born et al. to visualize the basis of AI decisions in lung ultrasound can transform AI from a "black box" into a transparent and educational tool for clinicians <sup>[17]</sup>.

Furthermore, future AI models should be specifically designed to address the inherent technical challenges of ultrasound imaging. The work of Lee, K., et al., who developed a novel architecture to handle speckle noise and imbalanced datasets in rotator cuff tear diagnosis <sup>[18]</sup>, and the two-stage framework by Yan et al. for improving the segmentation of small, challenging structures in fetal heart exams <sup>[19]</sup>, provide excellent roadmaps for developing more robust and specialized diagnostic aids.

As the platform network expands, data privacy will become paramount. Federated learning offers a powerful solution, allowing for the collaborative training of robust AI models across multiple institutions without sharing sensitive patient data. The feasibility of this approach in a real-world ultrasound setting has already been validated, demonstrating comparable performance to traditional centralized training while preserving privacy <sup>[20]</sup>. The underlying blockchain infrastructure should also evolve to support the dynamic nature of medical data. Implementing schemes that allow for incremental updates, as proposed by Wang, L., et al., would enhance the platform's flexibility and long-term viability <sup>[21]</sup>. Finally, the ultimate future may lie in hybrid systems that integrate multiple technologies. The framework developed by Jia et al., which combined electromagnetic tracking with deep learning for high-precision catheter localization, serves as an inspiring example of how fusing different technologies can solve complex clinical problems <sup>[22]</sup>.

## 5. Conclusion

In conclusion, this study provides compelling real-world evidence that a tele-ultrasound platform can be an effective tool for significantly improving the quality of diagnostic reporting in primary care institutions. Crucially, our findings demonstrate that the efficacy of such a platform is not a given; it is strongly associated with the intensity of user engagement. The observed disparity between improvements in cognitive (reporting) and psychomotor (imaging) skills suggests that the optimal strategy for comprehensive skill enhancement likely involves a blended model that combines the strengths of remote e-learning with targeted, hands-on training.

For healthcare administrators and policymakers, the take-home message is clear: the focus of investment and strategy should shift from merely expanding platform coverage to actively fostering deep and sustained user engagement. This represents the critical transition from providing a tool to cultivating a true learning ecosystem. By designing platforms that not only connect but also actively teach, and by integrating them with appropriate hands-on training, we can fully unlock the potential of

these powerful technologies to elevate the quality of care and empower physicians in the communities that need it most.

## Declarations

### Funding

This study was supported by the Chongqing Joint Medical Research Project of Science and Health 2026MSXM135 and the Shapingba District Science and Health Joint Medical Research Project (Grant Nos. 2023SQKWLH042, 2023SQKWLH044, and 2025SQKWLHMS079).

**Ethics approval and consent to participate** This study was approved by the Ethics Committee of Chongqing Shapingba District People's Hospital (Approval No.: KY202339). All procedures were performed in accordance with the Declaration of Helsinki and relevant national ethical guidelines and regulations. The requirement for informed consent was waived by the Ethics Committee due to the retrospective design of the study and the complete anonymization of all patient data prior to analysis.

### Consent for publication

Not applicable.

### Availability of data and materials

The datasets analyzed in this study contain protected clinical ultrasound data and are not publicly available to protect patient privacy. Access to the data may be granted by the corresponding author upon reasonable request, subject to approval by the Ethics Committee of Chongqing Shapingba District People's Hospital and in compliance with relevant data protection regulations.

## Author Contribution

Literature search: Xiaoli He, Kaiju Yang. Data extraction: Cuo Yi. Statistical analysis: Guoping Wang, Rong Chen. Manuscript revision: Xi Yang, Yan Zhang. Funding acquisition: Xi Yang, Yan Zhang, Cuo Yi. Supervision: Xiaoli He, Kaiju Yang. Validation: Xi Yang, Yan Zhang. Visualization: Cuo Yi

## References

1. An, K., Zhang, L., Qiao, R., Li, C., Zhong, Q., Ma, Y., Rao, X., Mao, T., Liu, F., Zhuo, Q., She, Y., Li, S., & Su, Q. (2022). Training needs and curriculum of continuing medical education among general practitioners in Tibet, China: A cross-sectional survey. *Frontiers in Public Health*, 10, 914847. <https://doi.org/10.3389/fpubh.2022.914847>
2. Schubert, N. S., Tsuzaki, T., Evans, R., Sen Gupta, T., Larkins, S., & Battye, K. M. (2024). Rural generalist medicine: A developing approach to health care in rural and island Japan. *Rural and*

