

Overcoming Cognitive and Contextual Challenges in Febrile Illness Diagnosis: Design Implications for Clinical Decision Support Systems in Sub-Saharan Africa

Faiza Umar Bawah

Department of Computer Science
University of Ghana
Accra, Ghana

Department of Computer Science and Informatics
University of Energy and Natural Resources
Sunyani, Ghana
fubawah@st.ug.edu.gh

Weston Baxter

Imperial College London
London, United Kingdom
weston.baxter@imperial.ac.uk

Jamal-Deen Abdulai

Department of Computer Science
University of Ghana
Accra, Ghana
jabdulai@ug.edu.gh

Talya Porat

Imperial College London
London, United Kingdom
t.porat@imperial.ac.uk

Abstract

Febrile illness contributes significantly to mortality and socioeconomic burden in Sub-Saharan Africa. Clinical decision-making is complex due to overlapping symptoms, limited lab infrastructure, resource constraints, and the cognitive demands placed on healthcare professionals. Despite growing deployment of clinical decision support systems (CDSS) and point-of-care diagnostics, adoption and sustained use remain limited, as many tools prioritize tests or guideline enforcement while overlooking diagnostic reasoning and contextual realities. We report findings from semi-structured interviews with 26 healthcare professionals in Ghana examining cognitive and contextual challenges in febrile illness diagnosis. Using reflexive thematic analysis, we identify interacting cognitive challenges (e.g., reasoning under uncertainty, heuristic decision-making, premature closure) and contextual constraints (test availability, patient costs, communication barriers, fragmented documentation) that shape diagnostic trajectories. We show how these challenges accumulate across diagnostic stages and reinforce empirical treatment. We outline implications for designing workflow-aligned CDSS that support diagnostic reasoning under real-world constraints in low-resource settings.

CCS Concepts

• Human-centered computing; • Empirical studies in HCI;

Keywords

Design, Clinical Decision Support System, Challenges, Africa

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1 Introduction

Febrile illnesses remain a leading cause of morbidity and mortality in sub-Saharan Africa (SSA) [25, 31], where healthcare professionals (HCPs) diagnose and manage overlapping infectious diseases amid limited laboratory infrastructure and constrained clinical resources [16, 17]. In malaria-endemic regions, malaria is often the default diagnosis for febrile illness, contributing to the routine administration of antimicrobial or antimalarial medications, increasing the risk of antimicrobial resistance (AMR) [26].

Diagnosis of febrile illness is a multi-stage cognitive activity shaped by contextual constraints, including limited access to diagnostic equipment and medications, stock-outs of essential supplies [18, 24], variability in training and high patient volumes [8, 9, 13]. HCPs must distinguish clinically similar conditions, reason under uncertainty, and interpret incomplete or ambiguous information, while sociocultural expectations, such as assumptions that fever requires antimalarial treatment, further influence diagnostic and prescribing decisions [24, 40]. Importantly, such contextual pressures do not merely limit available actions, they structure how clinicians attend to, interpret, and prioritize diagnostic information.

Clinical decision support systems (CDSS) and point-of-care (PoC) have been introduced to support diagnosis [10, 13] in SSA, but they often fall short of supporting the full diagnostic workflow and accommodating the diverse roles, responsibilities, settings, and decision-making needs of different healthcare providers [33, 35]. Furthermore, existing CDSS usually emphasize protocol enhancement, neglecting cognitive and contextual realities [1, 15, 21, 23, 36].



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There remains limited empirical understanding of how cognitive and contextual challenges shape diagnostic reasoning across the diagnostic process, and how these challenges vary by diagnostic stage [37]. Addressing this gap is essential for designing CDSS aligned with real-world workflows, supporting diverse healthcare roles, and meaningfully augmenting clinical decision-making rather than adding burden [5, 35].

The aim of this study is to identify the contextual and cognitive challenges that arise across the diagnostic process for infectious febrile illnesses in low-resource settings, using Ghana as a case study, and to derive design implications for a diagnostic decision support system (CDSS) that can support healthcare providers at each stage of this process.

2 Background and related work

Healthcare systems in SSA involve diverse healthcare professionals such as community health workers, doctors, nurses, physician assistants and pharmacists, whose diagnostic expertise and responsibilities vary across health facility levels [2]. This variety ensures broad access to care but also leads to variation in diagnostic expertise and decision-making abilities.

