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Clinical Validation of the ZaiDoc™ AI Digital Health Platform: Real-world Study

Mohammed Muze Edris[1,2]*

[1]Department of Nursing, College of Medicine and Health Science, Werabe University, Ethiopia, [2]ZAIDEH Global DMCC Clinical Validation Team, Dubai, United Arab Emirates. *Corresponding Author's Email: mohec53@gmail.com

Abstract

Timely and accurate diagnosis and treatment in healthcare settings remain critical healthcare challenges. Digital health technology is playing an increasingly vital role in offering solutions to the challenges facing the sector. Therefore, this study aimed to investigate the clinical validity of the ZaiDoc™ AI digital health platform in the outpatient departments of health facilities. A cross-sectional study was applied to investigate clinical validation of the platform in disease conditions present in outpatient departments. About 100 study participants presented with target disease conditions were included. The diagnostic accuracy of the platform was assessed by comparing the suggestions from the ZaiDoc™ AI Digital Health Platform to standard clinical practice guidelines. All validation metrics were analyzed using SPSS version 25 and Excel. The diagnostic capabilities of the ZaiDoc™ Platform were evaluated using 95% confidence intervals (CIs) for all metrics. The sensitivity of the platform was found to be 89.13% (CI = 76.96–95.28%). The specificity of the platform was 96.30% (CI = 87.45–98.98%). The Positive Predictive Value (PPV) of the platform was 95.35% (CI 84.52–98.72%). The Negative Predictive Value (NPV) of the platform was 91.23% (CI = 81.06–96.19%). The platform has the potential to support health care services by providing accurate diagnoses in the outpatient departments of the health facilities. Further full-scale study was essential for a wide range of conditions to enhance the scope of the application.

Keywords: Artificial Intelligence, Clinical Validation, Diagnostic Accuracy, Digital Health, Low-resource Settings, Outpatient Care.

Introduction

Digital health has emerged as a major strategy for strengthening healthcare systems and improving quality care and clinical decision-making, particularly in settings where health services face shortages of workforce, increasing patient demand, and limited diagnostic infrastructure (1). The increasing accessibility of artificial intelligence, electronic records, mobile health applications, and clinical decision-support tools has generated novel opportunities to assist clinicians in the early identification of diseases, the standardization of patient assessment, and the enhancement of care delivery efficiency (2). In outpatient departments, where most patients first enter the health care system and present with diverse symptoms, digital health platforms can assist clinicians in organizing clinical information, generating differential diagnoses and reducing delays in decision-making (3). Studies done in high-income countries showed that diagnostic errors occur in about 5% of outpatient adults and are responsible for approximately 10% of deaths among adult patients (4). Post-mortem analyses consistently reveal that 10–20% of autopsies show major diagnostic discrepancies that contribute to death (5, 6). Delayed, missed, or incorrect diagnoses can result in inappropriate treatment, unnecessary referrals, avoidable disease progression, increased healthcare costs, and preventable morbidity or mortality (7, 8). In resource-limited settings, diagnostic errors represent a critical and multifaceted problem, fundamentally rooted in the severe scarcity of both human and technological resources. The central issue lies in the perilous intersection of overwhelming patient volume, excessively high caseloads, and a critically low "figure" of skilled personnel and diagnostic equipment per capita (9). These two factors create an ideal environment for errors in patient treatment. The overworked clinicians must make quick medical decisions without the assistance of specialists in crowded clinics with little access to diagnostic tools (9). Consequently, they have no choice but to rely

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almost entirely on clinical symptoms and intuition to diagnose their patients. While these methods are useful and can be effective, the reliance on them increases the likelihood that patients will receive delayed, missed, or wrong diagnoses (10).

The integration of digital health technologies into outpatient department (OPD) workflows for symptom-based diagnosis has seen significant innovation (11, 12). Artificial intelligence-enabled diagnostic decision-support tools can analyze patient-reported symptoms, identify patterns, generate differential diagnoses, and provide evidence-informed suggestions to clinicians (13). When properly validated, these systems may reduce cognitive burden, support less-experienced clinicians, promote standardized assessment, and improve the timeliness of clinical decision-making. In addition, digital platforms may be particularly useful in busy outpatient departments because they can be deployed with relatively low infrastructure requirements compared with specialist services, advanced imaging, or laboratory-based diagnostic systems (14).

