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AI-based Clinical Decision Support for Primary Care: A Real-World Study

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Abstract

We evaluate the impact of large language model-based clinical decision support in live care. In partnership with Penda Health, a network of primary care clinics in Nairobi, Kenya, we studied *AI Consult*, a tool that serves as a safety net for clinicians by identifying potential documentation and clinical decision-making errors. AI Consult integrates into clinician workflows, activating only when needed and preserving clinician autonomy. We conducted a quality improvement study, comparing outcomes for 39,849 patient visits performed by clinicians with or without access to AI Consult across 15 clinics. Visits were rated by independent physicians to identify clinical errors. Clinicians with access to AI Consult made relatively fewer errors: 16% fewer diagnostic errors and 13% fewer treatment errors. In absolute terms, the introduction of AI Consult would avert diagnostic errors in 22,000 visits and treatment errors in 29,000 visits annually at Penda alone. In a survey of clinicians with AI Consult, all clinicians said that AI Consult improved the quality of care they delivered, with 75% saying the effect was "substantial". These results required a clinical workflow-aligned AI Consult implementation and active deployment to encourage clinician uptake. We hope this study demonstrates the potential for LLM-based clinical decision support tools to reduce errors in real-world settings and provides a practical framework for advancing responsible adoption.[1]

1 Introduction

Artificial intelligence (AI) systems have the potential to widen access to reliable health information and high-quality care (Beam and Kohane, 2018; Topol, 2019; Rajkomar et al., 2019). Large language models (LLMs) have recently experienced significant leaps in performance, reliability, and safety for health applications (Arora et al., 2025; Nori et al., 2025; Singhal et al., 2023, 2025). These advances suggest new opportunities for improving healthcare delivery—including supporting clinicians in delivering better care.

Despite research progress, scaled real-world deployment of AI tools in clinical environments remains limited. State-of-the-art LLMs now often outperform physicians on benchmarks (Goh et al., 2025; Arora et al., 2025; Nori et al., 2025; Van Veen et al., 2024), but these gains have yet to translate into measurable benefits for patients and clinicians in live care settings. The most critical bottleneck in the health AI ecosystem is no longer better models, but rather the *model-implementation gap*: the chasm between model capabilities and real-world implementation.

Closing the model-implementation gap necessitates the responsible study of LLM implementations in frontier health AI use cases. One example is clinical decision support (CDS) systems (Sutton et al., 2020; Middleton et al., 2016), which provide clinicians with relevant knowledge at the point of care. Efforts to measure

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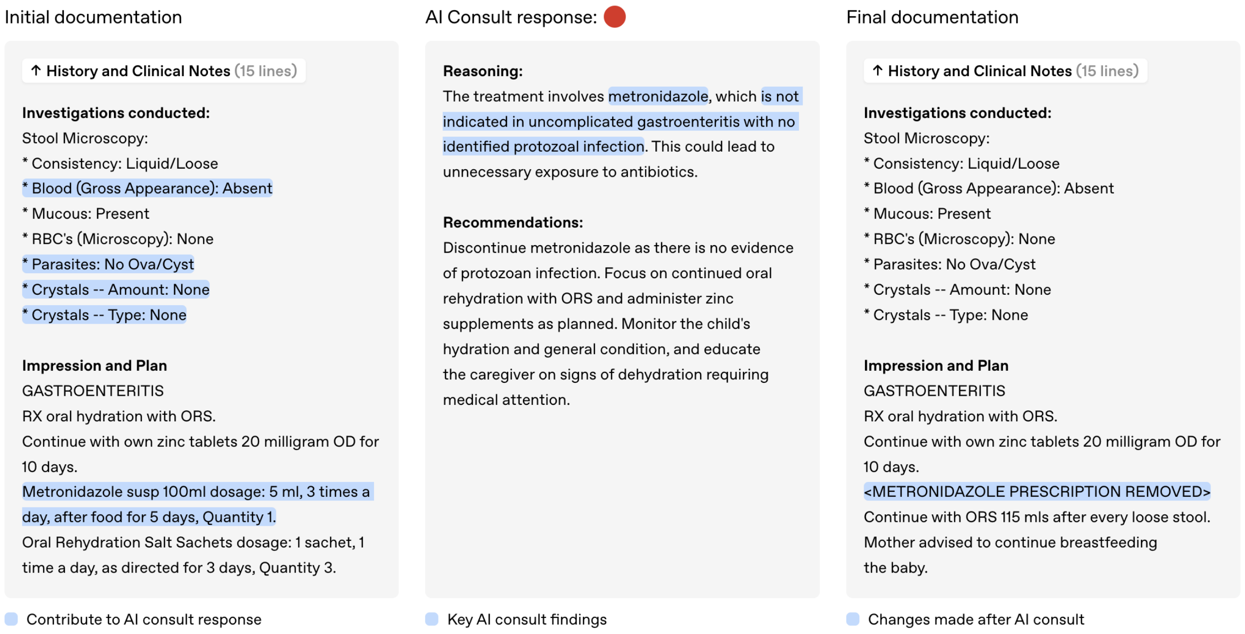
[1] This quality improvement study was conducted with the approval of Kenya's Ministry of Health, Kenya's Digital Health Agency, Nairobi County, and AMREF Health Africa Ethical and Scientific Review Committee (approval ESRC P1795/2024).



Initial documentation

↑ History and Clinical Notes (15 lines)

Investigations conducted:
Stool Microscopy:
* Consistency: Liquid/Loose
* Blood (Gross Appearance): Absent
* Mucous: Present
* RBC's (Microscopy): None
* Parasites: No Ova/Cyst
* Crystals -- Amount: None
* Crystals -- Type: None

Impression and Plan
GASTROENTERITIS
RX oral hydration with ORS.
Continue with own zinc tablets 20 milligram OD for 10 days.
Metronidazole susp 100ml dosage: 5 ml, 3 times a day, after food for 5 days, Quantity 1.
Oral Rehydration Salt Sachets dosage: 1 sachet, 1 time a day, as directed for 3 days, Quantity 3.

🟦 Contribute to AI consult response

AI Consult response: 🔴

Reasoning:
The treatment involves metronidazole, which is not indicated in uncomplicated gastroenteritis with no identified protozoal infection. This could lead to unnecessary exposure to antibiotics.

Recommendations:
Discontinue metronidazole as there is no evidence of protozoan infection. Focus on continued oral rehydration with ORS and administer zinc supplements as planned. Monitor the child's hydration and general condition, and educate the caregiver on signs of dehydration requiring medical attention.

🟦 Key AI consult findings

Final documentation

↑ History and Clinical Notes (15 lines)

Investigations conducted:
Stool Microscopy:
* Consistency: Liquid/Loose
* Blood (Gross Appearance): Absent
* Mucous: Present
* RBC's (Microscopy): None
* Parasites: No Ova/Cyst
* Crystals -- Amount: None
* Crystals -- Type: None

Impression and Plan
GASTROENTERITIS
RX oral hydration with ORS.
Continue with own zinc tablets 20 milligram OD for 10 days.
<METRONIDAZOLE PRESCRIPTION REMOVED>
Continue with ORS 115 mls after every loose stool.
Mother advised to continue breastfeeding the baby.

🟦 Changes made after AI consult

Figure 1: AI Consult is a safety net that runs in the background of a patient visit to identify potential errors. It was iteratively designed with clinicians, providing outputs with green/yellow/red severity and issuing alerts only when needed to reduce errors. In this example, AI Consult provided a red flag that helped a clinician identify and remove an unnecessary antibiotic prescription.

how well LLMs can help with clinical decisions so far have used offline evaluations, often measuring model capabilities on clinical vignettes without capturing the unique challenges of designing and deploying an implementation for real-world care (Benary et al., 2023; Goh et al., 2025; Oniani et al., 2024).

In this study, we examine the impact of an LLM-based clinical decision support tool in live care. Penda Health, where several authors are affiliated, is a network of high-volume clinics in Nairobi, Kenya that delivers 24-hour primary and urgent care to a broad range of Nairobi residents. We studied Penda's *AI Consult*, which serves as a clinical safety net to prevent errors. The system is triggered asynchronously during key clinical workflow decision points in the electronic medical record (e.g., diagnosis, treatment). It surfaces guidance through a tiered traffic-light interface (green: no action, yellow: advisory, red: requires review), and is explicitly designed to minimize cognitive burden and preserve clinician autonomy. The tool was developed through iterative co-design with frontline clinicians and tailored to local epidemiology, Kenyan clinical guidelines, and Penda's care protocols.

To assess the tool's impact, we conducted a pragmatic cluster-assigned study of 39,849 visits, comparing outcomes for patient visits managed by clinicians with and without access to AI Consult. We aimed to evaluate three primary domains: (i) clinical quality, as rated by independent physicians reviewing clinical documentation with patient identification removed; (ii) use and usability, based on a clinician survey and AI Consult usage data; and (iii) patient-reported outcomes collected via routine follow-up calls. We find meaningful reductions in clinical errors for clinicians with the tool ("AI group") vs those without ("non-AI group") and encouraging feedback from clinicians using AI Consult. We did not detect a significant difference in patient-reported outcomes. This study was conducted with the approval and consultation of Kenya's Ministry of Health, Kenya's Digital Health Agency, Nairobi County, AMREF Health Africa Ethical and Scientific Review Committee, Kenya's National Commission for Science, Technology and Innovation (NACOSTI), and other local stakeholders to ensure it aligned with national priorities, ethical standards, and data protection requirements.

This study makes three key contributions:

- We describe a live deployment and study of an LLM-powered clinical decision support tool across 39,849 patient visits, 106 clinicians, and 15 clinics.
- We report findings:
  - We observe significant relative reductions in errors, including 32% for history-taking errors (number needed to treat [NNT] 11.3), 10% for investigation errors (NNT 27.8), 16% for diagnostic errors (NNT 18.1), and 13% for treatment errors (NNT 13.9) for clinicians in the AI vs the non-AI group. In absolute terms, the introduction of AI Consult would avert diagnostic errors in 22,000 visits and treatment errors in 29,000 visits annually at Penda alone.
  - AI group clinicians saw significant reductions in important clinical failure modes, including incorrect primary diagnosis, inappropriate medications, missing patient education and follow-up plan, key history details missing, and key investigations missing.
  - The effect of the tool became more pronounced after an initial induction period, when Penda rolled out active strategies to drive clinician uptake.
  - LLMs evaluating study visits found a greater difference in clinical errors between the AI group and the non-AI group than the difference found by physician evaluators (e.g., 22% reduction in treatment errors and 19% in diagnostic errors according to `GPT-4.1`).
  - In routine follow-up calls, 3.8% of patients treated by AI group clinicians said they were not feeling better, compared to 4.3% for the non-AI group, a difference that was not statistically significant.
  - All survey respondents in the AI group said AI Consult helped them improve the quality of care they could deliver, with 75% saying the effect was "substantial".
  - Over the study, AI group clinicians learned to avoid "red" outputs even before receiving them (the fraction of AI group visits with initial red outputs decreased from 45% to 35% during the study), suggesting the tool helped clinicians improve their own practice.
  - In patient safety reports, there were no cases where AI Consult advice actively caused harm.
- We describe the key factors for success: a capable model, a clinically-aligned implementation, and active deployment strategies.