CDSS have demonstrated improvements in diagnostic quality and treatment decisions in high-income settings [30, 32]. Adoption and sustained use in LMICs, such as SSA, remain limited [11]. Existing CDSS deployed in SSA often prioritize protocol adherence, with limited support for clinical reasoning, uncertainty management, or result interpretation [15]. Adoption is further hindered by usability issues, limited trust, infrastructure constraints, and the mismatch between system design and users' training levels and workflows, particularly for Community Health Workers (CHWs) and nurses, for whom such systems may be too complex or poorly integrated into practice [11, 29, 33].

Research on the design of CDSS for the African context is sparse, with limited literature reporting misalignment between data entry and existing clinician workflows [7]. In similar low-resource contexts, it has been demonstrated that systems that are designed without regard for contextual factors and workflow integration do not achieve long-term adoption [22, 33]. To design effective CDSS that meaningfully support febrile illness diagnosis in low-resource settings, there is a need for empirical understanding of how contextual and cognitive factors shape diagnostic reasoning across stages of care to improve functionality and user acceptance [4].

3 Methods

We conducted semi-structured interviews with 26 healthcare professionals in Ghana (5 doctors (D), 6 physician assistants (PAs), 7 community health nurses (CHN), 5 general nurses (GN), and 3 pharmacists (P)) with varying years of experience, ranging from 2 to 17 years, across community health planning services (CHPS) compounds, health centers, polyclinics, maternity homes, and hospitals in Greater Accra and Bono regions. Participants were recruited through their health facility management. The interviews were conducted at participants' workplaces, averaged 45 minutes, and were audio-recorded. Interviews explored HCPs' diagnostic processes, cognitively demanding tasks, sources of uncertainty, use of guidelines, and existing decision support practices. Thematic

saturation [8, 32] was reached after 20 interviews, with the remaining 6 interviews confirming saturation across roles. Transcription was done automatically, and codes were assigned manually. This study was approved by the Ghana Health Service Ethics Review Committee (GHS-ERC) under number GHS-ERC:014/05/24.

We adopt a five-stage model of the diagnostic process (Figure 1) as an analytical framework for this study to identify the broader diagnostic workflow and decision points. This structure builds upon and adapts the diagnostic framework proposed by the National Academy of Medicine [19] and is consistent with established models of clinical reasoning and decision-making [6, 8, 14, 20].

4 Analysis

Interview data were analyzed using reflexive thematic analysis, following Braun and Clarke's approach [4]. Coding was inductive and iteratively refined. Transcripts were analyzed thematically using MAXQDA [4, 27] by developing codes to distinguish 'cognitive' from 'contextual' factors. To support analytical integration and interpretation, identified cognitive and contextual challenges were subsequently mapped onto the five-stage diagnostic process framework adapted from the National Academy of Medicine [19].

5 Findings

Thematic analysis of interviews [4] revealed two overarching categories of challenges: (1) cognitive challenges, relating to reasoning and decision-making processes; and (2) contextual challenges, stemming from environmental, structural, and organizational constraints.

5.1 Cognitive Challenges across the diagnostic process

This theme captured difficulties related to clinical reasoning during the diagnostic process. Subthemes included reasoning under uncertainty, experience-based clinical judgement, critical thinking and diagnostic reasoning, and information gathering and interpretation.

Reasoning under uncertainty reflects cognitive challenges that arise when HCPs must make diagnostic decisions despite incomplete, ambiguous, or unreliable information. "... Sometimes, you may be confused as to what is actually the cause, especially in cases where patients may have taken some drugs that did not work for them. Then, you have to really think outside the box" (P3). This indicated that the pharmacist was unsure of the state of the patient but had to decide on a treatment plan.

Experience-based clinical judgement highlights reliance on heuristics, pattern recognition and tacit knowledge, necessary shortcuts, but also potential sources of bias. As one doctor explained, "If the results are negative but I strongly suspect an infection, I rely on the history and physical examination findings" (D1). This suggested that the doctor relied more on his experience to provide a diagnosis when he did not trust test results.