Current electronic health records (EHRs) in hospital systems have many limitations in supporting primary diagnosis in the outpatient department. These limitations of EHRs can cause errors and patient deaths (15). Another main limitation of current EHRs is the lack of interoperability between different platforms, which leads to fragmentation of patient information, redundancy in diagnosing symptoms, and poor-quality data due to missing or unstructured documentation; these issues contribute to clinician burnout, especially in environments with high patient volumes and limited resources (16-18). Although electronic health records are important for documentation and continuity of care, many systems were not primarily designed to provide real-time symptom-based diagnostic support during clinical encounters. As a result, they may store information without adequately assisting clinicians to interpret symptoms, prioritize differential diagnoses, or identify potential diagnostic risks. AI-enabled tools specifically designed to complement clinical workflows and strengthen diagnostic decision-making in outpatient care present an important opportunity (19, 20).

The combination of AI and the pre-consultation system can help raise the efficiency of clinical work. However, while the pre-consultation system and AI combination may assist in increasing the efficiency of clinical work, it is still a challenge to allow the AI to process and evaluate the complex EHR data (21). Prior research has indicated potential for AI-driven diagnostic and decision-support systems; however, many have been designed for limited clinical domains, particular disease states, image-centric diagnosis, or specialized hospital environments, rather than comprehensive outpatient symptom evaluation. For example, existing research has investigated AI applications in specific fields such as orthodontic diagnosis, chronic obstructive pulmonary disease, cardiac arrhythmia detection, and breast cancer screening (22-27) or acute care settings like triage (28).

Therefore, while outpatient settings are also critically important with high-volume patients, time constraints, and undifferentiated presentations, they require a unique support system to improve diagnostic accuracy and resource utilization within an environment that is not disrupted from normal practice patterns. This study addresses the gap by examining a new AI-enabled support system developed for outpatients, which may provide insight as to its potential application, effectiveness, and fairness in resource-limited settings (29, 30).

Therefore, an important research gap remains, there is limited real-world evidence on the clinical validity, diagnostic performance, usability, and workflow compatibility of broad symptom-based AI diagnostic platforms in outpatient departments of resource-limited settings. There is insufficient evidence from African primary-care and outpatient contexts, where digital diagnostic tools may have substantial value but must be evaluated under real clinical conditions before wider implementation (31). The present study addresses this gap by clinically validating the Zaidoc™ AI Digital Health Platform as a symptom-based diagnostic support tool in outpatient health facilities in Nigeria.

Methodology

Study Design and Population

A cross-sectional study was conducted to validate ZaiDoc™ Digital Health Platform in Nigeria, 2024. This study was carried out at the outpatient departments of Yola Specialist Hospital, Yola, Adamawa State, Nigeria (approximate GPS coordinates 9.27668° N 12.44791° E), and Bekaji Primary Health Care Centre, Adamawa State, Nigeria (approximate GPS coordinates 9.25952° N 12.43938° E). These facilities have a high patient load and a diverse range of cases. The ZaiDoc™ AI Digital Health Platform was configured to diagnose. Participants were recruited from the outpatient departments of Specialist Hospital Yola and Primary Health Care Centre Bekaji during the study period. Patients presenting with symptoms or disease conditions within the diagnostic scope of the ZaiDoc™ AI Digital Health Platform were screened for eligibility and enrolled using purposive sampling after written informed consent was obtained. Participants were included if they attended the outpatient department, presented with target symptoms or conditions covered by the platform, provided informed consent, and had sufficient clinical information for comparison between platform-generated diagnoses and clinician diagnoses. Patients were excluded if they presented with emergency conditions requiring immediate intervention, had conditions outside the diagnostic scope of the platform, declined consent, or had incomplete clinical information.

The study population consisted of participants who were attending the health facility during the study period. The study excluded patients presenting with conditions beyond the scope of the ZaiDoc™ AI Digital Health Platform. By using purposive sampling, 100 patients with disease conditions were included in the study.

ZaiDoc™ AI Digital Health Platform

The digital platform is a tool designed for outpatient departments that helps doctors quickly analyze patient-reported signs and symptoms to create initial diagnoses. It was developed using a user-centered design and development methodology with iterative testing and feedback from clinicians. The digital platform has three components; first, the symptom input interface allows clinicians to enter patient symptoms into the system. Second, AI-driven machine learning algorithms have been trained on large amounts of deidentified clinical data for identifying patterns in patient symptoms. Third, output modules are used to display differential diagnoses based on guidelines from organizations such as the World Health Organization (WHO) and National Institute for Clinical Excellence (NICE).

