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Willing but Not Ready? Documentation Quality as a Barrier to Artificial Intelligence Adoption in Nigerian Healthcare

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Abstract

Nigeria has demonstrated a commitment towards nationwide integration of artificial intelligence products into healthcare. However, concerns remain regarding feasibility due to historic challenges with data quality. Currently, there are no guidelines for scrotal ultrasound documentation—a prerequisite for generating high-quality data, and robust models. This study was carried out to assess routine scrotal ultrasound documentation quality as a proxy measure for AI readiness in Nigerian healthcare. To achieve this, we conducted a retrospective, descriptive cross-sectional study of scrotal ultrasonographic reports retrieved from health institutions in South Eastern Nigeria. Three hundred reports, generated between 2020 and 2025 were randomly selected and assessed for documentation quality across four domains using a de-novo structured checklist. Overall and domain specific compliance scores were then computed.
Overall documentation quality was suboptimal, with a mean compliance score of 56·41 ± 8·45%. Removing the demographic elements of the reports resulted in a notable decline in mean compliance scores (49·05%), suggesting that overall completeness is inflated by administrative fields rather than clinically informative content. Tertiary institutions demonstrated higher compliance than secondary institutions (61·72% vs 53·76%; 95% CI: 6·24–9·75), though deficiencies persisted across all domains. Documentation quality was highest in the demographic domain. Our findings suggest that current documentation practices may undermine robust model performance and equitable deployment. Addressing this through standardized reporting and regulatory alignments are prerequisites for producing usable, trustworthy evidence in the digital health era.

KEYWORDS
artificial intelligence; documentation quality; reporting standards; scrotal; ultrasonography

Introduction

Machine learning is a rapidly evolving field of computer science that aims to create machines capable of performing tasks that typically require human intelligence (1). Its application in healthcare continues to grow rapidly, with multiple publicly available products supporting diagnoses, prognostication, and personalized medicine. (2–5) The 1970s marked the beginnings of AI in medicine, the first of these being INTERNIST-1, created in 1971. Its success inspired other information systems such as MYCIN and DXplain (6)

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The beginning of the 21st century marked a major turning point in the history of machine learning, driven by three synchronous developments: the emergence of “big data”, the reduction in the cost of parallel computing and memory, and the improvements in deep learning techniques (7,8). The Nigerian healthcare system stands to benefit immensely from artificial intelligence. It currently faces enormous strain due to unfavorable doctor-to-patient ratios, rising healthcare costs, and increasing administrative burdens (9–11). Machine learning has the potential to alleviate these problems and help reduce health inequalities (12–14).

Encouragingly, the Nigerian government has recognized this potential. In recent times, several national programs have been launched to encourage local model development and deployment across key sectors, including healthcare. The Federal Ministry of Communications, Innovation, and Digital Economy, in October 2024, announced a ₦2·8 billion grant secured from Google that was distributed among selected startups, including a healthcare startup (15). Similarly, the Nigerian Healthcare AI Implementation Group was launched in September 2025 with the goal of bringing together important stakeholders to deploy AI models into healthcare workflows(16).

AI readiness refers to an organization's capacity to implement and utilize AI technology effectively through an approach that enhances its value. AI readiness facilitates the valuation and description of an organization's AI capabilities (17). Oxford Insights lay out 40 indicators across three domains (government, technology, data and infrastructure) for assessing government AI readiness (18). A major barrier to effective artificial intelligence utilization is data quality (19,20) the quality of the training data has been shown to be a primitive determinant of model quality(21). It lays the foundation and simultaneously sets the limits of the resulting AI application: the better the generated data reflects the population’s base reality, the better the resulting model. More sophisticated models have been shown to “learn” and amplify the biases of the training data, raising concerns of fairness and the perpetuating of prejudices amongst developers and regulators(22). Data quality has historically resisted a single, comprehensive definition. Early attempts emphasized intrinsic data properties, treating data quality as a static attribute. However, these definitions proved to be insufficient in guiding use particularly in applied domains, where the same dataset may be adequate for one purpose and inadequate for another. Clinical data are generated primarily to support patient care and not secondary uses like machine learning. Consequently, documentation that is clinically tolerable may be analytically fragile, introducing hidden biases, ambiguity, or loss of signal when repurposed. This drove a gradual conceptual shift toward “fit-for-purpose” definitions of data quality. Here, dataset quality is judged by the degree to which it is capable of supporting a specified use case. (23) Among these, the recently developed METRIC framework is particularly useful as it explicitly links data quality to downstream usability. It emphasizes how multiple attributes, such as accuracy, consistency, precision, representativeness, and robustness interact to determine whether a dataset can reliably support inference, prediction, or automation(Schwabe et al., 2024).