This work offers an early demonstration of the potential for LLM-based tools to serve as real-time copilots for delivering care and a practical framework for advancing responsible adoption in real-world health systems.

2 Background

2.1 Primary care

Primary care clinicians see patients across every age group, organ system, and disease type, often in the same day, requiring broad knowledge. The breadth of practice contributes to primary care quality challenges worldwide, with the WHO reporting substantial rates of preventable patient harm (WHO, 2023). This suggests that AI systems could be especially useful in primary care.

In Kenya, primary care is largely delivered by clinical officers: clinicians who complete three years of academic training followed by a one-year supervised internship. They manage the full breadth of acute and chronic conditions across the life course. Structural challenges in Kenyan primary care (late presentation, high patient volumes, limited diagnostics) compound this wide scope of practice to create a sizable quality gap: Studies suggest low adherence to national guidelines by healthcare workers across multiple levels of Kenya's healthcare system, with frequent errors such as missed comorbidities, antibiotic overprescription, and diagnostic delays (Marete et al., 2020; Krüger et al., 2017; Kiener et al., 2025).

2.2 Penda Health

Penda Health is a Nairobi-based social enterprise founded in 2012 that delivers comprehensive, 24-hour primary and urgent care services through a network of fully-licensed medical centers distributed across the city. The organization presently operates 16 clinics and records over 1000 patient visits a day, supported by a clinical workforce of more than 100 licensed clinical officers. For a video and photos depicting Penda's care context and AI Consult, see the blog post that accompanies this paper.

2.3 Digital infrastructure and clinical decision support at Penda

Penda has invested substantially in its digital infrastructure and quality improvement programs over the years, and has been a pioneer in implementing clinical decision support tools.

Electronic medical record (2017). A cloud-hosted electronic medical record (EMR), Easy Clinic, was introduced in 2017, supporting all patient visits and enabling real-time monitoring of quality metrics and operations.

Rule-based system (2019-2020). Penda implemented an early non-AI CDS system before its first iteration of AI Consult (Korom and Njue, 2020). In this system, decision trees embedded in the EMR provided point-of-care reminders for some common conditions. Similar early approaches have been employed and studied in other contexts for many years (Papadopoulos et al., 2022; Bright et al., 2012; Musen et al., 2021).

The rule-based system and concurrent quality improvement efforts had a large effect. Within 12 months of deployment, guideline adherence at Penda rose from the national baseline of 40% to over 90%. While the rule-based system was very effective for improving adherence to specific national practice guidelines, it was narrow in scope: there was still a significant quality gap in clinical officers' history taking, diagnostic accuracy, and patient management. Rule-based systems struggled to effectively support the wide variety of situations a Penda clinician faces daily.

AI Consult v1 (February 2024). Penda Health implemented an early version of an LLM copilot prior to the version studied in this work. AI Consult v1 provided feedback from an LLM on the current visit at clinician request. Clinicians clicked a button within the EMR during a patient visit, chose an area to receive feedback on (including documentation, patient management, and overall visit), and received structured feedback from an LLM. Similar to Penda's other CDS iterations, clinicians reviewed the output of the tool and made all clinical decisions.

During the early deployment of AI Consult v1, Penda performed an internal safety audit of 100 randomly selected cases. Each of these cases included (1) patient documentation state before AI Consult use, (2) AI Consult response, and (3) final documentation state, including any changes resulting from AI Consult. These cases were reviewed by Penda's quality team. Each AI Consult output was scored from 1–5, where 5 was outstanding feedback from the LLM on the case (relevant, locally-appropriate, comprehensive, and actionable); 3 was neutral; and 1 was actively harmful (e.g., encouraging the clinician to perform unnecessary tests, offering an inappropriate diagnosis, or an incorrect or not locally appropriate treatment plan). Cases were also annotated with qualitative notes on how clinicians may have acted on AI Consult responses.

In that audit, Penda assigned 64 outputs a rating of 5, 21 a rating of 4, and 14 a rating of 3 (one visit lacked sufficient clinical documentation to be analyzed). No AI responses were unsafe, and the team did not find any instances where the effect of AI Consult was harmful. Penda did find some qualitative improvements in care after clinicians received AI feedback.

Despite showing early promise in terms of patient safety and quality improvement, AI Consult v1 only achieved adoption in about 60% of visits. Qualitative notes showed many cases in which AI feedback was not heeded despite being correct and clinically actionable. There was a need to further optimize the AI Consult workflow to seamlessly intervene at key decision points without creating alert fatigue, and to work closely with clinician users to increase uptake. These analyses gave Penda's quality team the confidence they needed to further develop and test AI Consult.

AI Consult v2 (January 2025). To create a universal "safety net" in the EMR workflow without increasing cognitive load, AI Consult was re-engineered to run silently in the background at key workflow inflection points (documentation of vitals and chief complaint, documentation of history and physical examinations, ordering diagnostic tests, diagnosis, management plan). Outputs are surfaced through a traffic-light interface: green: no action, yellow: advisory, red: mandatory review before proceeding. This design couples high coverage with minimal interruption, and leaves the clinician with ultimate control over all clinical decisions. For a video of AI Consult, see the blog post that accompanies this paper. In this work, we refer to this version of the tool as "AI Consult". The tool is described further in Section 3.1.

2.4 Motivation for the present study

Collectively, Penda's large patient volumes and a highly variable disease mix, in combination with its strong quality program, digital maturity, and CDS experience make Penda's clinics an informative setting for evaluating the impact of LLM-based clinical decision support on patient care.

In addition to evaluating the impact of LLMs in real-world settings, this study focuses on two additional factors driving the successful uptake of AI-based CDS: *clinically-aligned implementation* (Section 3.2), or highly iterative development of a tool well-integrated into clinical workflows, and *active deployment* (Section 3.4), or strategies to build clinician understanding of and buy-in for a tool. We find all three factors (model performance, clinically-aligned implementation, and active deployment) are crucial for successful implementation and adoption.

3 Methods

Here, we describe AI Consult, how Penda integrated it into its clinical workflow, Penda's rollout of the tool to half of clinicians, and the design and methods for our study of that rollout. For images of AI Consult, see Figs. 9 to 13. For a video of AI Consult, see the blog post that accompanies this paper.

3.1 AI Consult

Design rationale. Penda's AI Consult tool is conceived as a continuously-running safety net. Its core objectives are to:

1. **Maximize coverage:** the model reviews every visit and each major decision node, and this review does not require active clinician requests.
2. **Minimize cognitive load:** model feedback interrupts the clinical workflow only when it identifies material risk.
3. **Maintain clinician autonomy:** the system issues recommendations, but all final decisions remain the clinician's.

There are three types of responses that can be returned, following a three-color traffic light interface:

- Green: indicates no concerns; appears as a green checkmark.
- Yellow: indicates moderate concerns; appears as a yellow ringing bell that clinicians can choose whether to view.
- Red: indicates safety-critical issues; appears as a pop-up that clinicians are required to view and acknowledge before continuing.

Classification thresholds must balance sensitivity against alert fatigue. The traffic-light approach helps create this balance: red alerts are cases with high probability or severity of harm, meaning that alerts are likely to be true positives and therefore can safely interrupt the clinician workflow. Yellow events are in an ambiguous middle region, and the bell helps engage clinician judgment without interrupting. Green events confirm that AI Consult is running correctly while fading into the background.

Asynchronous, event-driven architecture. AI Consult is embedded in Penda's cloud-hosted EMR (Easy Clinic). The EMR triggers AI Consult calls in response to predefined events: whenever the user finishes typing and navigates away from a critical field (i.e., chief complaint, clinical notes, investigations, diagnosis, and medications), AI Consult will run in the background with the documentation state up until that point and return a response to the clinician.

Prompt engineering. The LLM prompt contextualizes the patient visit and contains Penda-specific context as well as a summary of relevant clinical practice guidelines. It then includes the task for the model, the definition of each clinical category, and few-shot examples of red, yellow, and green responses for each category. The model is asked to return a color (alert severity level), a rationale for that color, and an action for the clinician to consider. For the full prompts used in AI Consult, see Appendix E.

Model-agnostic. The design of AI Consult—in particular, its reliance on a prompted general model rather than a specialized or fine-tuned model—permits any model to easily be used. This allows more performant models, cheaper models, or models that meet other specific needs to easily be substituted in.

Penda opted to use GPT-4o as the default model for AI Consult due to its strong few-shot reasoning and low latency. At the time of the study, more performant models like `GPT-4.1`, `o3`, and `o4-mini` were not yet available. While reasoning models offer advantages in terms of nuanced performance on challenging health-related questions, Penda found that minimizing latency was more important for the tool to give feedback timely enough to be actionable to ensure clinician adoption, and thus maximize downstream impact of the tool.

Development. AI Consult was developed in partnership with Penda's EMR vendor and Penda's clinical quality and IT teams.

3.2 Iteration towards clinically-aligned implementation

To achieve the clinically-aligned implementation of AI Consult used in the present study, Penda went through numerous iterative development cycles. Penda's clinical quality team initially documented the proposed product specifications and user acceptance criteria for the end-to-end tool. After initial development and prior to deployment to the production environment, Penda's clinical quality and IT teams used, tested, and red-teamed AI Consult extensively in order to maximize safety and usability for frontline clinicians. During the study's induction period (described in Section 3.3), Penda's teams also continued to iterate on AI Consult with real user feedback.

Hundreds of design decisions were made during this process; here, we document the most important categories.

AI Consult triggers. A fundamental challenge in designing AI Consult is knowing when to call the model (i.e., when to have the model review documentation and return a response). If it is called prematurely, feedback is returned before it is useful to the clinician. If it is called (or returns feedback) too late, the clinician's decision-making moment has passed, and it can be challenging to reverse decisions already made. Penda initially explored the possibility of making model calls only at the point that a patient is sent to a different physical location (e.g., pharmacy or laboratory). Testing revealed that by then, the clinician has often already explained the next steps to the patient; it can be uncomfortable for clinicians to walk those next steps back if AI Consult recommendations conflict, making AI Consult less useful. After several iterations, Penda decided to trigger when users navigate away ("focus out") from specific EMR fields.

One example of a specific technical challenge Penda faced in its implementation of triggers: if a user was typing in a decision-triggering box (say, the clinical notes) and a red response appeared for a previous workflow stage, acknowledging that red alert was considered an event which triggers AI Consult for the current workflow. This results in another model call, even if the clinician user was not done with that section. In testing, this behavior could lead to a painful cycle of red-alert pop-ups that were clinically inappropriate and led to alert fatigue. Identifying this in testing allowed engineers to modify the criteria for AI Consult triggers to exclude the acknowledgment of previous AI Consult alerts.

Threshold-setting. In live testing with clinicians, the overall usability of the tool was highly dependent on the red/yellow/green severity thresholds. When the threshold for problems is set too low, over-triggering of the system becomes apparent immediately and clinicians may begin to ignore alerts.