Measurements and Data Collection Tools

After installing the ZaiDoc™ AI Digital Health Platform on a laptop, data were collected. The source of information was doctor-patient interactions at the clinic. The platform-generated diagnoses were made after the data was fed into the platform and compared against standard clinical practice guidelines. Prior to the interaction, the platform was configured with diagnostic suggestions; then patient data was entered, and the platform's output was compared against the standard clinical practice guideline. Similarly, user experience data were collected from users to assess the practicality and convenience of the platform. Easiness of platform use was measured by asking for the user's feedback on interface design and navigation. The interactions were carefully observed to ensure patient safety. The attending doctor also examines the platform's suggested diagnosis, its appropriateness, and safety, ensuring alignment with standard practice guidelines. The participants' written consent was obtained at the time of data collection. The confidentiality of responses was maintained throughout the research process.

Data Processing and Analysis

Data were cleaned and analyzed using IBM SPSS Statistics for Windows, Version 26.0 (IBM Corp., Armonk, NY, USA). Descriptive summaries were used to describe the study variables such as diagnostic accuracy, specificity, sensitivity, true positive (TP), true negative (TN), positive predictive value (PPV), and negative predictive value (NPV). Diagnostic outcomes of the platform were compared with clinicians' final diagnoses to determine accuracy. User experience, or feedback from patients and healthcare providers, was qualitatively analyzed to assess ease of use.

Results

Diagnostic Performance

The diagnostic capabilities of the platform were evaluated using 95% confidence intervals (CIs) for all metrics. The sensitivity of the platform was found to be 89.13% (CI = 76.96–95.28%). Sensitivity has shown a strong capability to detect true positives. The specificity of the platform was 96.30% (CI = 87.45%–98.98%), which demonstrates a small number of false positives generated by the platform and an excellent capability to identify negatives as such.

The positive predictive value of the platform was 95.35% (CI = 84.52–98.72%), indicating that if the platform identifies a case as positive, then there is a strong likelihood that it will be identified correctly. The negative predictive value of the platform was 91.23% (CI = 81.06–96.19%), showing that negative calls generated by the platform are reliable, although less so than positive calls. While the platform's negative predictive values remain high and strong, they provide a greater degree of uncertainty regarding the identification of negatives than positives, as shown in Figure 1.

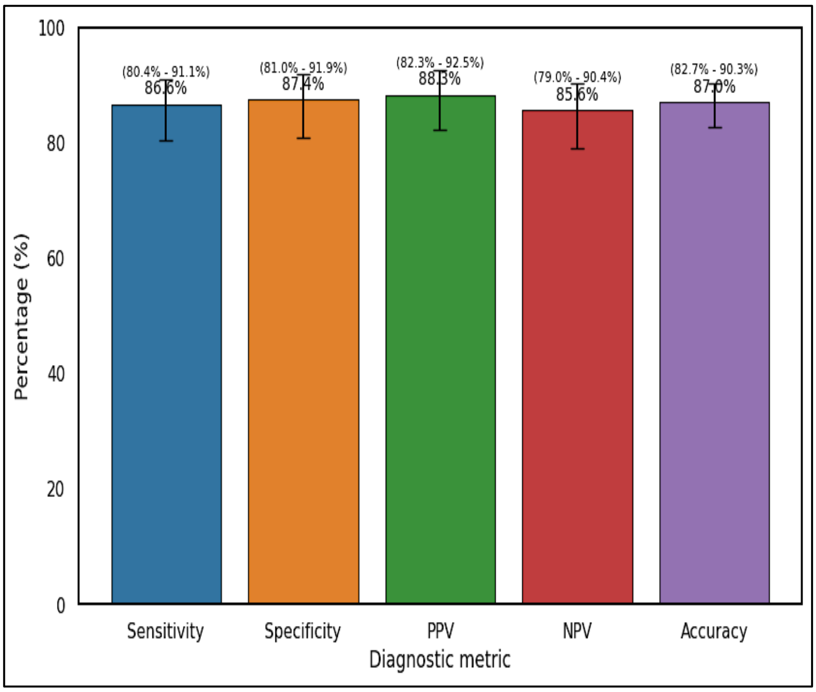

Figure 1: Diagnostic Performance of the ZaiDoc™ AI Digital Health Platform in the Validation Output. This shows Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy with 95% Confidence Intervals

The platform was able to achieve an operating point with a true positive rate of 0.891 (or 89.1% sensitivity) and a false positive rate of 0.037 (or 3.7%) at the selected operating point. In practical terms, the result indicates that the system identifies approximately 9 of every 10 true positives and only falsely flags approximately 4 of every 100 true negatives. There is a beneficial balance between identifying true positives and reducing false alarms; such a balance is typically considered desirable in many screening or triage applications because false positives create additional unnecessary workload downstream, whereas false negatives represent lost opportunities to provide timely clinical interventions, as shown in Figure 2.