Critical thinking and diagnostic reasoning involved analytical evaluation under time pressure. A physician assistant described having vague complaints such as "my body is hot" (PA6). This reflects hypothesis generation, cue evaluation, and differential diagnosis under time pressure. It also demonstrates cognitive shortcuts,

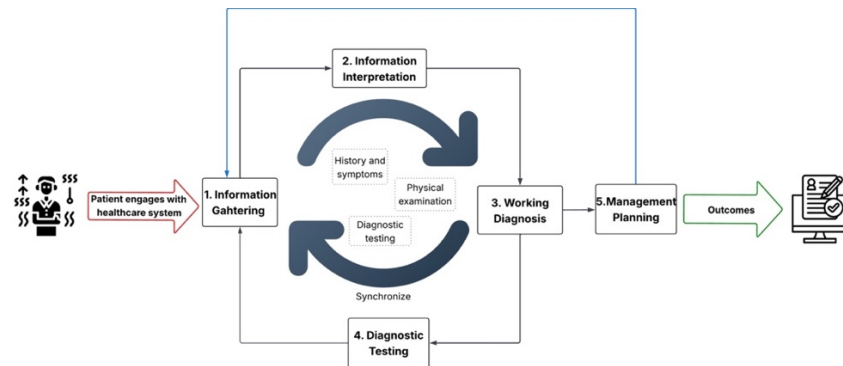


Figure 1: Five-stage Diagnostic Process. Adapted from National Academies of Sciences, Engineering and Medicine [19].

which may lead to a premature diagnosis, especially when febrile illnesses share overlapping symptoms.

Information gathering and interpretation required HCPs to select and connect multiple symptoms, a cognitively demanding process in contexts where cues may be vague or overlapping. “At this point, I am looking out for symptoms of malaria, given the fever and chills. So, I ask for general symptoms, like bitterness in the mouth; they are all positive. So that is pointing us to malaria” (D1). This shows how reliance on pattern recognition when interpreting non-specific cues and reliance on pattern matching and bias increase the risk of premature diagnosis.

5.2 Contextual Challenges across the diagnostic process

Contextual challenges related to the environmental and systemic constraints surrounding clinical practice. Subthemes included financial constraints of patients, language and communication barriers, inadequate diagnostic equipment, and systemic and workflow barriers.

Financial constraints of patients were used to describe patients’ inability to afford healthcare costs. One of the doctors complained that “Some patients can’t afford the prescribed medications, so we try to find alternatives...” (D2). This poses a challenge for HCPs to come up with alternative treatment plans in such situations, particularly for inexperienced HCPs.

Language and communication barriers captured instances in which patients and HCPs differ in language and health literacy, making it difficult for HCPs to elicit symptoms from patients. One of the pharmacists explained how understanding the patient is crucial, saying, “Sometimes patients struggle to express themselves clearly or may use terms we don’t understand. For example, someone might say they have a ‘sore in the stomach’ when they mean abdominal pain. If you don’t probe further, you may misinterpret their condition” (P2).

Inadequate diagnostic equipment referred to lack of essential diagnostic tools, while systemic and workflow barriers highlighted structural issues with the healthcare system, such as staff shortages. One of the physician assistants described the lack of equipment as not ideal, stating, “We sometimes share oxygen monitors between patients, which isn’t ideal” (PA2). Systemic and workflow barriers

include high patient volumes, staff shortages and time constraints. A general nurse said, “The work can be stressful, especially when patients present with complex conditions or when resources are limited” (GN1), expressing how it affects her.

5.3 Mapped Challenges onto the five-stage diagnostic process and design implications

The identified contextual and cognitive challenges were mapped onto the five-stage diagnostic process [19]. The five stages include (1) information gathering, including symptom elicitation and patient history; (2) information interpretation, where signs and contextual cues are integrated; (3) working diagnosis, involving hypothesis generation and refinement; (4) diagnostic testing, including selection and interpretation of results; and (5) management planning, including treatment and referral decisions. The mapping highlights key decision points, current practices and breakdowns across the diagnostic pathway, revealing design opportunities to improve clinical decision support systems in sub-Saharan Africa (Figure 2).

6 Discussion

Diagnostic breakdowns emerge from interacting cognitive demands and contextual constraints that accumulate across stages, rather than isolated decision errors. This section discusses (1) what is distinctive about febrile illness diagnosis in Sub-Saharan Africa (SSA) and (2) how these insights advance the design of clinical decision support systems (CDSS) beyond protocol enforcement or test-centric approaches.