- Remote Health, 24(2), 8641. <https://doi.org/10.22605/RRH8641>
3. Konkin, J., Williams, S., Brooks, R., Couper, I., Campbell, D. G., & Walters, L. (2025). Investigating clinical courage: An international survey of rural doctors. *Rural and Remote Health*, 25(1), 8852. <https://doi.org/10.22605/RRH8852>
  4. Zang, G. M., Guo, S., Lin, Y., Yang, M., & Yang, B. (2022). A Comprehensive Tele-ultrasound (TUS) Guide for COVID-19 Management. *Ultrasound in Medicine & Biology*, 48(6), 967–979. <https://doi.org/10.1016/j.ultrasmedbio.2022.02.007>
  5. Wang, Z., Zhang, L., Jiang, W., Jiao, J., Liu, Y., Li, Y., Zhu, A., Wu, X., & Tang, S. (2021). E-learning effectiveness for TB workers in China: A mixed-method evaluation. *Infectious Diseases of Poverty*, 10(1), 72. <https://doi.org/10.1186/s40249-021-00843-1>
  6. Quan, G., Yao, Z., Chen, L., Fang, Y., Zhu, W., Si, X., & Li, M. (2023). A trusted medical data sharing framework for edge computing leveraging blockchain and outsourced computation. *Heliyon*, 9(11), e22542. <https://doi.org/10.1016/j.heliyon.2023.e22542>
  7. Li, Y., Li, T., He, K., Cui, X.-x., Zhang, L.-l., Wei, X.-l., Liu, Z., & Wu, M. (2025). A predictive nomogram of thyroid nodules based on deep learning ultrasound image analysis. *Frontiers in Endocrinology*, 16, 1504412. <https://doi.org/10.3389/fendo.2025.1504412>
  8. Czajkowska, J., Polańska, A., Szymoniak-Lipska, M., Dańczak-Pazdrowska, A., Szymańska, D., Dańczak-Pazdrowska, A., & Korzekwa, S. (2024). Automated ultrasound analysis in atopic dermatitis. *Scientific Reports*, 14(1), 84051. <https://doi.org/10.1038/s41598-024-84051-6>
  9. Wang, L., Xia, D., Wang, J., Chen, S., Cui, X., Shen, L., & Huang, Y. (2024). Deep Learning Detection and Segmentation of Facet Joints in Ultrasound Images Based on Convolutional Neural Networks and Enhanced Data Annotation. *Diagnostics*, 14(7), 755. <https://doi.org/10.3390/diagnostics14070755>
  10. Rusu-Both, R., Socaci, M.-C., Palagos, A.-I., Buzoianu, C., Avram, C., Vălean, H., & Chira, R.-I. (2025). A Deep Learning-Based Detection and Segmentation System for Multimodal Ultrasound Images in the Evaluation of Superficial Lymph Node Metastases. *Journal of Clinical Medicine*, 14(6), 1828. <https://doi.org/10.3390/jcm14061828>
  11. Ito, Y., Nakajima, T., Inage, T., Otsuka, T., Sata, Y., Tanaka, K., Sakairi, Y., Suzuki, H., & Yoshino, I. (2022). Prediction of Nodal Metastasis in Lung Cancer Using Deep Learning of Endobronchial Ultrasound Images. *Cancers*, 14(14), 3334. <https://doi.org/10.3390/cancers14143334>
  12. Jessup, B., Tran, N., Stevens, T., & Barnett, T. (2023). Rural origin student representation in health courses at the University of Tasmania: 2011–2020. *Australian Journal of Rural Health*, 31(5), 944–956. <https://doi.org/10.1111/ajr.13027>
  13. Papadakis, S., Anastasaki, M., Gergianaki, I., Koek, G., Mendive, J., Anastasiou, F., Heyens, L., Garcia-Retortillo, M., Muris, J., & Lionis, C. (2023). Development and implementation of a continuing medical education program on non-alcoholic fatty liver disease for primary care practitioners in Europe. *Frontiers in Medicine*, 10, 1034626. <https://doi.org/10.3389/fmed.2023.1034626>
  14. Clark, M., Allan, A., Wylie, J., & Bye, C. (2025). CanREACH training and impact on rural primary care provider comfort, knowledge and clinical practices in managing child and adolescent mental health