It is within this conceptual lens that the quality of clinical documentation becomes a proxy for AI readiness. In the present study, scrotal ultrasound reports are not evaluated merely for stylistic completeness, but as data-generation instruments. Documentation inadequacy directly undermines AI readiness as accuracy and precision are compromised when key parameters are omitted or ambiguously described; consistency and robustness suffer when reporting practices vary widely intra/extra institutionally; representativeness is weakened when key anatomical structures or procedural contexts are systematically under-reported, etc.

Importantly, these limitations arise before any algorithmic modelling, this constituting structural barriers to equitable and responsible AI deployment.

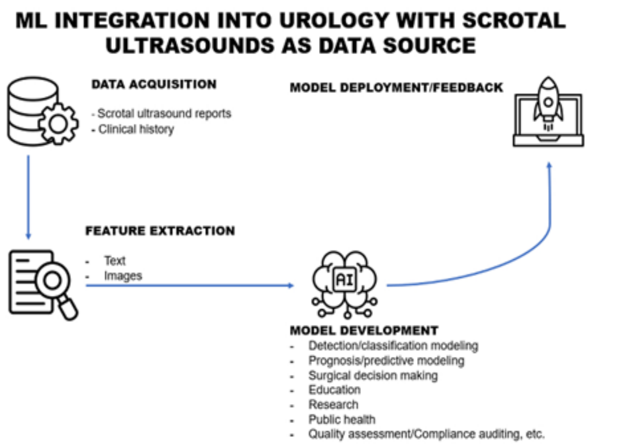
Artificial intelligence has already seen increased deployment within global urology, ranging from incorporation into surgical workflows, tumor detection and prognostication, and genomics, to fertility profiling (see Figure 1). (25,26) However, as of yet, no machine-learning models have been deployed in the urological arm of the Nigerian healthcare system. The 2024 Oxford Insights report into AI readiness ranked Nigeria 94th out of 188 countries, and 7th in sub-Saharan Africa. Despite this, we found no published evaluations of AI readiness in the Nigerian healthcare system.

Scrotal ultrasound reports provide an excellent test case for exploring AI readiness in Nigeria. Scrotal ultrasound examinations are frequently requested by urologists for their role in the assessment of a wide range of clinical conditions. Their non-invasive nature, accessibility, and high diagnostic accuracy make them indispensable. There is substantial research in the literature regarding ultrasound AI applications in body areas which are less affected by overlying structures, and for the binary task of tumor characterization (27).

Additionally, comprehensive and standardized reporting in scrotal ultrasonography is essential not only for clinical management, but also for longitudinal comparisons and identifying incidental findings that may point to systemic pathologies. Accurate and comprehensive documentation enhances confidence in the robustness of the investigative process. Poorly structured reporting can lead to ambiguity, mismanagement repeat examinations, follow-up delays, ultimately imposing additional financial and emotional burdens on patients(28).

Despite these considerations, there remains a notable gap in the adoption of standard reporting protocols in Nigeria. Neither the Nigerian Association of Urological Surgeons nor the Association of Radiologists

Figure 1. Potential use cases for scrotal ultrasound in development of urological ML models



in Nigeria currently provide a template for scrotal ultrasound documentation. This lack of standardization often leads to wide inter- and intra-facility variability, affecting report consistency and quality.