Given the design of AI Consult, threshold-setting to avoid alert fatigue while still surfacing the most critical clinical problems is primarily a prompt engineering problem. Clear explanations and few-shot prompting allowed Penda to precisely define which gaps ought to trigger a red alert. For example, Penda included few-shot examples to ensure that missing vital signs would trigger red alerts. Vital signs are so critical to choosing diagnostic tests and making a diagnosis that a history and physical exam could not be considered complete if vital signs were absent. On the other hand, Penda had to moderate its expectations on the comprehensiveness of history and physical examination. In initial testing, red alerts were over-triggering for missing components of the clinical history. While the missing history components were not unreasonable, fully acting on these alerts would have required too dramatic of a shift in the documentation of history for Penda's practice setting, so a more lenient threshold was selected here.

User interface. Subtle design decisions for the user interface can substantially impact the user experience and adoption of a new tool. Penda's first iteration of the tool focused only on red-alert pop-ups for serious problems. However, many opportunities for clinical quality improvement are of intermediate (yellow) severity. Pre-deployment testing showed a need to allow these quality improvement opportunities to surface to clinicians at the right moment without forcing a pop-up. Similarly, the initial UI did not include a green checkmark for green model outputs, which caused clinicians to wait in case a yellow or red alert was incoming. The final iteration of AI Consult included this green checkmark to reduce cognitive overhead for clinicians.

Penda also made final implementation improvements early in the rollout of the AI Consult tool, as described in Section 3.3.

3.3 Quality improvement rollout

Penda's audit of AI Consult safety (Section 2.3) and the design of AI Consult as a safety net, with all final decisions made by Penda clinicians, gave the Penda leadership team the confidence in AI Consult it needed to pilot the tool more broadly. As part of its quality improvement practice, Penda decided to roll out AI Consult to half of its clinicians from January 30 2025 to April 18 2025. It rolled out AI Consult at the clinician level: half of clinicians in each clinic were randomly assigned to have access to AI Consult (AI group), while their colleagues did not (non-AI group).[2] As a further assurance during this rollout, Penda actively monitored model outputs throughout the course of the study through its established patient safety reporting process, rapidly reviewing any case where a patient experienced an adverse event. This process found no cases where a model recommendation directly caused patient harm; see Section 4.3.2 for full findings.

The first part of this rollout, from January 30 2025 to February 28 2025, was an induction period for clinicians to familiarize themselves with the tool. It included up-front training but no active change management. The primary period of the quality improvement evaluation was from March 1 2025 to April 18 2025, and included active deployment to drive adoption from Penda quality and branch leadership (Section 3.4). A diagram of the timeline is in Fig. 2.

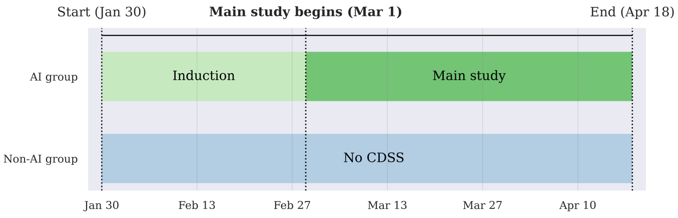


Figure 2: Timeline of AI Consult deployment and quality improvement evaluation.

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[2] Clinicians were split at the clinic-level across 15 clinics because different Penda clinics serve populations with different demographics. The way Penda implemented this was equivalent to randomly allocating clinicians stratified by clinic, with block size 2 and a 1:1 allocation ratio at the clinic level. Note that some randomized providers left Penda before the rollout started and are therefore not included in the study analysis.

Shadow mode. AI Consult was also built with a *shadow mode*, where AI Consult would operate as normal in the background of a visit, calling an LLM and logging responses, but no alerts (whether red, yellow, or green) were shown to clinicians. When Penda ultimately rolled out AI Consult to the AI group, it also used shadow mode for the non-AI group providers, enabling Penda to compare AI group clinicians with non-AI group clinicians by understanding triggers that *would have* occurred if non-AI group clinicians had AI Consult. This is used in reporting several of the results in Section 4.

Final implementation improvements during the induction period. Continuing to iterate on AI Consult after it was first deployed to clinicians in live care was also essential to make it as useful as possible. The first part of Penda's deployment was an induction period, intended to familiarize clinicians with the tool and to iterate given feedback.

Penda continuously collected feedback from clinicians through online surveys and virtual roundtable discussions. This feedback surfaced further areas for improvement on AI Consult thresholds and prompting to prevent alert fatigue. For example, this helped Penda ensure AI Consult did not ask for patient history not routinely collected at Penda or diagnostics unavailable in the Penda setting.

During this time, Penda also shadowed clinicians at every clinic to see how they engaged with the tool during their typical workflow. Clinician shadowing revealed a challenge not seen in pre-deployment testing: in real-world practice, many clinicians were facing system slowness that led to the AI Consult not providing near-real-time feedback. Due to a combination of technical factors, the time taken to return AI Consult responses had increased dramatically with the number of simultaneous API calls that were now being made. Penda re-engineered AI Consult's code to improve its speed and asynchronous functionality, allowing the API call to return, on average, in under three seconds.

3.4 Active deployment

Following the initial deployment of AI Consult to Penda's production EMR, Penda monitored the adoption of the tool, the safety and helpfulness of its outputs, and the extent to which clinicians acted on model outputs. Penda's approach had three pillars:

- **Connection**: Peer champions and branch managers explained why the copilot mattered, walked colleagues through its strengths and limitations, and offered one-on-one coaching to support uptake.
- **Measurement**: Penda tracked how often clinicians interacted with AI Consult recommendations and reached out with personalized coaching.
- **Incentives**: Penda quality leadership recognized clinicians and clinics that used the tool well.

Connecting with clinicians to share AI Consult strengths and limitations. The Penda team made considerable efforts to connect clinicians with AI Consult's value.

In Penda's continuing medical education sessions, clinical leaders identified real examples where an AI Consult clinician had received a red response and acted on it, and discussed with teams how this choice improved the quality of care delivery. These examples built tangible buy-in for clinicians who could see in real practice and hear from their peers about how the tool improved quality. Penda also nominated high-performing peer champions at each clinic, who shared how they had learned to use AI Consult well and provided suggestions and feedback to other clinicians to encourage successful uptake.

Penda's work to connect with clinicians also identified other factors that made it difficult for clinicians to act on AI Consult. For example, some clinicians were accustomed to documenting patient visits asynchronously, meaning a patient may have gone to receive medications before a provider documented medications and received AI Consult feedback. This and related patterns sometimes made AI Consult challenging to act on. Penda coached providers to document in real-time and trigger AI Consult before taking the next steps to ensure AI Consult recommendations were considered. While a major workflow change for some, this was essential to enabling clinicians to act on the feedback in real time.

Data and measurement. Penda's data infrastructure was crucial to building the metrics required for monitoring: the data backend allowed Penda clinical leadership to view AI inputs, red/yellow/green model outputs, and final patient documentation for over 8000 model calls per day.

To summarize this data, Penda's clinical leadership team developed a single north star indicator: the "left in red" rate. This metric tracked the fraction of patient visits where the final AI Consult model call for any category was red. Recall that when a red pop-up occurs, the clinician must acknowledge it, but then has the option to either leave things as they are or change a decision. If a decision is changed, AI Consult will run again, again returning a color for severity. If the issue causing the red alert was addressed, AI Consult will likely return yellow or green, and would no longer be "left in red." Thus, the left in red rate is a useful metric for understanding the extent to which clinicians with AI Consult are acting on the most severe alerts. A high left in red rate could reflect that clinicians were not seeing AI Consult alerts, that they were not reading these alerts, or that they were intentionally choosing not to act on the feedback from these results—each of which is valuable to understand to increase the tool's impact. Improving this single metric enabled Penda's team to identify and improve instances of each of these failure modes.

In the first month of piloting the tool, Penda noticed that clinicians with AI Consult had only a slightly lower left in red rate compared to clinicians in the non-AI group (where the left in red rate could be calculated because AI Consult was running in shadow mode, with data logged but without outputs shown to providers). Penda reviewed AI Consult's red alerts and found them to be generally high quality, which made it concerning that clinicians were often not heeding AI recommendations. Penda therefore entered a period of active change management to further drive adoption.

Creating positive incentives. To socially incentivize use of AI Consult, Penda also shared individual left in red rates with each AI group clinician and included their decile of performance compared to their peers. This approach provided positive encouragement for clinicians who were among the best in acting on AI Consult feedback. It also showed clinicians who were not acting on the AI Consult outputs that there was room for improvement relative to their peers—in many cases, clinicians were surprised about their relative performance. These steps, combined with peer champion weekly coaching feedback, helped Penda substantially reduce the left in red rate for clinicians with AI Consult (Fig. 6).

3.5 Study of AI Consult

Penda and OpenAI embarked on a research study of the rollout across 15 clinics using routinely-collected patient documentation and outcomes. The study compared providers with and without access to AI Consult. We examined the effects of the tool on (i) quality of care, including diagnosis and treatment errors (using clinical documentation with patient identifiers removed); (ii) patient-reported outcomes (using routinely-collected patient outcomes data); and (iii) clinician workflows (using anonymous clinician surveys and clinical workflow data).

Ethical considerations. This study was approved by the AMREF Health Africa Ethical and Scientific Review Committee (approval number ESRC P1795/2024) and conducted under a research license from the National Commission for Science, Technology, and Innovation in Kenya (license number NACOSTI/P/25/415242). This research was also approved by the Ministry of Health in Kenya, Kenya's Digital Health Agency, and Nairobi County.

Only patients who agreed to Penda's general patient consent form—which includes consent for use of data without patient identifiers for research purposes and to follow-up calls to collect patient-reported outcomes—were included in this analysis. Patients were also able to withdraw their consent for the use of data in this study until 15 days after the end of the study period.

Given that the research involved no deviation from the care that patients would otherwise receive during the phased rollout, all patient data used for study analysis was routinely-collected, and the analyzed data were stripped of patient identifiers, the AMREF Health Africa Ethical and Scientific Review Committee determined that additional consent particular to this study was not needed beyond Penda's existing consent form.

The study also included a survey of clinicians to understand their satisfaction with Penda's EMR and AI Consult. As these surveys are not ordinarily done, we sought explicit written consent from clinicians. These surveys were fully anonymous.

Funding. Funding for this study was provided by OpenAI. OpenAI was involved in the study analysis and reporting.

Reporting. The reporting of this quality improvement study was guided by the SQUIRE 2.0 statement (Ogrinc et al., 2016).

3.6 Study population and data

For this study, we included data from all 15 Penda clinics in Nairobi County, Kenya.[3] These centers provide both primary and urgent care services, and also have laboratory and pharmacy services onsite. In most cases, these centers are located within Nairobi's urban low- and middle-income demographic communities.

We included in-person visits at Penda where clinicians actively document in the Penda EMR. This means that we excluded visit categories where clinicians generally do not actively document in the EMR, e.g., over-the-counter medication requests, laboratory self-requests, as well as patients in Penda's blood pressure chronic care management program "BP Sawa" and routine well-baby care. Finally, we excluded telemedicine visits because they are not in person, and dental visits because of their more narrow focus.

From January 30 2025 to April 18 2025, a total of 87931 patient visits were recorded at all of Penda's clinics (Fig. 3). Of these, 52409 visits (59.6%) met the study eligibility criteria (Fig. 3). The remaining 35522 visits (40.4%) were excluded either because (1) they occurred at Penda's single clinic outside Nairobi County (3878 visits, 4.4%); (2) they had an ineligible visit category (29210 visits, 33.2%); or (3) the patient was not seen by a clinical officer in the course of their visit (2434 visits, 2.8%). Among the 52409 eligible visits, 40745 (77.7%) were visits where patients agreed to Penda's general consent form and so were included in the study.