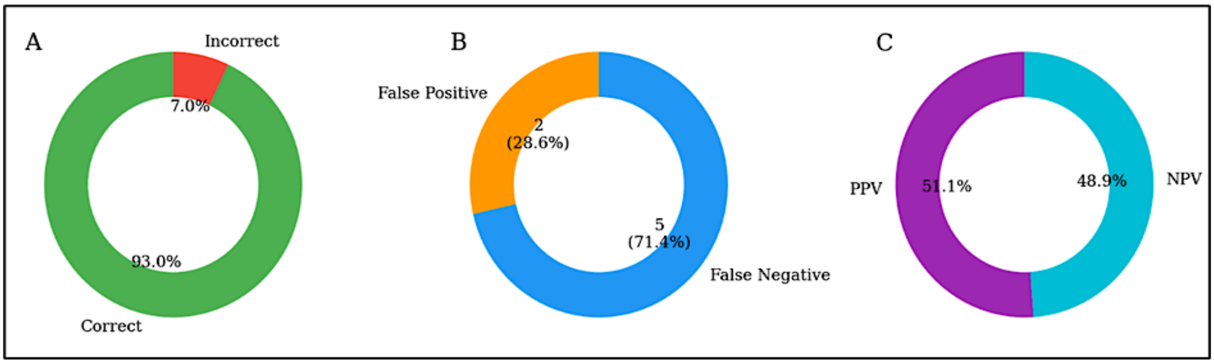

Figure 2: Summary of Zaidoc™ Platform Performance Across Three Diagnostic Summaries. (A) Overall Accuracy, (B) Error Distribution, (C) Predictive Values

Figure 2A shows the proportion of correct versus incorrect classifications, Figure 2B shows the split between false positives and false negatives and Figure 2C shows positive predictive value and negative predictive value.

The Radar Plots

Figure 3 provides an initial form visualization of how the ZaiDoc™ Platform's performance compares to each of the five major metrics. The polygon in the radar plot is close to the outside edge of the radar plot along all axes. This diagram visualizes the fact that the ZaiDoc™ Platform is operating very strongly and consistently on all metrics versus being extremely successful on one metric and weak on others. The highest axis values for the radar plot are specificity (96.30%) and PPV (95.35%). This indicates that the ZaiDoc™ Platform is particularly good at avoiding false positives, and when it does predict positive, it is correct most often. In addition to high specificity and PPV, accuracy (93.0%) and NPV (91.23%) are also relatively high, which supports the idea that the predictions made by the platform are generally reliable. The lowest axis value for the radar plot is sensitivity (89.13%), which matches the earlier error distribution analysis, which indicated that false negatives occurred significantly more frequently than false positives. This suggests that the primary opportunity for improving performance is reducing missed positives in the clinical workflow and thereby capturing all true cases.

The radar chart in Figure 3 summarizes the platform's key validation metrics, including sensitivity, specificity, PPV, NPV, and accuracy, in a single visual display. The shape of the plot gives a quick look at how well the metrics are balanced, with bigger values meaning better diagnostic performance. All values were derived from the uploaded validation dataset of 300 cases. The radar plot is intended as a compact summary of overall diagnostic strength and balance rather than a substitute for the underlying confusion matrix and confidence intervals.