Addressing these gaps is critical for improving patient care and advancing AI readiness within the Nigerian healthcare system(29).

Therefore, the central aim of this study is to evaluate artificial intelligence readiness within the Nigerian healthcare system by assessing the quality of scrotal ultrasound documentation as a proxy measure of our data-generation capacity.

Hypotheses

1. Overall compliance (H1, directional): The overall compliance of scrotal ultrasound reports will fall below "excellent" (≤80%). Most reports will be categorized as "moderate" or "good."
2. Institutional comparison (H2, directional): Reports from tertiary health institutions will have higher compliance scores than those from secondary health institutions.
3. Domain-specific adherence (H3, directional): Higher scores will be obtained in the demographic domain in comparison to technical/procedural and sonographic domains.

Methods

This is a retrospective, descriptive, cross-sectional study.

Population and Sample/Informants

The study population comprised scrotal ultrasonographic reports generated between January 1st, 2020 and November 30th, 2025 within the selected institutions. Purposive sampling was employed to select the study institutions based on their relative accessibility to the researchers, diagnostic capacity, availability of archived sonographic reports, and relatively high volume of scrotal ultrasound examinations. A total of 905 scrotal ultrasound reports were retrieved: 172 from the tertiary institution, 580 from secondary institution 1, and 153 from secondary institution 2. Reports with no or illegible text, as well as follow-up scans without standalone reports, were excluded. Within each institution, simple random sampling was conducted using a random selection procedure to identify eligible reports. From each institution, 100 reports were reviewed. This sample size was determined following a power analysis conducted using G*Power software to identify the minimum number of reports required to detect medium-sized effects at an alpha level of 0.05 with 90% statistical power.

Research Location

The study was conducted across three health facilities in Enugu State, southeastern Nigeria. Of these institutions, one was a tertiary health institution providing, amongst other services, urological and radiological services, and the other two were private secondary health facilities that provide a wide range of urological services. The inclusion of both tertiary and secondary facilities was intended to allow for the comparison of practices across different levels of healthcare delivery.

Instrumentation or Tools

A structured, pretested checklist was developed based on the American Institute of Ultrasound in Medicine (AIUM) Practice Parameter for Documentation of an Ultrasound Examination and the AIUM Guideline for the Performance of Scrotal Ultrasound Examinations (Appendix 1) ("AIUM Practice Guideline for the Performance of: Scrotal Ultrasound Examinations," 2015; "AIUM Practice Parameter for Documentation of an Ultrasound Examination," 2020)(30,31).

Data Collection Procedures

Data abstraction and scoring were carried out independently by a urologist and a radiologist, with conflicts resolved through collaborative deliberation. Variables that were fully documented were assigned a score of 2, partially or incompletely documented variables a score of 1, and undocumented variables a score of 0. Overall compliance scores were calculated by summing the individual variable scores. Pre-deliberative agreement was 83·8% (7541/9000) with most disagreements occurring in the scoring of the sonographic details' domain. The mean of the overall compliance scores was calculated using, as denominators, the total possible score for each report. Reports were then categorized thus:

- Excellent: 80–100%
- Good: 70–79%
- Moderate: 50–69%
- Poor: <50%

Data Analysis

All statistical analyses were conducted using R version 4·5·1. For hypothesis 1, a one sample t-test was employed. For hypothesis 2, Welch's t test was used to compare mean compliance scores across institutions. For hypothesis 3, repeated-measures ANOVA was applied to compare mean scores across reporting domains. Sensitivity analyses were conducted by repeating all primary analyses with the demographic domain removed, in order to assess the extent to which demographic reporting affected overall compliance categorization. To address potential confounding arising from institutional, domain specific compliance scores were stratified by institution, and subgroup means were compared. While we are unable to exclude all confounding due to the retrospective study design, this stratification allows for meaningful interpretation of institutional effects.