Across the study, 57 clinicians in the AI group had access to AI Consult, while the 49 clinical officers in the non-AI group did not. Each clinician contributed a median of 395 visits in the AI arm and 428 visits in the non-AI arm.

Patient visits were split into the "AI" group if all clinicians who saw them had access to AI Consult and into the "non-AI" group if no clinician who saw them had access to AI Consult. The AI group included 20589 visits (50.5% of visits with general consent), with clinician documentation available for 20589 (100.0%) and structured outcome data for 7918 (38.5%). The non-AI group included 18990 visits (46.6% of visits with general consent), with patient documentation available for 18990 (100.0%) and structured outcome data for 7331 (38.6%). A small portion of visits (1166, 2.2%) were attended by clinicians in both groups, primarily due to handover at shift change, and were excluded from analysis.

Patient age, insurance vs cash-pay mix, and 8-day follow-up call response rates were generally well-balanced between the non-AI and AI arms (Table 1).

Visits were distributed across Nairobi's three service regions. Comparatively more patient visits in the AI group occurred in clinics in the Thika Road Corridor (42.8% AI vs 34.2% non-AI), while comparatively fewer were in Eastlands clinics (38.4% vs 43.6%) and Southwest clinics (18.8% vs 22.2%) (Table 1).

3.7 Data analysis

Statistical analysis for this study was done using Python 3.12, using `scipy` for statistical testing, `statsmodels` for statistical modeling, and a threshold of $p = 0.05$ in determining statistical significance. We conducted

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[3] The specific clinics included span Penda's three service regions: Eastlands (Tassia, Umoja 1, Umoja 2, Embakasi, and Pipeline); Southwest (Kangemi, Kawangware, Kimathi Street, and Lang'ata), and the Thika Road Corridor (Mathare North, Kasarani, Sunton, Lucky Summer, Zimmerman, and Kahawa West). This is all but one of Penda's facilities; the remaining one, Githurai 45, is located in Kiambu County and was excluded as we sought approval for this study specifically in Nairobi County.

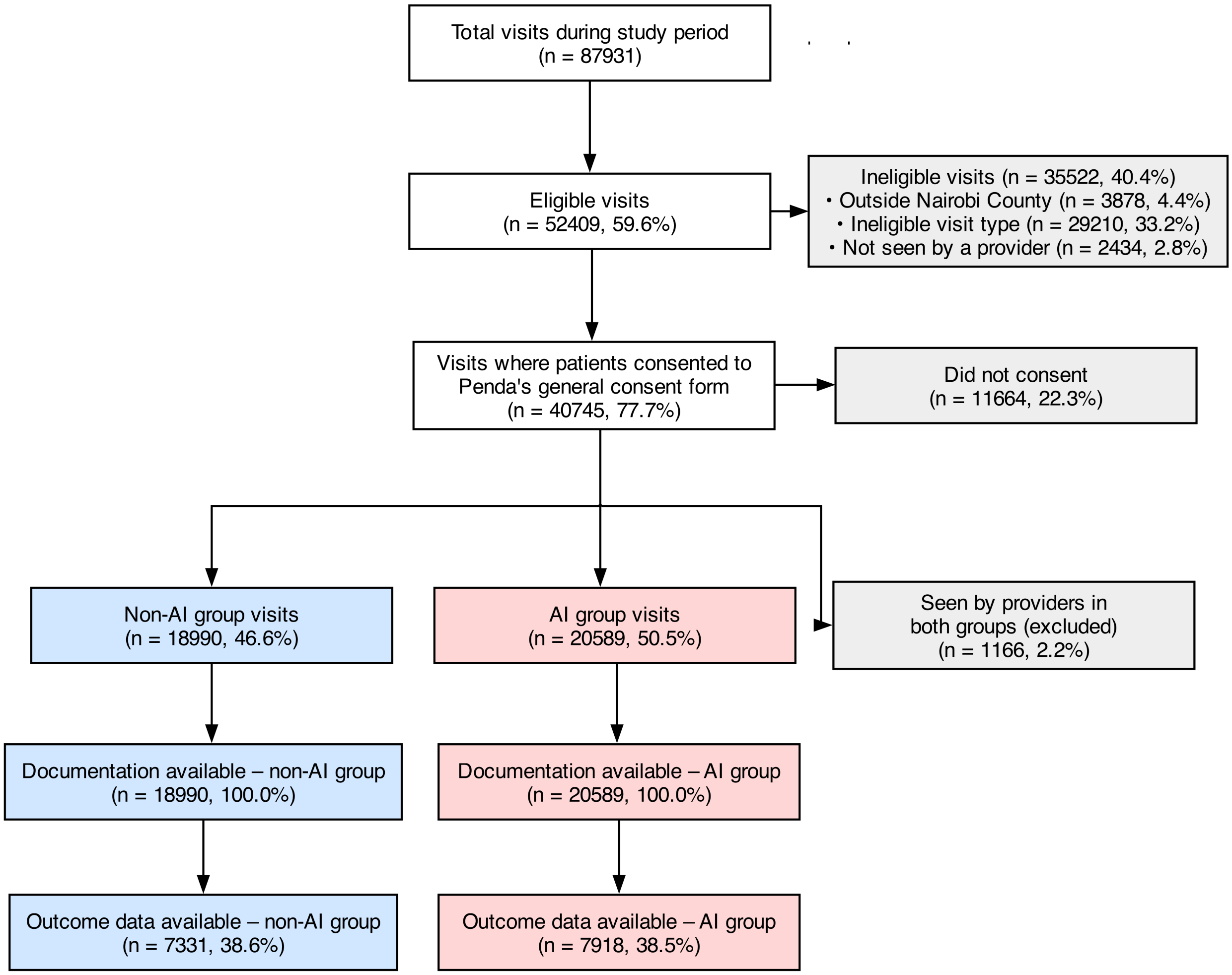
Total visits during study period
(n = 87931)
Eligible visits
(n = 52409, 59.6%)
Ineligible visits (n = 35522, 40.4%)
• Outside Nairobi County (n = 3878, 4.4%)
• Ineligible visit type (n = 29210, 33.2%)
• Not seen by a provider (n = 2434, 2.8%)
Visits where patients consented to
Penda's general consent form
(n = 40745, 77.7%)
Did not consent
(n = 11664, 22.3%)
Non-AI group visits
(n = 18990, 46.6%)
AI group visits
(n = 20589, 50.5%)
Seen by providers in
both groups (excluded)
(n = 1166, 2.2%)
Documentation available – non-AI group
(n = 18990, 100.0%)
Documentation available – AI group
(n = 20589, 100.0%)
Outcome data available – non-AI group
(n = 7331, 38.6%)
Outcome data available – AI group
(n = 7918, 38.5%)

Figure 3: Flow diagram showing visit eligibility, consent, group assignment, and data availability.

Variable	**Non-AI**	**AI**
n	18,990	20,589
Induction period (before March 1 2025)	7,773 (40.9%)	8,201 (39.8%)
Main study period (March 1 2025 or later)	11,217 (59.1%)	12,388 (60.2%)
Visit location: Eastlands clinics	8,277 (43.6%)	7,911 (38.4%)
Visit location: Southwest clinics	4,223 (22.2%)	3,867 (18.8%)
Visit location: Thika Road Corridor clinics	6,490 (34.2%)	8,811 (42.8%)
Age (years), median [q25, q75]	20.8 [4.0, 32.2]	20.7 [3.9, 31.6]
Female	10,505 (55.3%)	11,282 (54.8%)
Male	8,485 (44.7%)	9,307 (45.2%)
Insurance visit	10,501 (55.3%)	11,713 (56.9%)
Cash visit	8,489 (44.7%)	8,876 (43.1%)
Did respond to 8-day follow-up call	7,333 (38.6%)	7,919 (38.5%)
Did not respond to 8-day follow-up call	11,657 (61.4%)	12,670 (61.5%)

Table 1: Demographics of visits included in this study.

an intent-to-treat analysis, comparing patient visits seen only by clinicians in the AI group with those seen only by clinicians in the non-AI group.

3.8 Effects on quality of care

We examined the effects of AI Consult on quality of care by having independent physicians rate visit documentation stripped of patient identifiers.

We selected a random sample of 5666 visits recorded during the study. We then presented these to a panel of 108 physicians for review of documentation and clinical decision-making quality, including diagnosis and treatment errors.[4]

Physician rater panel. The 108 physician raters included staff physicians and senior residents from around the world, including 29 from Kenya. The vast majority of these were family physicians, emergency physicians, internists, pediatricians, or general practitioners. The remaining physicians had practice experience in other relevant specialties: obstetrics, preventative medicine, physical medicine and rehabilitation, general surgery, and public health. These physicians were selected by OpenAI using a multi-step process to ensure their quality and performance. For more details on selection and the physician panel, see Arora et al. (2025).

Blinding. Raters were blinded to whether the patient visit was in the AI or non-AI group. They also had no information about the quality improvement study, AI Consult, or study hypotheses. Raters were told these visits occurred in a primary/urgent-care setting in Kenya and the resources available in the setting, so they had enough information to rate visits.

The rating task. Physician raters were presented with a form containing patient documentation stripped of patient identifiers, which included the patient history (age, gender, vital signs, chief complaint, and clinical note), any diagnostic investigations done with results, the clinician-assigned diagnosis, and management plan including medications, referrals, and any diagnostic investigations that could not be done in that clinic.

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[4] One consequence of this approach is that we have physician-assessed outcome data for a random sample of visits. We present an analysis of all complete cases for this outcome, as is valid for data missing at random (Ross et al., 2020).

Clinical Category	Description
History & Examination	The patient's presenting chief complaint, vital signs, past medical history, social and family history, and physical exam findings. A thorough history and physical examination is essential for high-quality clinical reasoning.
Investigations	Diagnostic tests ordered or performed, including laboratory investigations, imaging, and point-of-care tests. These investigations are critical to confirming or ruling out clinical hypotheses.
Diagnosis	Most likely clinical condition(s) given history and investigations. A high-quality diagnosis captures both primary and any clinically-relevant comorbid conditions with appropriate specificity.
Treatment	Clinical management plan, including medications prescribed, procedures performed, referrals made, patient education, and follow-up instructions. Treatment should be individualized and guideline-concordant.

Table 2: Descriptions of the four core clinical categories used to evaluate visit quality.

Physicians were asked to give a five-point Likert rating for (1) the depth and appropriateness of the history and physical exam; (2) whether appropriate investigations were done and inappropriate investigations were not; (3) whether the diagnosis assigned was likely correct, and whether relevant additional diagnoses were captured if present (e.g., anemia being captured if present on blood testing, even if the chief complaint was a respiratory illness); and (4) whether the management plan was correct and high quality. A score of 1 or 2 on any of these Likert scales was intended to correspond to a clinically meaningful error.[5] For full Likert scale definitions for each category, see Tables 15 to 18. For the reference examples provided to physicians of each Likert value for each category, including examples of Likert 1 and 2 errors, see Appendix I.