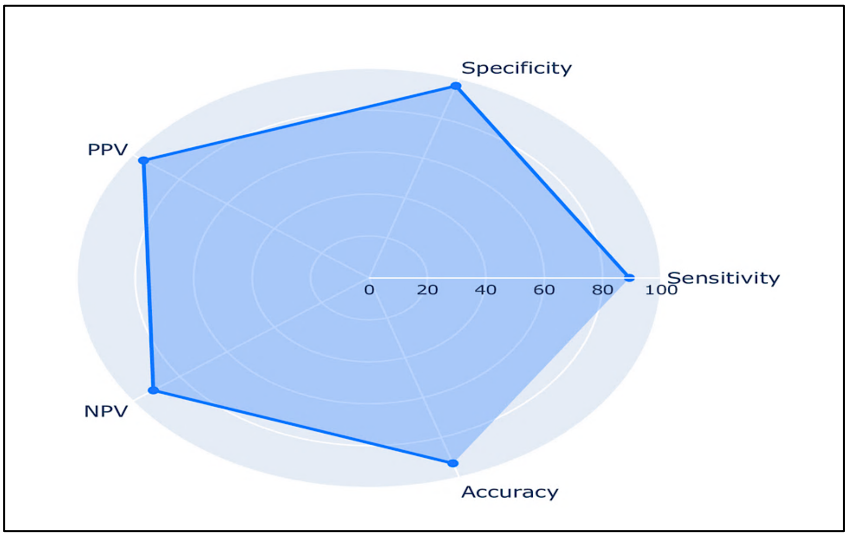

Figure 3: Radar Plot of Diagnostic Performance Metrics for the ZaiDoc™ AI Digital Health Platform

Receiver Operating Characteristic (ROC) Curve

The trade-off between the genuine positive rate (sensitivity) and the false positive rate (1-specificity) for all potential platform operating settings is depicted in Figure 4 - Receiver Operating Curve (ROC). The ROC curve is unmistakably situated above the diagonal reference line, indicating that the model's discrimination is noticeably superior to that of a random classifier. At the chosen operating point, the platform was able to attain a true positive rate of 0.891 (or 89.1% sensitivity) and a false positive rate of 0.037 (or 3.7%). Practically speaking, Figure 4 shows that the algorithm detects about 9 out of 10 true positives and only incorrectly flags about 4 out of 100 true negatives.

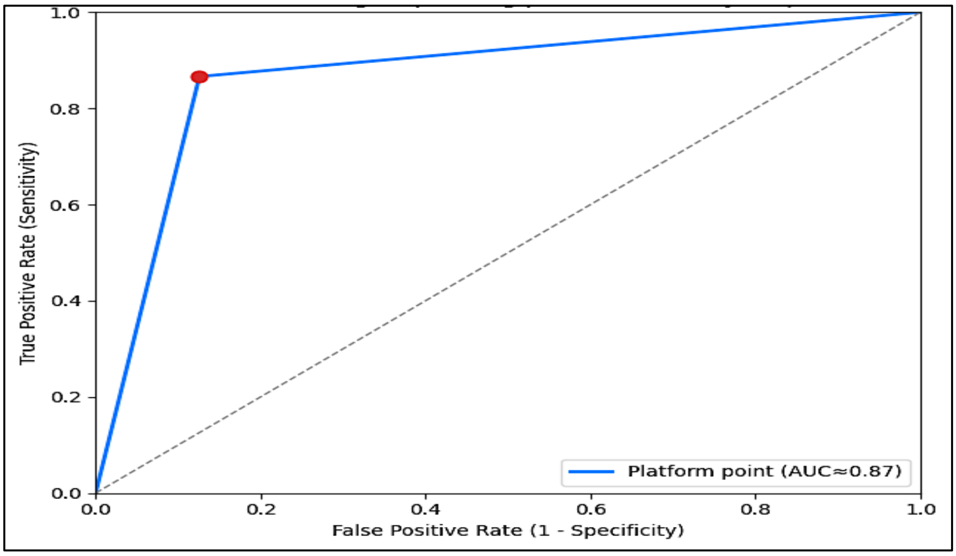

Figure 4: Receiver Operating Characteristic (ROC) Curve for the ZaiDoc™ AI Digital Health Platform

The ROC plot in Figure 4 shows the relationship between the true positive rate and the false positive rate for the platform's diagnostic classification in the validation process. The marked operating point represents the observed performance at the deployed decision threshold, illustrating the tradeoff between sensitivity and false-positive rate.

User Experience

This study found positive experiences regarding the platform as ease to use. Both patients and clinicians described the platform as well organized and easy to navigate. Many users valued that the platform has a simple layout and clear instructions, which reduced confusion during data entry and consultation processes. Clinicians noted that the system required minimal training and blended seamlessly with their daily routines and can be implemented even in a busy clinical setting.