Ethical Approval (Optional)

Ethical clearance was obtained from the Health Research Ethics Committee of the University of Nigeria (NHREC/05/01/2008B–FWA00002458–IRB00002323). Institutional permissions were also secured for access to ultrasound archives. This was a retrospective study with no direct patient contact. All retrieved data were anonymized, and confidentiality was maintained in accordance with institutional policies and international ethical principles.

Result and Discussion

A total of 300 scrotal ultrasonography reports, selected from a population of 905 reports, were analyzed. The mean overall compliance score for all reports was 56·41 ± 8·45% with most reports clustered around the mean (see Appendix 2). Overall compliance with the standardized 30-itemchecklist was determined to be suboptimal (significantly below the "excellent" standard). This finding was statistically significant when tested against the 80% threshold (t = 56·50, p < 0·001; Cohen's d = -3·26).

The distribution of overall compliance scores showed a strong clustering around the mean with a range of 44·78%-points (76·92 – 32·14). When stratified by defined quality standards, the reports demonstrate a clear lack of high-quality documentation, as visualized in Figure 2. Compliance varied significantly across institutional lines. The mean overall compliance score for the tertiary institution was 61·72 ± 6·66%), which was 7·96 points higher than the mean score for the secondary institutions (53·76 ±8·01). This difference was statistically significant (95% CI: 6·24 – 9·75, p < 0·001).

Despite the clear advantage demonstrated by the tertiary institution, the maximum observed score in the entire cohort did not reach the excellent standard.

Tertiary institutions had higher scores across all domains except the technical domain, with a 2.8% difference (see Table 1). In the demographic and interpretative domains, tertiary institutions demonstrated differences of approximately 13 –14 points. The differences between the mean domain specific scores for tertiary and secondary institutions across all domains were statistically significant (p < 0.05).

A repeated-measures ANOVA confirmed a highly significant effect of reporting domain on mean compliance score across the four established domains (F(3, 297) = 408·53, p < 0·001) with a 32·43%-point gap between the highest and lowest scoring domains.

Demographic details were, on average, the most documented features of the ultrasonographic reports, with interpretative and technical details the least documented (see Figure 3). Excluding the high-scoring demographic domain resulted in a "core report" mean compliance score of 49·05%, a 7·36-point drop from the overall mean. Tertiary institutions experienced a larger drop off in absolute (-10·11%-points vs -7·27%-points) and relative (relative to overall compliance score) mean compliance scores (16·38% vs 13·52%).

This research is part of ongoing efforts to increase the capacity of the Nigerian healthcare system to accommodate automation and machine learning within routine clinical workflows. (32) High-quality data is a prerequisite for the development of robust models. Consequently, there is a pressing need for machine-learning-grade data.

The mean score for compliance was 56·41 ± 8·45%, consistent with our first study hypothesis. This is a troubling finding, as it indicates that, on average, reports contain just above half of the required data points they should contain. Importantly, there is need for the establishment of patient baseline parameters. While a particular scrotal structure might not be the primary subject of investigation, the ultrasound examination offers the opportunity to obtain baseline measurements. Examination of all retrieved reports revealed no cases in which a patient presented solely to establish a baseline, yet baseline parameters are important in medicine: they offer the best chance of tracking longitudinal change, thereby enabling more personalized clinical care. This is particularly valuable for scrotal features that do not experience significant fluctuations in measurement.

We noted the general under-reporting of key features such as the characterization of extra-testicular structures, the spermatic cord, the scrotal wall, and the tunica (Appendix 3). One might be tempted to overlook some of these details because, ultimately, what would likely be of greatest use to machine-learning models developed for scrotal ultrasound are sonographic details combined with the patient’s clinical history. However, there still remains a need for proper reporting beyond model development and the introduction of artificial intelligence(33). Such needs include improving physician–patient trust, and physician–physician trust, and patient care. Typically, urologists and radiologists do not hold face-to-face conferences in the management of relatively uncomplicated cases; communication occurs primarily through radiological reports. The more thorough the report and the more rigorous the documentation, the better the clinical decisions that can be made.