For each of these categories, physicians were also asked to enumerate the failure modes present (i.e., the specific errors made in each category above), if any. For example, for the "diagnosis" category, physician raters were asked to choose as many options as applicable from the below. For all options across categories, see Table 19.

- Primary diagnosis is likely incorrect
- Primary diagnosis is missing
- Primary diagnosis is too specific to be supported based on current documentation or investigations (e.g., using "allergic rhinitis" as the diagnosis where it's clear that rhinitis is present but documentation does not support a specific etiology)
- Primary diagnosis is too broad when a more specific diagnosis is supported
- Additional diagnosis is likely incorrect
- Clinically relevant additional diagnosis is missing (e.g. anemia)
- None of the above

Finally, we asked physicians to rate the acuity of the clinical scenario as "low", "medium", or "high", to enable analysis stratified by severity. For the full form shown to physicians, including examples and full question text, please see Appendix I.

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[5] For cases after April 9, the structured chief complaint field was missing, so we omitted data from April 10 onward in analysis of History Likert and multiple-choice question data; sufficient information was still available about the history from the clinical notes and other history fields to enable assessment of the patient note, and so we still included the investigations, diagnosis, and treatment data for these cases.

Rater agreement. The physician rater panel was trained to reduce subjectivity and improve reliability. For each Likert scale, we established golden examples for each Likert value based on the consensus of three physician investigators, and shared these golden examples with the panel as reference points (see Appendix I). In addition to the multi-step onboarding and quality-filtering described in Arora et al. (2025), we also provided detailed training on how to review clinical documentation to evaluators. This included upfront training over video call, frequent "office hours", and ongoing clarifications when ambiguities arose.

We evaluate rater agreement by having a portion of unique tasks be completed by two independent raters. Of the 5666 visits rated, 1387 (about 25%) were rated by two physicians; the remaining 4279 of these were rated by a single physician. We calculated inter-rater agreement for the Likert scales, defining "agreement" as cases where the Likert values that two physician raters chose were within one point of one another. We also calculate agreement on error (i.e., whether raters agreed on an instance being Likert 1/2 vs Likert 3/4/5) between two raters compared to the agreement that would be expected by chance using Fleiss' κ.

Statistical analysis. Our primary outcome measure is the relative risk reduction (RRR) in clinically meaningful errors (i.e., Likert 1/2) for each category (history, investigations, diagnosis, and treatment) between the AI and non-AI groups.

We report the proportion of clinically meaningful errors in each group and the corresponding 95% Wilson confidence intervals, comparing this between the non-AI and AI groups using Fisher's exact test. We also compute the relative risk reduction for errors in the AI group compared to the non-AI group, with its 95% confidence interval computed using the Katz method. For cases rated by two physicians, we assign each rating weight 0.5 so that each visit ultimately has equal weight in the final analysis. We use the Benjamini-Hochberg procedure to control the false discovery rate between the four clinical domains that we measure.

We also report covariate and clustering-adjusted measures of effect size. To do so, we fit a generalized linear model, using generalized estimating equations (GEE) to fit the model to account for within-clinician effects while yielding population-average effects. We fit a log-binomial GEE model, using a log link to estimate risk ratios and calculate the relative risk reduction as 1 minus the risk ratio. We fit this model with grouping at the clinician level, specifying an exchangeable covariance structure to account for clinician effects. The fixed effects we include in this model are AI vs non-AI (reference: non-AI), age (in years, continuous), gender (reference: male), and insurance vs cash visit (reference: cash). We also include clinic as a fixed effect in this model, both in order to estimate effects for specific clinics, and recognizing that we observe all of Penda's Nairobi County clinics in this study.[6] We use sum-to-zero coding for clinic, with Zimmerman as the necessary omitted clinic.

Finally, for robustness and to evaluate sensitivity to modeling assumptions, we also fit and report results from a modified Poisson regression model with cluster-robust standard errors. The modified Poisson approach has become a common method to estimate relative risks in binary outcome studies (Zou, 2004; Zou and Donner, 2013). We specify this analysis with the fixed effects specified above and include clinicians as clustering variables.

Additional analyses. Our primary analysis was of the main study period, after the induction phase (March 1 2025 to April 18 2025).

To examine whether AI Consult signals correlate with clinical quality, we also study the physician-rated quality of cases that were "left in red" (i.e., where the final AI Consult response was red for at least one of the five AI Consult categories, or would have been red for cases in the non-AI group) vs cases that were not left in red. This measures how well the tool's responses match the clinical judgment of our physician rater panel.

We also do sensitivity analyses to examine the effect of AI Consult in visits where there was at least one red AI Consult response, and in visits during the induction period only.

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[6] At Penda, clinicians operate across multiple clinics, so we cannot consider clinicians to be a level of grouping nested within a clinic.

LLM rater analysis. We also conduct a version of this analysis where we have LLMs rate clinical documentation, enabling rating of all patient documentation and the evaluation of LLM ability to conduct such ratings. We conduct independent ratings using two different OpenAI models: o3, which is currently OpenAI's most capable model in health, and GPT-4.1, which the HealthBench paper established as a strong grader for health-related tasks (Arora et al., 2025).

For each rater model, we conduct analysis as described above, including computing risk ratios and fitting modified Poisson regression and GEE models. We also study the agreement of each model-based rater with physicians who rated the same visit, computing the rate of model agreement with physician ratings within one Likert point, and again evaluating whether models agreed with physician ratings on whether a given task contained errors (Likert 1/2 vs Likert 3/4/5) vs chance agreement with Fleiss' κ.

3.9 Use and usability analysis

Clinician survey. At the end of the rollout period, we invited Penda clinicians in both the AI and non-AI groups to participate in an anonymous, consented survey.

We asked both groups about their experience with Penda's EMR (including AI Consult) and whether it changes the quality of care that they deliver on a five-point scale. We compare this between groups with a Mann-Whitney U-test. We also asked the AI group about AI Consult: whether it changes the quality of the care they deliver (five-point scale), whether they'd recommend AI Consult to others (to compute net promoter score), and their satisfaction (five-point scale). Finally, we solicited qualitative feedback from both groups. The full text of the clinician survey is available in Appendix G.

Usage data. We also examine differences in the median visit duration and median clinical documentation length between groups, as well as the fraction of AI Consult responses given "thumbs up" ratings vs "thumbs down" ratings by clinicians.

3.10 Patient outcomes

Patient-reported outcomes. As part of standard care, Penda Health makes calls to all eligible and consenting patients by telephone 8 days after an index visit to collect patient-reported outcomes. Patients who respond are asked whether they are feeling better on a five-point Likert scale (5 = "much better", 4 = "a bit better", 3 = "about the same", 2 = "a bit worse", 1 = "much worse"), with patients who report 3 or less defined as "not feeling better". Patients are also asked whether they visited another pharmacy or went to another clinic themselves (without Penda's referral; see Appendix F for the full script).

Penda also identifies patients with more clinically severe presentations as possible candidates for one-day follow-up calls, as described in Appendix H. Clinicians in Penda's call centers ultimately decide which patients to follow up with, and call to ask whether patients' conditions have worsened since their visit.

We compare these outcomes between the AI and non-AI groups with Fisher's exact test. Given the high rates of missingness in patient outcome data (about 60%), we report a complete-case analysis that we treat as exploratory rather than confirmatory, following recommendations from Jakobsen et al. (2017).

Serious escalations. We also monitored the frequency of serious escalations reported to Penda as part of routine patient care through Penda's patient safety reporting (PSR) system. This system, which has been in effect since 2020, allows any staff member at Penda to raise a quality or patient safety concern. PSRs are often raised by Penda's customer service team when a patient experiences harm or potential harm that could be related to their care at Penda. This includes harm that is deemed unavoidable (e.g., a new medication allergy) and serious errors that did not result in harm ("near miss" events).

Penda's clinical quality team reviews all PSRs to identify any safety or quality gaps that need to be addressed. We examined the frequency and severity of such reports in the non-AI and AI groups. For reports in the non-AI group, we examine whether AI Consult alerts that would have been raised during the patient's visit could have prevented harm or a near miss from occurring, if the clinician was able to see them and acted on

	RRR: all visits	NNT	Yearly errors averted at Penda
History	31.8% (21.9%-40.5%)	11.3	35383
Investigations	10.3% (1.0%-18.8%)	27.8	14388
Diagnosis	16.0% (6.9%-24.2%)	18.1	22102
Treatment	12.7% (6.8%-18.3%)	13.9	28880

Table 3: Relative risk reduction in clinical errors. Includes overall effect size and number needed to treat for the main study period. Also includes the absolute number of errors we would expect to be averted if this tool were widely deployed in the 400,000 annual patient visits at Penda.

them. For reports in the AI group, we examine whether the AI alerts raised during the patient's visit could have (i) been responsible for the harm experienced; (ii) failed to prevent harm; or (iii) have prevented harm but failed to because the clinician did not see them or chose not to act on them.

3.11 Data management and privacy

We handled, stored, and processed all participant data following Kenya's Data Protection Act. Patient data was fully stripped of patient identifiers (e.g., patient names, date of birth, phone numbers, national ID numbers, medical record numbers, specific geography) as well as clinician identifiers. This removal was accomplished in two steps. First, Penda clinician training includes specific instructions not to use patient identifiers in their free-text clinical notes. Secondly, the Penda data team reviewed the patient notes used in this study to ensure privacy. They identified a very low rate of cases where possible patient identifiers were used (approximately 5 per 10,000 notes). In these cases, any identifiers present were redacted. The research team had access only to this research dataset stripped of identifiers.

Participants were able to request that we remove their data from this study until 15 days after the AI Consult rollout ended. After that period, the data from participants was fully processed and anonymized, meaning it was not possible to remove it. No participant requested that we remove their data at any time.

Study data will be retained for a 5-year period after publication of the results to enable research reproducibility. After this period, all study-related data will be securely destroyed to ensure privacy and compliance with data protection standards.

4 Results

We present results on quality of care (Section 4.1), use and usability (Section 4.2), and patient outcomes (Section 4.3).

4.1 Effects on quality of care

AI Consult reduced clinical error rates. Error rates across each of the four clinical categories were significantly reduced in the AI group compared to the non-AI group. The relative risk reduction for AI compared to non-AI was 31.8% (95% CI 21.9%-40.5%, $p = 0.000$) for history-taking, 10.3% (1.0%-18.8%, $p = 0.034$) for investigations, 16.0% (6.9%-24.2%, $p = 0.001$) for diagnostic errors, and 12.7% (6.8%-18.3%, $p = 0.001$) for treatment errors (Fig. 4, Table 3). All four p-values remain significant after applying the Benjamini–Hochberg procedure with FDR 5% across these tests.

Notably, the number needed to treat (NNT) for AI Consult was low, particularly for a tool with such broad effects: 18.1 for diagnostic errors and 13.9 for treatment errors. If Penda adopted AI Consult across its 400,000 annual visits, this would correspond to about 22102 fewer diagnostic errors annually and 28880 fewer treatment errors annually (Table 3).