Discussion

The current research represents the first to provide a comprehensive assessment of the validity of the ZaiDoc™ AI digital health platform as a symptom-based diagnostic aid in the outpatient clinic setting in Nigeria. The results show the system can produce excellent overall diagnostic performance, which demonstrates the need for reliable and accessible diagnostic aids that are both scalable and affordable to use in low-resource primary care settings. The discussion addresses the implications of the main statistics found from this research, defends them based on the clinical context they were developed in and places the results of this study in the larger body of literature on validating diagnostic systems using artificial intelligence.

The platform's 93.0% overall accuracy provides a strong indication of high-level agreement between the proposed platform and reference diagnoses. A tool with this level of reliability in a high-volume, resource-constrained environment, such as a busy outpatient department, could provide significant support to clinicians by reducing diagnostic uncertainty and supporting clinical decision-making (32). The distribution of errors, 5% false negatives compared with 2% false positive, is also important to consider when interpreting the performance of the algorithm. The distribution suggests that the algorithm is inherently conservative in its operation. Specifically, it prioritizes specificity to minimize false alarms. By minimizing false alarms, the number of unnecessary referrals and investigations can be reduced and thus limit the use of a limited set of resources (33).

Nevertheless, there is also a risk of missing positive cases, which indicates that the main clinical risk of using ZaiDoc™ digital health platform in its present form is an under-diagnosis of patients, rather than over-diagnosis of patients. Additionally, the specificity (96.30%) and positive predictive value (95.35%) of the platform are of particular interest. High specificity is important in primary care screening and triage tools, especially in low prevalence settings or when false positives could lead to costly or invasive follow-up testing (34). Additionally, the positive predictive value (PPV) indicates that when the platform suggests a patient has a specific condition, clinicians can be highly confident in that conclusion, which is essential for both clinician trust in the tool and its eventual use; this aligns with the principle of diagnostic precision (3).

Consistent with research into the use of AI-based diagnostic tools in primary care, these results demonstrate that the sensitivity (89.13%, CI: 76.96-95.28%) was greater than that of the other tools, as it had the largest upper and lower bounds on the confidence intervals. The larger confidence interval around the sensitivity indicates the natural statistical variability that occurs when the sample size is small and the number of positive cases is limited. Statistically speaking, many false negatives will be present. A high sensitivity is important in settings like Nigeria, where many infectious diseases are present, to ensure that individuals who have been misdiagnosed do not experience adverse outcomes from missed treatment (35).

The sensitivity achieved in this study is higher than those of other symptom checkers in low- and middle-income country settings; however, it demonstrates the importance of augmenting the use of these tools with clinical judgment (36). The negative predictive value of 91.23% supports this statement by showing that negative predictions can be made reliably, although there may be slightly less certainty surrounding positive predictions compared to negative ones.

The multi-metric nature of this performance is a major asset for an OPD tool since it will be required to assess a broad range of possible differential diagnoses. Although the ROC analysis provided a theoretical perspective on the platform's ability to achieve a beneficial tradeoff at an operational point with both high sensitivity, 89%, and a relatively low false positive rate, 3.7%, the operational point selected by the tool provides a clinical advantage to the user because it identifies a large proportion of actual disease cases while simultaneously minimizing the volume of false alerts, thereby reducing the potential for alert fatigue (2).

There are increasing studies on the use of AI at the front line of healthcare, and these findings are part of this larger body of evidence supporting the use of AI at the front line of healthcare. The systematic review of diagnostic AI in low- and middle-income countries found that the successful diagnostic AI tools will typically have a sensitivity and positive predictive value greater than 90% (37).

The platform also achieves both criteria as well as aligning with the WHO's recommendations for the development of digital diagnostic tools, including a balanced risk assessment for deployment in a specific setting that includes the epidemiological context and the capabilities of the health care system in that location (38, 39). Perhaps most importantly, the tool's ability to perform at high levels of accuracy based solely on symptoms and does not require complex laboratory or imaging data makes it relevant to the needs of decentralized care in low-resource environments.

The positive user experience remarks regarding ease of use, ease of training, and seamless integration into very busy clinical workflows are not secondary outcomes; rather, they are a primary factor in determining real-world impact. Ultimately, successful deployment of digital health solutions in Africa is likely to be most determined by usability and workflow compatibility rather than the performance of algorithms alone (40). ZaiDoc's ease of navigation and clearly stated instructions help overcome two of the most common barriers to adoption in developing countries, i.e., lack of digital literacy and time constraints, and therefore have the potential to be sustainable and scalable in various resource-constrained environments (40, 41).