- conditions. BMC Primary Care, 26(1), 172. <https://doi.org/10.1186/s12875-025-02872-4>
15. Papachristopoulos, I., Skafida, E., & Lionis, C. (2023). General practitioners' views and practices on mental health management in Greece: A cross-sectional study. BMC Primary Care, 24(1), 63. <https://doi.org/10.1186/s12875-023-02017-5>
  16. O'Sullivan, B. G., Boyer, S., Stratton, A., McGrail, M. R., Phillips, J., & Faoro, J. (2023). Outcomes of rural generalist internship training in Victoria, Australia. Rural and Remote Health, 23(4), 7889. <https://doi.org/10.22605/RRH7889>
  17. Born, J., Wiedemann, N., Cossio, M., Buhre, C., Brändle, G., Leidermann, K., Goulet, J., Aujayeb, A., Moor, M., Rieck, B., & Borgwardt, K. (2021). Accelerating Detection of Lung Pathologies with Explainable Ultrasound Image Analysis. Applied Sciences, 11(2), 672. <https://doi.org/10.3390/app11020672>
  18. Lee, K., Kim, J. Y., Lee, M. H., Choi, C.-H., & Hwang, J. Y. (2021). Imbalanced Loss-Integrated Deep-Learning-Based Ultrasound Image Analysis for Diagnosis of Rotator-Cuff Tear. Sensors, 21(6), 2214. <https://doi.org/10.3390/s21062214>
  19. Yan, K., Song, L., Sun, M. R., Ren, X. H., & Fan, W. (2024). Fetal heart ultrasound segmentation for the three-vessel and trachea view (3VV) with a deep learning method. BioMedical Engineering OnLine, 23(1), 39. <https://doi.org/10.1186/s12938-024-01230-2>
  20. Lee, H., Chai, Y. J., Joo, H., Lee, K., Hwang, J. Y., Kim, S. M., Kim, K., Nam, I. C., Choi, J. Y., Yu, H. W., Lee, M. C., Masuoka, H., Miyauchi, A., Lee, K. E., Kim, S., & Kong, H. J. (2021). Federated Learning for Thyroid Ultrasound Image Analysis to Protect Personal Information: Validation Study in a Real Health Care Environment. JMIR Medical Informatics, 9(5), e25869. <https://doi.org/10.2196/25869>
  21. Wang, L., Liu, X., Shao, W., Guan, C., Huang, Q., Xu, S., & Zhang, S. (2024). A Blockchain-Based Privacy-Preserving Healthcare Data Sharing Scheme for Incremental Updates. Symmetry, 16(1), 89. <https://doi.org/10.3390/sym16010089>
  22. Jia, F., Wang, S., & Pham, V. T. (2022). A Hybrid Catheter Localisation Framework in Echocardiography Based on Electromagnetic Tracking and Deep Learning Segmentation. Computational Intelligence and Neuroscience, 2022, 8483. <https://doi.org/10.1155/2022/2119070>

## Tables

**Table 1. Baseline (Q1) Diagnostic Quality Scores of High- and Low-Intensity Usage Groups.**

| Characteristic              | Low-Intensity Group<br>(n=12) | High-Intensity Group<br>(n=11) | P-value |
|-----------------------------|-------------------------------|--------------------------------|---------|
| Mean Report Score (Q1) ± SD | 99.46 ± 0.61                  | 99.44 ± 0.43                   | 0.941   |
| Mean Image Score (Q1) ± SD  | 99.65 ± 0.38                  | 99.54 ± 0.53                   | 0.561   |

Data are presented as Mean ± Standard Deviation (SD);P-values were calculated using the Independent-Samples;T-Test.

**Table 2. Temporal Changes in Institutional Diagnostic Quality Scores (Q1 vs. Q3).**

| Quality Metric | Quarter 1 (n=23)<br>Mean ± SD | Quarter 3 (n=23)<br>Mean ± SD | Mean Difference<br>(95% CI) | t-<br>statistic | P-<br>value |
|----------------|-------------------------------|-------------------------------|-----------------------------|-----------------|-------------|
| Report Score   | 99.45 ± 0.53                  | 99.68 ± 0.23                  | 0.23 (0.02 to 0.45)         | 2.33            | 0.031*      |
| Image Score    | 99.59 ± 0.45                  | 99.70 ± 0.27                  | 0.11 (-0.11 to 0.33)        | 1.04            | 0.311       |

Data derived from Paired-Samples T-Test;SD: Standard Deviation; CI: Confidence Interval;\* p < 0.05 indicates statistical significance.