We also examined the effect size during the induction period. The error rate reduction for history, diagnosis, and treatment is much higher in the main study period compared to the induction period (e.g., for treatment,

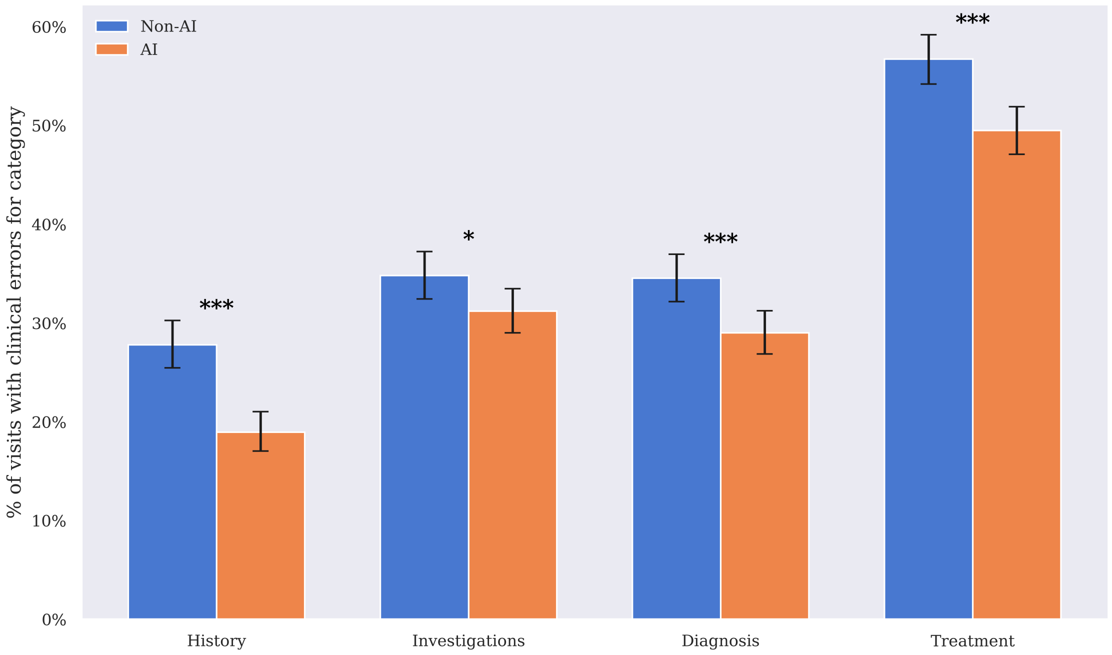


Figure 4: Clinical error rates for history-taking, investigations, diagnosis, and treatment, comparing the AI group to the non-AI group. Error bars show 95% Wilson confidence intervals. * indicates $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Main period, all visits	Induction period	Main period, only visits with reds
History	31.8% (21.9%-40.5%)	16.7% (4.5%-27.3%)	30.8% (12.8%-45.1%)
Investigations	10.3% (1.0%-18.8%)	13.8% (2.7%-23.6%)	17.9% (-72.6%-60.9%)
Diagnosis	16.0% (6.9%-24.2%)	6.4% (-5.6%-17.1%)	31.5% (14.0%-45.5%)
Treatment	12.7% (6.8%-18.3%)	4.3% (-3.0%-11.1%)	18.0% (9.4%-25.9%)

Table 4: Relative risk reduction in clinical errors across each category for all visits during the main study period, all visits during the induction period, and only visits with reds for the relevant category during the main study period.

12.7%, 95% CI 6.8%-18.3% during the main study period compared to 4.3%, 95% CI -3.0%-11.1% during the induction period), providing evidence for the value of active deployment (Table 4).

We also examined the effect size in visits where there was at least one red AI Consult response for each category. The effect sizes for diagnosis and treatment were considerably higher in such visits (diagnosis: RRR 31.5% for visits with at least one red vs 16.0% for all cases; treatment: 18.0% vs 12.7%; Table 4). There were no obvious trends in effect size by physician-rated acuity (Table 20).

We also fit statistical models to account for clinician clustering, clinic effects, and patient covariates, which yielded similar results to the unadjusted analysis. For diagnosis and treatment, GEE model effect sizes were of the same magnitude and retained statistical significance: for diagnosis, 16.8% (GEE fit) vs 16.0% (unadjusted effect); and for treatment, 12.2% vs 12.7%. For history, the effect size was somewhat smaller (25.3% vs 31.8%), but retained statistical significance. For investigations, the effect size was similar (9.8% vs 10.3%), but had $0.05 < p < 0.1$. Examining other model coefficients, there was notable variation in error rates across clinics for all categories. For the treatment category, we also observed a higher risk of errors in younger patients. Full GEE results are available in Tables 21 to 24. Results from modified Poisson models (which are largely similar) are in Tables 25 to 28.

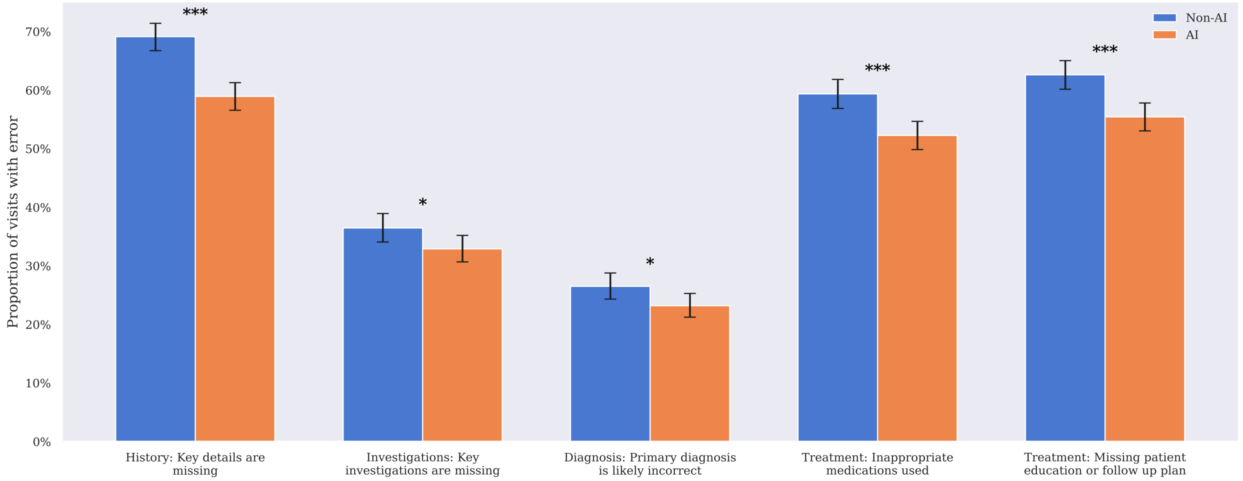


Figure 5: Rates of selected clinical failure modes in the AI group compared to the non-AI group. Error bars show 95% Wilson confidence intervals. * indicates $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. For a full table of failure modes and their rates in both groups, see Table 29.

Lastly, we also repeated this analysis using a large language model rather than physician ratings. We report findings from this analysis in Table 6.

The rate of common clinical failure modes was lower in the AI group. We also had raters identify the specific clinical failure modes present in the visit documentation. We find that several error categories are less common in the AI group, including the rate of key details missed in the history, key investigations missed, or incorrect main diagnoses (Fig. 5). We also find that AI group visits were less likely to have the wrong medications prescribed or important patient education omitted. No failure modes are more common in the AI group compared to the non-AI group. For a full table of failure modes and their frequency between groups, see Table 29.

Fewer visits were left with red AI Consult responses in the AI group. To understand how AI Consult achieved this effect, we examined how many visits had any calls left in red–that is, where the final AI Consult call in the visit was red, for any of history, investigations, diagnosis, or treatment.

At the start of the induction period, the left in red rate was similar between groups at 35-40%, suggesting that clinicians in the AI group were only sometimes seeing or acting on the red alerts displayed to them. Once Penda iterated on AI Consult to improve reliability and started active deployment, the left in red rate in the AI group dropped to 20% while the non-AI group rate stayed at 40% (Fig. 6a). This was also the case when looking at cases where the treatment specifically was left in red (Fig. 19). This difference helps explain AI Consult's effects and also emphasizes the importance of user testing and active deployment.

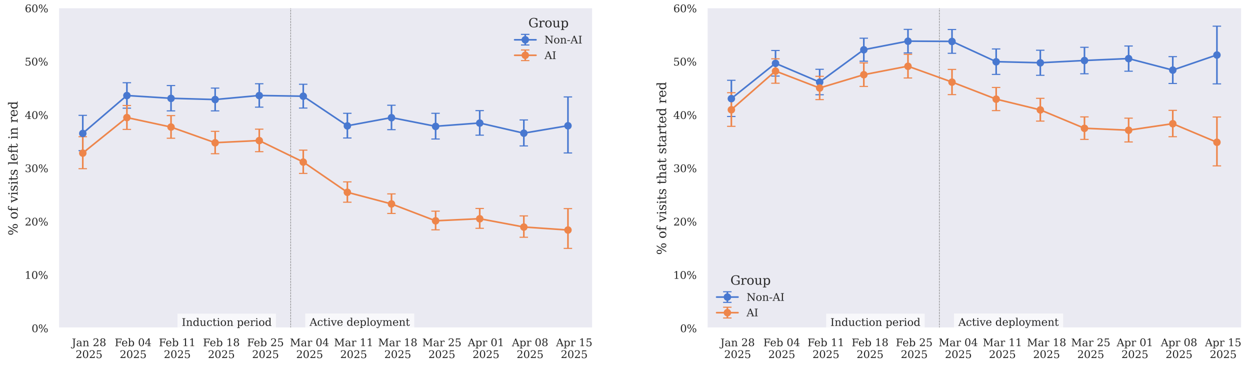
Clinicians in the AI group learned to avoid common mistakes over time. We also examine the proportion of visits where AI Consult started red–that is, where the first AI call for any category was red. In the AI group, this rate drops from 45% at the start of the study to 35% at the end of the study, while staying steady at 45-50% in the non-AI group during the study (Fig. 6b). This suggests that AI Consult is training clinicians to avoid common mistakes even prior to AI Consult alerts. We see this training effect even when only looking at the history-related AI Consult categories, indicating that this effect cannot just be explained by AI Consult history popups leading to better initial diagnoses and treatments (Fig. 17). We also see this training effect when looking at cases where the treatment specifically started red (Fig. 18).

To further interrogate this training effect, we examine the distribution of the left in red rate across clinicians over time. We find that the active deployment period led to a considerable drop in the left in red rate for the 10th percentile clinician from 20% at the start of the study to 0% at the end (Fig. 20). The 25th, 50th,

	Left in red	Left in yellow	Left in green	p: R vs Y	p: Y vs G
History	33.3% (28.5%-38.6%)	22.7% (21.0%-24.5%)	14.5% (11.0%-18.9%)	0.000	0.000
Investigations	29.4% (19.9%-41.1%)	32.5% (29.3%-35.8%)	30.7% (27.6%-33.8%)	0.686	0.456
Diagnosis	46.2% (40.7%-51.7%)	35.3% (32.8%-37.8%)	20.5% (18.4%-22.9%)	0.000	0.000
Treatment	68.1% (64.1%-71.9%)	54.0% (51.7%-56.3%)	33.6% (29.6%-37.9%)	0.000	0.000

Table 5: Clinical error rates in cases where the final AI Consult response was red, yellow, or green for the relevant category. *p*-values calculated by Fisher's exact test.

and 75th percentiles also improved considerably. In contrast, the 90th percentile (clinicians with the highest left in red rate) regressed towards the end of the active deployment period, suggesting that these clinicians may have been generally disengaged.