When demographic details are removed, the mean compliance score for secondary health institutions was 46·49%, and 51·61% for tertiary institutions. These values are even lower than the overall means because demographic details boosted the original composite scores. Examination of the distribution of reports (excluding demographic details) shows that 27% were poor, 70·67% moderate, 2·33% good, and none excellent. Thus, even

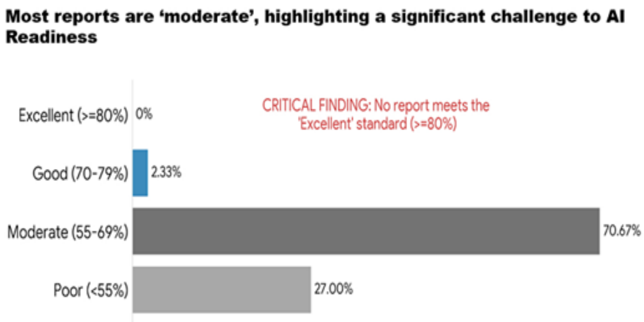


Figure 2. Categorization of overall compliance scores

removing demographic details, the hypothesis still holds true: most reports are poor, and lower scores are obtained than when demographic details are included.

Regarding the second hypothesis, tertiary institutions had a mean compliance score of 61·72 ± 0·66%, whereas secondary institutions had 53·76 ± 0·56%. The maximum compliance scores observed were 76·92% for tertiary and 75·93% for secondary institutions. No institution had an average score within the excellent category. A noteworthy observation is the approximately eight-point difference between tertiary and secondary institutions. On average, this means that tertiary institutions included roughly four additional required data points compared with their secondary counterparts.

This pattern persists when broken down by reporting domains. Tertiary institutions had higher scores across all

To determine the underlying cause, we will need to consider workload stratification, compare reporting behaviors across institutions, and conduct interviews with radiologists. Whatever the root cause, the data-quality problem is evident and must be urgently addressed. One potential solution, employed in other settings, is the provision of standardized documentation templates (Koh & Ahmed, 2021).

This is especially relevant because secondary institutions are often the first point of contact for many patients. It is reasonable to conclude that the majority of scrotal ultrasound reports available for model building will likely originate from secondary health institutions. We worry that this discrepancy may detract from the potential quality of any machine-learning model developed. Radiologists in the tertiary institution informed us of ongoing efforts to produce guidelines for standardizing reports. The important question, therefore, is how to ensure that these reporting standards, when fully developed, do not remain confined to tertiary institutions but are disseminated to secondary, and even primary levels of healthcare.

Regarding the third hypothesis, compliance with the documentation of demographic details was the highest, with a mean score of 73·07 ± 0·70%, while technical details were the least documented, with a mean score of 44·10 ± 0·59%. An important detail is the relative non-inclusion of ultrasound images within patient reports. When produced, these images are not stored within the patient's electronic health record, but rather in a separate database disconnected from the patient's clinical records. This poses a significant obstacle to developing patient phenotypes and clinical matrices that could support predictive models. It is also particularly worrying that technical details are poorly documented, especially from secondary health institutions that do not provide urological

domains except the technical domain. In the demographic and interpretative domains, tertiary institutions demonstrated differences of approximately 13–14 points. Anecdotal evidence indicates that the tertiary center typically has lower patient loads, which may grant more time per report and thereby contribute to higher quality. It is also plausible— though speculative— that reports may also be influenced by the need for social or administrative approval. If these are the reports produced despite such influences, what then was the true quality of the procedures performed? care. Reporting technical details such as transducer type and settings is important because these factors influence how results are interpreted. There is also the documented lack of examination of the scrotal contents under Valsalva. This is problematic because early-stage varicocele (implicated in male-factor infertility) is often noticed only under Valsalva(35). In addition, poor documentation of adverse patient reactions and failures to obtain standard views places patients at risk of repeat insult or harm.