**Table 3. Association Between Platform Usage Intensity and Endpoint (Q3) Diagnostic Quality Scores.**

| Quality Metric<br>(at Q3) | Low-Intensity Group (n=12)<br>Mean ± SD | High-Intensity Group (n=11)<br>Mean ± SD | t-<br>statistic | P-<br>value |
|---------------------------|-----------------------------------------|------------------------------------------|-----------------|-------------|
| Report Score              | 99.56 ± 0.24                            | 99.82 ± 0.12                             | 3.83            | 0.001*      |
| Image Score               | 99.67 ± 0.26                            | 99.73 ± 0.29                             | 0.54            | 0.596       |

Data derived from Independent-Samples T-Test;SD: Standard Deviation;\* p < 0.01 indicates a statistically significant difference between the two groups.

## Figures

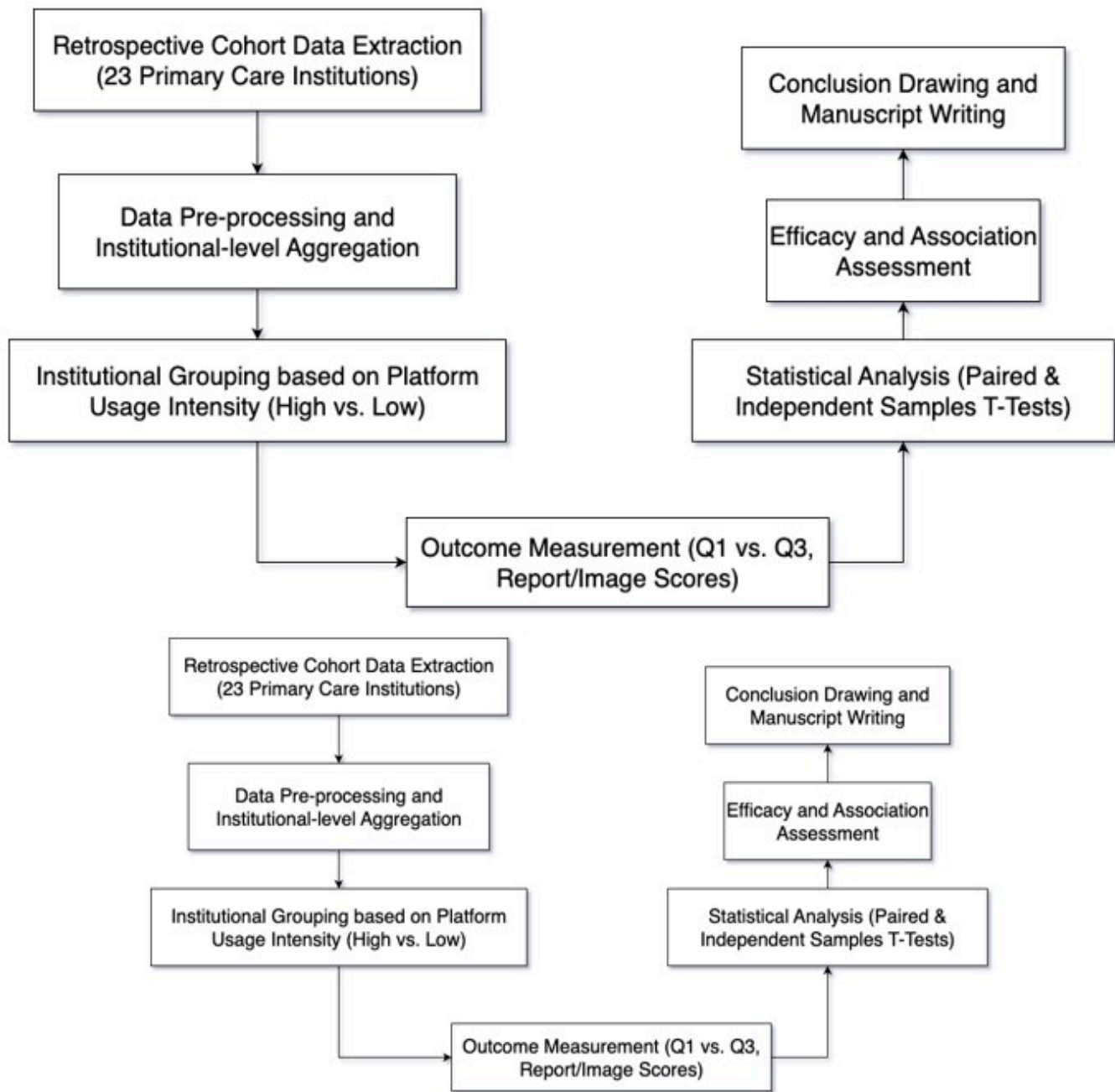


Figure 1

Flowchart of the Study Design and Analytical Process.