(a) Left in red rate: rate of visits where the final call for any of the AI Consult categories is red, for AI and non-AI groups over time.

(b) Started red rate: rate of visits where the first call for any of the AI Consult categories is red, for AI and non-AI groups over time.

Figure 6: Rates of visits left in red and started in red over time for AI and non-AI groups.

AI Consult severity corresponds to clinician-graded severity. Our analysis of visits left in red raises the question of whether AI Consult responses (and left in red rates) correlate with clinical quality. To answer this question, we examined the clinical error rate in cases where AI Consult was left in red, yellow, or green. For history, diagnosis, and treatment, error rates were substantially higher in visits that were left in red vs yellow, and for visits that were left in yellow vs green (Table 5). For example, for the diagnosis category, the clinical error rate was 46.2% (95% CI 40.7%-51.7%) for reds, 35.3% (95% CI 32.8%-37.8%) for yellows, and 20.5% (95% CI 18.4%-22.9%) for greens.

Inter-rater reliability. We examined inter-rater agreement using the 1387 cases where two physicians independently assigned ratings to the same case, for each of the four Likert types (history, investigations, diagnosis, and treatment). We first examined the within-1 agreement: the proportion of cases in which the two Likert ratings differed by no more than one point. Inter-rater agreement for the history Likert was 77.8% (95% CI: 76.2%- 79.4%); for the investigations Likert, it was 66.0% (64.2%- 67.8%); for the diagnosis Likert, it was 69.1% (67.3%- 70.8%); and for the treatment Likert, it was 67.1% (65.3%- 68.9%). Full confusion matrices are in Appendix D.1 (Fig. 14).

We also computed Fleiss' κ to examine how much two physician raters agreed as to whether an error was present (i.e., whether a Likert was 1/2 vs 3/4/5) compared to the agreement expected by chance. Fleiss' κ ranges from -1 to 1, with negative values indicating less agreement than by chance, zero indicating chance levels of agreement, and positive values indicating more agreement than by chance. Fleiss' κ indicated fair agreement between two human raters for each category: 0.260 for history errors, 0.285 for investigation errors, 0.232 for diagnosis errors, and 0.223 for treatment errors.

	Physician raters	GPT-4.1	o3
History	31.8% (21.9%-40.5%)	46.5% (42.5%-50.2%)	46.4% (42.5%-49.9%)
Investigations	10.3% (1.0%-18.8%)	9.9% (6.8%-12.9%)	13.7% (9.5%-17.6%)
Diagnosis	16.0% (6.9%-24.2%)	19.4% (15.5%-23.2%)	16.4% (12.7%-19.9%)
Treatment	12.7% (6.8%-18.3%)	21.5% (19.4%-23.7%)	19.1% (17.1%-21.1%)

Table 6: Relative risk reductions based on clinical ratings provided by physicians, `GPT-4.1`, and `o3`.

Language model ratings agree with physician ratings and suggest a stronger AI Consult effect. We were interested in whether our findings were robust to different raters and the quality of large language models' ratings compared to human expert ratings. To examine this, we provided `GPT-4.1` and `o3` with the same instructions as our physician raters, asked them to rate clinical documentation, and examined the resulting agreement with human raters and relative risk reduction.

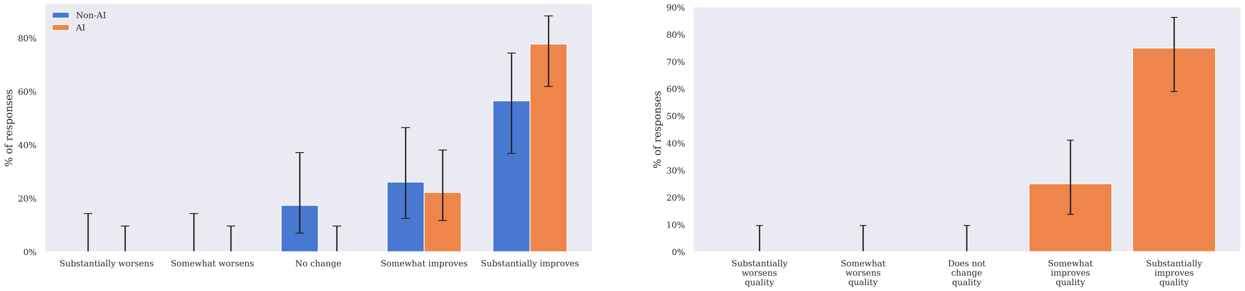
We found that the agreement between model ratings and physician ratings exceeded the agreement between two physicians: for example, the within-1 agreement for history was 87.0% for `GPT-4.1` and physicians and 86.6% for `o3` and physicians, compared to 77.8% for physician-physician agreement (Table 30). This was also true for Fleiss' κ on whether an error was present: `GPT-4.1` and physicians had $\kappa = 0.283$ and `o3` and physicians had $\kappa = 0.306$, while the physician-physician $\kappa = 0.260$ (Table 31).

Both the `GPT-4.1` and `o3` analyses find that AI Consult significantly reduces clinical errors across categories, and generally find larger effect sizes compared to physician raters. For example, physician raters found a treatment error RRR of 12.7% (6.8%- 18.3%). For `GPT-4.1`, the corresponding RRR was 21.5% (19.4%-23.7%) and for `o3`, it was 19.1% (17.1%-21.1%; Table 6 and Figs. 21 and 22).

We also ran modified Poisson regression and GEE regression models for both `GPT-4.1` and `o3` graders. These show a statistically significant and favorable effect from AI Consult. Modified Poisson models generally have similar effect sizes to the unadjusted analysis; the effect sizes for the GEE models are sometimes similar (e.g., GPT-4.1 diagnosis) and sometimes smaller (e.g., GPT-4.1 treatment), but retain statistical significance. Full regression tables are available in Tables 32 to 47.

4.2 Use and usability

We surveyed clinicians in both groups to ask them how the EMR affects the quality of care that they deliver. We also asked clinicians in the AI group for their feedback on AI Consult. Note that response rates for this anonymous survey were relatively low, with 23 clinicians in the non-AI group (47%) and 36 clinicians in the AI group (63%) responding, meaning that these results should be interpreted with caution.



(a) Impact of the EMR (including AI Consult, if present), on quality of care in both the AI and the non-AI group.

(b) Impact of AI Consult specifically on quality of care.

Figure 7: Clinician survey results: impact of AI Consult on quality of care.

Clinicians felt that AI Consult improved quality of care. Significantly more respondents in the AI group than in the non-AI group noted that the EMR (including AI Consult) improved the quality of care they were able to deliver ($p = 0.046$, Fig. 7).

In their qualitative EMR feedback, the **non-AI group** mostly emphasized operational improvements—speed, tidy documentation, easier stock checks—and in one case asserted that the *EMR doesn't give option in terms of treatment. The treatment depends on me.* In contrast, the **AI group** framed the EMR as an active clinical partner: *"It has helped me in multiple occasions to make the correct clinical judgment,"* and highlighted support for *"comprehensive management … from nutrition [to] pharmacological"* alongside provision of *"real-time evidence-based practices"*. Both cohorts stressed time savings, workflow efficiencies, and improved documentation: *"EMR is fast as compared to manual system."*

Overall feedback on AI Consult was quite positive. All clinicians in the AI group said that AI Consult improved quality of care, with 75% saying that it substantially improved care (Fig. 7). Clinician net promoter scores for AI Consult were also favorable, with an overall net promoter score of 78 (minimum possible -100, maximum possible 100; for reference, the average net EHR experience score, a similar construct, was 33 in one study across multiple EMR implementations (KLAS, 2003); Fig. 23). While satisfaction was generally high, more clinicians noted that they were "somewhat satisfied" with AI Consult (58%) than "very satisfied" (42%), indicating that room for improvement remains (Fig. 24). In qualitative feedback, clinicians described AI Consult as "helpful, easy to use, and improves the quality of care." One clinician "noted an improvement in our clinical notes, which has had a ripple effect on non users of AI" (Table 7).

Opportunities for improvement included localization, alert fatigue, and workflow integration. Constructive feedback covered broader clinical refinement (*"Although there are errors or AI hallucination cases, overall performance … has done tremendous improvement in service delivery"*), error-detection enhancement, and localization needs (e.g., *"keep updating the software to include locally available drugs and management options available in a resource limited medical centers"*). Clinicians also cited alert fatigue and shifting recommendations (*"At some point it keeps on changing the approach of management…"*), documentation burden, and workflow integration gaps (e.g., *"In cases where you give a stat dose… it flags red saying the management is incomplete"*).

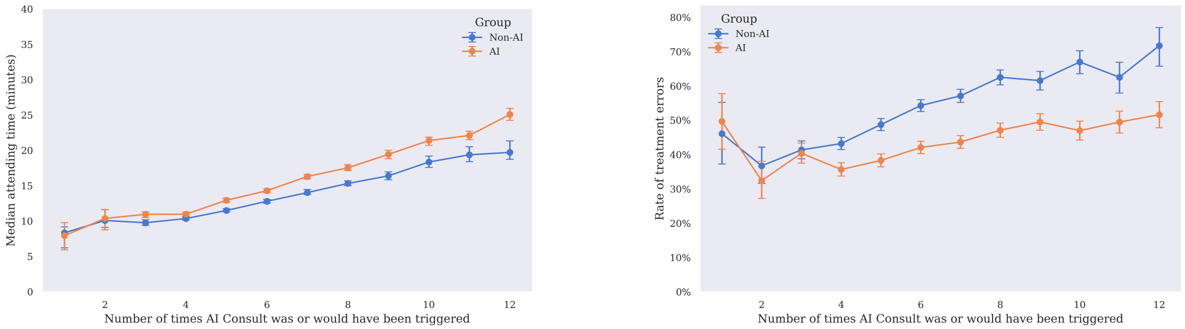
Clinicians in the AI group had longer attending times, which they used to resolve AI Consult triggers and improve quality. EMR data reveal that the clinician attending time is higher for visits in the AI Consult group (median 16.43 minutes) compared to the non-AI Consult group (13.01 minutes; $p = 0.000$).

To examine how AI Consult affects this, we plot median clinician attending time by number of AI Consult triggers in both the non-AI and AI groups (Fig. 8a). This includes red, yellow, and green triggers, reflecting case complexity as clinicians revisit and change the documentation over time. We see very similar attending times between groups for a small number of AI Consult triggers. The AI group attending time increasingly exceeds the non-AI group attending time with more triggers, suggesting that this increased time is being spent by clinicians in responding to AI Consult feedback. Moreover, we also see improved clinical performance for cases with a higher number of AI calls: the rate of treatment errors (here based on `GPT-4.1` ratings, to increase sample size and reduce noise) is similar for low numbers of AI Consult triggers and increases more rapidly for the non-AI group compared to the AI group (Fig. 8b). We also observe that the rate of treatment errors in the AI group is less than in the non-AI group in visits with the same attending time, suggesting that AI Consult reduces errors even when controlling for visit duration (Fig. 25).