6.1 Febrile illness diagnosis in SSA: what is context-specific?

While diagnostic uncertainty is universal, several challenges are structurally specific to febrile illness diagnosis in SSA. Diagnosis constrained by test availability and cost fundamentally alters clinical reasoning, leading to test-driven rather than hypothesis-driven diagnostic strategies, reinforcing empirical treatment. Trust in negative results is fragile; antimalarials or antibiotics are often prescribed due to clinician uncertainty or patient pressure [3, 28] as they are interpreted within a broader socio-cognitive system

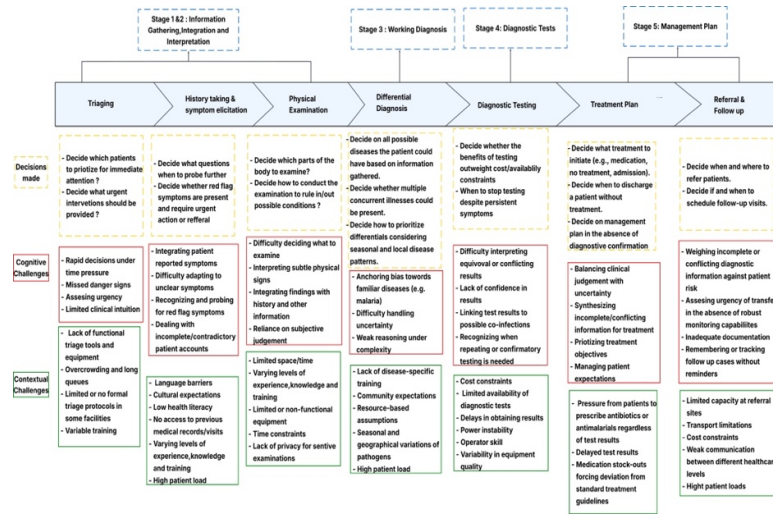


Figure 2: Mapped decisions, cognitive and contextual challenges to diagnostic stages

shaped by disease prevalence, patient expectations, and fear of missing serious illness.

Role diversity amplifies variability in diagnostic reasoning and confidence but also presents an opportunity: appropriately designed CDSS could support task-shifting and align with HCP's expertise and workflow [35, 36]. Lastly, seasonality and local disease ecology play a more prominent role in diagnostic reasoning. Clinicians explicitly referenced seasonal patterns (e.g., meningitis season) when forming differentials, highlighting the importance of temporality and geography in diagnosing febrile illness. However, current CDSS rarely integrate such contextual epidemiological knowledge in a way that is visible and actionable for frontline providers.

6.2 Implications for CDSS design: beyond protocol enforcement and test integration

Our analysis identified stage-specific design implications across the diagnostic process (information gathering, working diagnosis, testing, and management). Here, we summarize four cross-cutting design directions that emerged across stages.

Differential-Preserving Interfaces (Working Diagnosis Stage)

To counter malaria-centered anchoring, CDSS should maintain a visible, dynamically updating differential diagnosis rather than collapsing uncertainty into a single recommendation. Alternative hypotheses should remain visible throughout testing and management, with prompts for reconsideration following negative or inconsistent results.

Resource-Aware Recommendation Engines (Testing & Management Stages)

Decision support should reflect real-world feasibility. Instead of assuming ideal pathways, CDSS should recommend the “best feasible next step” based on local test availability, cost, and stock constraints, aligning diagnostic reasoning with contextual realities.

Trust-Building Explanatory Interfaces (Testing & Management Stages)

Given fragile trust in negative results, CDSS should surface clinician-facing rationales and patient-shareable explanations linking symptoms, risks, and test outputs. Making reasoning visible may reduce empirical prescribing driven by uncertainty or social pressure [5, 9, 12, 34].

Role-Adaptive Scaffolding (Information Gathering & Triage Stages)

Because diagnosis involves diverse healthcare roles, CDSS should adapt guidance depth and interface complexity to user expertise [39]. Structured prompts for CHWs and flexible navigation for physicians can support task-shifting without increasing cognitive burden.

While some findings are specific to malaria-endemic and resource-constrained settings, the underlying dynamics are not unique to Ghana. Prevalence-driven anchoring, reasoning under uncertainty, fragile trust in diagnostic outputs, and variability across healthcare roles are observed across health systems globally, including pandemic and resource-strained primary care settings [5, 33, 37]. In this sense, malaria represents a broader phenomenon: when one condition dominates epidemiologically or culturally, it reshapes diagnostic cognition [26, 38]. Our stage-based framing, therefore, offers a transferable lens for CDSS design in other infectious disease and cost-constrained contexts, while recognizing that implementation must remain locally adapted.

7 Conclusion

Diagnostic challenges in febrile illness care in low-resource settings arise from the interaction of cognitive and contextual constraints during diagnosis that accumulate across stages of care. Our findings explain why test- or protocol-driven solutions alone have had limited impact: diagnostic reasoning is shaped by uncertainty, resource availability and patient expectations. Effective CDSS must

therefore move beyond guideline enforcement to support sense-making under uncertainty through stage-aware, workflow-aligned, and context-sensitive design.

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