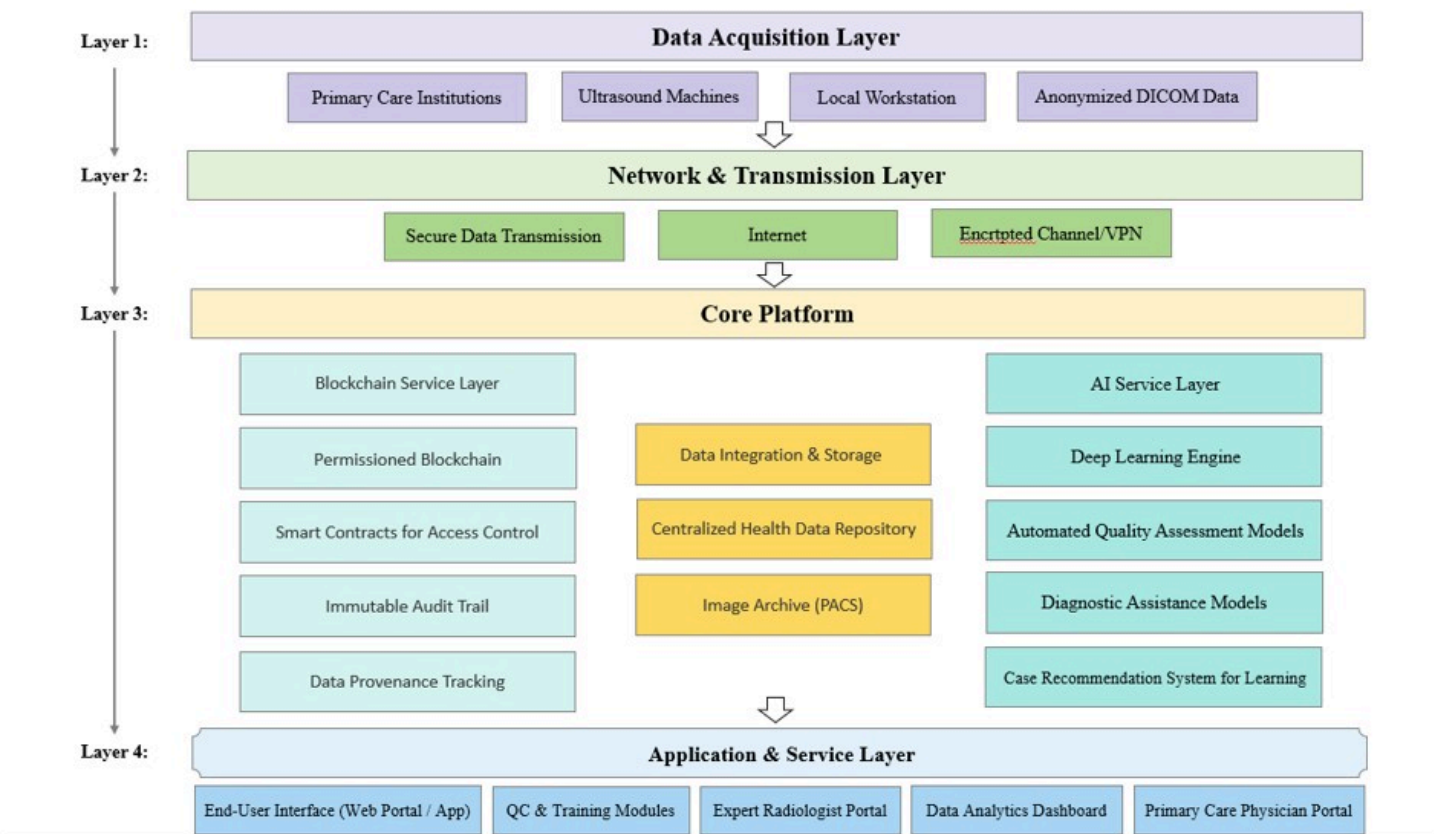


Figure 2

Architecture of the Blockchain-Powered Tele-ultrasound Platform.