Future Research and Practical Implications

The findings of this study provide preliminary evidence that the ZaiDoc™ AI Digital Health Platform may support diagnostic decision-making in outpatient healthcare settings. In practical terms, the platform could assist clinicians by organizing patient symptoms, generating diagnostic suggestions, reducing diagnostic uncertainty and supporting more consistent clinical decision-making, particularly in high-volume and resource-limited outpatient departments. The platform may also be useful for supporting less-experienced healthcare workers, improving patient flow, and promoting more efficient use of limited diagnostic resources. However, the platform should be used as a clinical decision-support tool and not as a replacement for professional clinical judgment.

Future research should focus on larger, multi-center prospective studies involving more diverse patient populations, wider disease categories, and different levels of healthcare facilities.

Independent external validation is also needed to confirm the generalizability of the platform's diagnostic performance beyond the current study sites. Further studies should assess the platform's impact on clinical outcomes, diagnostic safety, workflow integration, cost-effectiveness, clinician acceptance, patient satisfaction, and long-term implementation in routine outpatient practice.

Limitations

This research has some constraints. The sample size, though sufficient for an initial validation, is related to the width of the confidence interval, especially for sensitivity. Due to the simulated nature of the ROC curve, it is necessary to use caution when interpreting these results, with future studies involving a full threshold sweep of a larger, prospective cohort. The nonprobability sampling technique and the limited disease spectrum may have introduced spectrum bias and reduced the generalizability of the findings to broader outpatient populations. The other limitation of this study is that it used a single real-world validation cohort from two outpatient health facilities, and no independent external validation cohort was included. Therefore, the generalizability of the findings to other populations and clinical settings may be limited. Future studies should include larger, multi-center external validation cohorts to confirm the platform's diagnostic performance across diverse healthcare contexts.

Conclusion

This validation study demonstrates that the ZaiDoc™ AI Digital Health Platform has promising clinical validity as a symptom-based diagnostic support tool for outpatient healthcare settings. The platform showed strong diagnostic performance, with high sensitivity, specificity, positive predictive value, and negative predictive value. The platform has potential to support clinicians in identifying probable disease conditions and improving diagnostic decision-making. Its high specificity and positive predictive value suggest that the platform may be particularly useful in strengthening clinicians' confidence when confirming suspected diagnoses, while its favorable user experience indicates that it can be integrated into routine outpatient workflows with minimal disruption. The findings are especially relevant for resource-limited settings, where outpatient departments often face high patient volumes, limited diagnostic infrastructure, and shortages of specialized healthcare professionals. By providing structured, AI-supported diagnostic suggestions, the ZaiDoc™ platform may help reduce diagnostic uncertainty, support timely clinical decisions, and promote more efficient use of available healthcare resources. However, the platform should be used as a clinical decision-support tool rather than a replacement for professional clinical judgment.

Although the results are encouraging, further large-scale, multi-center, prospective validation studies are required to confirm the platform's performance across broader patient populations, diverse disease conditions, and different levels of healthcare facilities. Future research should also assess long-term clinical outcomes, cost-effectiveness, workflow integration, health-worker acceptance, and the platform's impact on diagnostic safety. Overall, this study provides important preliminary evidence supporting the potential role of the ZaiDoc™ AI Digital Health Platform in strengthening outpatient diagnostic services in Nigeria and similar low- and middle-income healthcare settings.

Abbreviations

AI: Artificial Intelligence, EHR: Electronic Health Record, NICE: National Institute for Clinical Excellence, NPV: Negative Predictive Value, OPD: Outpatient Department, PPV: Positive Predictive Value, TN: True Negative, TP: True Positive, WHO: World Health Organization.

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Author Contributions

Mohammed Muze: Conceptualization, Formal Analysis, Investigation, Data Curation, Validation, Formal Analysis, Data Curation, Investigation, Methodology, Writing- Review, Editing, Manuscript Preparation.

Conflict Of Interest

The author declares that there are no competing interests.

Data Availability

Data sets used and analyzed during the current study are available from the corresponding author on a reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

This work was developed with the assistance of artificial intelligence tools to support clarity, the flow of ideas and drafting and editing. All final content was reviewed, verified and approved by the author, who remains fully responsible for its accuracy, originality and integrity.

Ethics Approval

Ethical clearance was obtained before data collection was initiated. At the time of data collection, written consent was obtained from the study participants. Those not willing to participate were given the right to do so. Confidentiality of response was also maintained throughout the research process.

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