Attempts to develop reporting standards must be collaborative, with input from end-users, in this case, surgeons. Guidelines should not be developed remotely, but rather collaboratively at the national level. Guidelines developed with data from different institutions and regions can support this effort. Importantly, these guidelines should not only apply to tertiary health institutions but should also bind secondary institutions, which serve a significant portion of the population for urological investigations. Additionally, there should be greater encouragement of data sharing among institutions, and we should take more seriously the need for integrated patient health records.

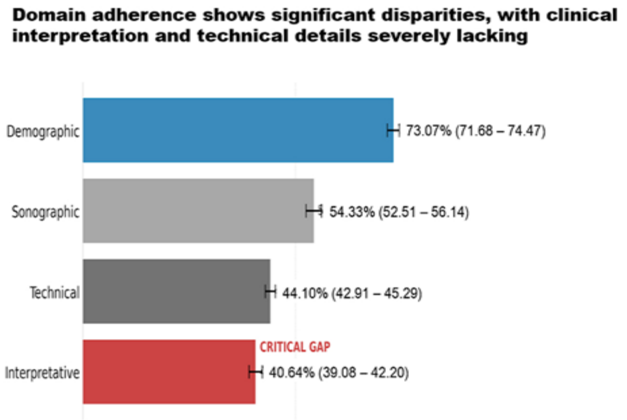


Figure 3. Differences in mean compliance scores across domains

Table 1. Institutional differences across domains

	Demographic domain	Technical domain	Sonographic domain	Interpretative domain
Tertiary	82·2±10.1%	42·2±7.5%	58·0±13.5%	49·8±10.8%
Secondary	68·5±10.6%	45·0±11.6%	52·5±16.8%	36·1±12.8%

Limitations and Cautions

The major limitation of this study was our inability to include more institutions in our study due to a lack of comprehensive record-keeping in many institutions. We also recognize the inherent subjectivity in certain scoring judgments, particularly that concerning when recommendations are required. While this may have introduced small variability in scoring, its influence on overall compliance was deemed minor enough not to alter the primary conclusions. A potential controversy raised by this study is the implication that secondary institutions (despite serving the majority of patients) produce documentation of lower quality than tertiary centers. This raises uncomfortable questions regarding equitable access to high-quality diagnostic care.

Regarding representativeness, the study population was limited to one state in Nigeria. This decision was based on ease of access to the included institutions by the researchers. We admit that this limits the immediate generalizability of this study's findings and may increase the risk of selection bias; however, the reporting patterns observed are consistent with long-standing national concerns regarding record-keeping, and therefore still serve as a meaningful window into AI readiness in the nation. The inclusion of both tertiary and secondary institutions strengthens the applicability of these findings to similar health-system hierarchies across Nigeria.

Recommendations for Future Research

Future research should seek to include additional institutions across multiple geopolitical zones to improve representativeness and assess regional variability. Prospective studies incorporating direct observation of sonographic technique, digital image capture, and the integration of electronic health records would provide a more thorough understanding of data-generation processes. Standardized templates, once implemented should be evaluated for their effectiveness in improving data quality.

Conclusion

This study demonstrates that current documentation practices may undermine attempts at robust model development, performance, and equitable deployment. To address this, nationally deployed standardized reporting and regulatory frameworks are urgently required to ensure the generation of producing usable, trustworthy evidence in this digital health era.

Author contributions

Prince I. Chukwuemeka contributed to conceptualization, formal analysis, research execution, methodology, project administration, software development, supervision, visualization, and writing—review and editing. Ime E. Aaron contributed to data preservation, software development, and validation. Ochimana O. David contributed to funding acquisition, resource provision, and original draft preparation. Chukwu O. Josephate contributed to methodology, resource provision, and original draft preparation. Obodo O. Prosper contributed to funding acquisition, validation, and visualization. All authors reviewed and approved the final manuscript.

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