Clinical notes were typically longer for clinicians in the AI group. AI Consult encouraged clinicians to provide more detail in their clinical notes. The median clinical note length was higher in the AI group than the non-AI group over the course of the study (initially, 500 vs 400 characters in the AI vs non-AI group), and this difference grew larger when the active deployment period started (during the week of March 10th, 600 vs 450 characters; at the end of the study, 600 vs 490 characters; Fig. 26).

Theme	Representative positive quotes	Representative constructive quotes
Patient Safety	• "It always alerts whenever there is a quality concern… can see the small things we overlook." • "Good reminder in case I miss something." • "I have been able to identify gaps in treatment and this improved treatment quality." • "Acts like a consultant in the room."	• "It improves quality but also can mislead." • "It is not 100% detecting errors." • "When am prescribing injectables to my patients the AI rates me red even after documenting that my patient vomits everything and can't retain any medication." • "The Ai tool can work on not exaggerating certain conditions that require simple management"
Knowledge and Professional Development	• "It's very informative and broadens my knowledge." • "It sharpens my skills." • "Helps one know when they are on the right track, as it also guides on what next step to take or forgotten inputs." • "It's also a learning tool."	• "If possible you update it with the current guidelines of management for selective groups e.g. Pregnant mothers."
Guideline-Based Management and Stewardship	• "Has made me be thoughtful on prescriptions of medication that we unnecessarily administer for certain conditions." • "It keeps one in line with the current guidelines."	• "Aligning it more to our protocol and guidelines managements published in Kenya would be amazing." • "Needs to be updated with Kenyan guidelines on disease management… I encountered [issues] on meningitis, heart attack, hypertensive emergency."
Workflow and Efficiency	• "Helps... make better decisions and reduce errors."	• "It takes much time because it requires adequate documentation in history and examination bucket." • "Would be nice if the speed is enhanced and red alerts come before the other alerts."
Overall Enthusiasm	• "It's one of the best innovation to happen at Penda." • "It should be provided to all health care providers." • "AI is a good idea whose time has come."	• "AI is a good tool in clinicals because it provides thoughtful information… but key factor is to make diagnosis more broader and reducing prompts otherwise it is generally a good tool."

Table 7: Representative clinician user quotes on AI Consult, grouped by theme.



(a) Median clinician attending time by number of AI Consult triggers in the non-AI and AI groups. 95% CIs calculated with 1000 bootstrap samples. Includes only visits with 12 or fewer AI Consult calls.

(b) Rate of treatment errors from `GPT-4.1` by number of AI Consult triggers in the AI vs non-AI groups. 95% CIs calculated with 1000 bootstrap samples. Includes only visits with 12 or fewer AI Consult calls.

Figure 8: Median clinician attending time and rate of treatment errors by number of AI Consult triggers in the non-AI and AI groups. Results suggest that in visits where there were more AI Consult triggers, clinicians in the AI group spent time responding to AI alerts and made fewer treatment errors as a result.

	Rate in non-AI group	Rate in AI group	p
Rate of patients not feeling better	4.3% (3.7%-4.9%)	3.8% (3.3%-4.4%)	0.234
Saw a pharmacist	3.5% (3.0%-4.1%)	3.4% (2.9%-3.9%)	0.687
Self-referred to another clinic or hospital	2.9% (2.4%-3.4%)	3.0% (2.5%-3.5%)	0.803
Unplanned visit at penda	6.2% (5.8%-6.7%)	6.0% (5.6%-6.5%)	0.532
Feeling worse on one-day follow-up	2.2% (0.8%-6.3%)	3.3% (1.5%-7.1%)	0.737

Table 8: Rates of patient outcomes in the AI vs non-AI group.

Clinicians generally gave positive feedback on AI Consult responses. When clinicians received an AI Consult response, they could give feedback by clicking thumbs up or thumbs down buttons. Among 155450 AI Consult responses in the AI group, raters gave feedback on 19493 (12.5%). Of these, they gave thumbs up feedback on 18424 (94.5%), and thumbs down feedback on the remaining 1069 (5.5%). Much of the thumbs down feedback happened within the first two weeks of the induction period, while the prompts were still being iterated on (thumbs down rate of about 13%); after that period, the thumbs down rate was between 4% and 7% in any given week (Fig. 27).

4.3 Patient outcomes

4.3.1 Patient-reported outcomes and unplanned follow-up visits

There were no statistical differences in patient-reported outcomes. The share of patients who still felt unwell seven days after the visit fell slightly from 4.3% (95% CI 3.7% –4.9%) in the non-AI arm to 3.8% (95% CI 3.3% –4.4%) in the AI arm (Fisher's exact test $p = 0.234$; Table 8), reflecting no statistical difference. The present study was not powered to detect an effect of this magnitude. Moreover, this analysis should be treated as exploratory rather than confirmatory given the high rate of missingness (Jakobsen et al., 2017).

The rates of patients who sought unplanned, unreferred follow-up care was also quite similar between groups (Table 8). The sample size of patients who responded to one-day follow-up calls at Penda was quite low (about 500) with low outcome rates, making it challenging to draw conclusions.

Patients were less likely to seek care outside Penda if inappropriate medications were given. We conducted a post-hoc analysis to investigate how often patients sought care outside Penda depending on whether inappropriate medications were given, as rated by a physician. This rate was lower if inappropriate medications were given (7.9%, 95% CI 6.7%-9.4%) than if only appropriate medications were given (12.3%, 95% CI 10.4%-14.4%; $p = 0.000$), suggesting that these patient-reported outcomes are tied to patient perception of the care they received and whether they feel their needs for medication were met, regardless of whether the needs were well-justified.

4.3.2 Patient safety reports

Across the 10-week study, 12 patient safety reports (PSRs) were documented: five in the non-AI group and seven in the AI group. Each event was independently reviewed for (i) whether a clinical quality lapse was present, (ii) severity of the event, and (iii) whether AI Consult contributed to harm (if present) or could have mitigated harm.

AI Consult advice could have prevented errors in some cases if available or heeded. In the non-AI group, three events had AI Consult reds not visible to the clinician that, if visible and followed, might have prevented the lapse (missed anemia work-up, unsafe neonatal prescription, and unrecognized high-risk chest pain). This included one mortality event, in a young adult with chest pain and tachycardia, where AI Consult (which was silent to the clinician) flagged multiple red alerts regarding closer cardiopulmonary evaluation.

In the AI group, there were similarly three cases where AI Consult issued red or yellow-alert guidance that, if seen by clinicians or heeded, would likely have averted or reduced harm. This also included one mortality event, during the induction period. This event was in an infant with vomiting, fever, and low oxygen saturation. AI Consult produced multiple red alerts recommending respiratory reassessment and oxygen administration. It is unclear whether these alerts were acknowledged or seen by the clinician, as this event occurred early in the induction period before acknowledgment was tracked and when AI Consult red alerts were not reliably visible.

While AI Consult failed to prevent harm in some cases, it did not actively cause harm in any cases. Three AI group patient safety reports revealed limitations of AI Consult in which it did not prevent harm. In these three cases-pediatric peptic-ulcer misdiagnosis, use of a contraindicated medication in the first trimester of pregnancy, and a missed positive H. pylori test-the AI system failed to suggest a safer alternative. These were all cases where AI Consult did not change the course of the clinical encounter. In no patient safety report did AI Consult make suggestions that created new risk for patients.

AI Consult advice could not have prevented errors in other cases. Two non-AI group events and one AI group event centered around limited history or documentation. In these visits, AI Consult could not have changed the outcome because the necessary clinical detail was never entered or the patient left before care could be completed.

5 Discussion

Our findings demonstrate that a large language model–based clinical decision support tool can meaningfully reduce diagnostic and treatment errors when deployed in live outpatient care. This improvement occurred not in simulation or review of EMR data, but in the context of routine, real-world practice across nearly 40,000 patient visits in 15 clinics—supporting our view that AI systems, when carefully implemented in clinician workflows, can enhance care quality.

The scale and scope of AI Consult are also notable. Unlike prior decision support systems which target narrow conditions, specialties, or workflows—such as drug interactions or chronic disease screening—AI Consult operated continuously, across all patient visits and key decision points.

One of the most important implications of this work is the potential for AI tools to further improve the quality of care delivered by primary care clinicians. By functioning as an asynchronous safety net and surfacing real-time feedback at decision points, AI Consult provides lightweight supervision that improved care without undermining clinician autonomy. In this sense, the system serves not only as a quality assurance mechanism but as an empowering tool for clinicians.

Beyond reducing errors in real-time, AI Consult appeared to foster substantial skill gains. During the study period, the proportion of visits that “started red”—a proxy for clinicians missing a critical issue on first pass—for treatments specifically fell by about 10–15 absolute percentage points in the AI group while remaining flat in the non-AI group. Because these initial alerts precede AI feedback on treatments, the decline signals that clinicians internalized the system’s feedback and preemptively avoided common failure modes. The magnitude of the effect is notable; for every 7-10 patients AI group clinicians saw, they avoided one important initial treatment error. Such learning effects were evident not only for treatment decisions but also for history-taking, suggesting AI Consult facilitates broader learning rather than narrow protocol adherence. These findings, together with survey responses citing the tool as “very informative,” “a learning tool,” and helpful in “sharpening my skills,” support the view that well-designed copilots can function as continuous, case-based education—uplifting individual competence while simultaneously safeguarding patients.

Clinically-aligned implementation was a key factor in the effectiveness of AI Consult. Penda’s previous iteration of AI Consult (Section 2.3) achieved limited uptake because it required clinicians to interrupt the flow of a patient visit to request AI feedback. The iteration we studied here provided a tiered, low-friction interface, enabling broad coverage with minimal disruption and alert fatigue. These changes reflect learnings from the implementation science literature, which has found that avoiding alert fatigue and surfacing CDS recommendations automatically instead of on demand improved clinician adherence (Kawamoto et al., 2005; Van de Velde et al., 2018; Seidling et al., 2011). Clinician feedback affirmed the utility of the tool–all AI group survey respondents reported that AI Consult improved the quality of care they could deliver–and indicated overall enthusiasm (“It should be provided to all health care providers”).

Active deployment was another key factor for the success of AI Consult. The tool had a significantly greater effect during the main study period (when active deployment strategies were employed) compared to the induction period (Table 4), with a clear divergence between AI and non-AI groups for left in red rate and started red rate over the seven weeks of the main period (Fig. 6). Based on these strong improvements over a short period, we would expect further gains from longer active deployment efforts. We expect the change management pillars introduced in Section 3.4–connection, measurement, and incentives–to be similarly important for future AI CDS tools.

Patient safety reports show that AI Consult has clear potential to reduce patient harm. In half of the reviewed reports, harm might have been prevented if AI Consult had been used and its guidance followed. Both deaths reviewed were judged to be potentially preventable with correct AI Consult use. The reports highlight the importance of adherence: AI group users ignored critical alerts in some cases, highlighting the need for improved clinician trust and responsiveness to AI recommendations as part of active deployment efforts. While there were no cases where AI Consult recommendations actively caused harm, in some reports, AI Consult failed to prevent minor or moderate harm, suggesting room for improvement. In other cases, AI Consult was unable to help due to inadequate clinician documentation, emphasizing the importance of clinician buy-in and training.

Localization to Penda’s clinical context was important to clinicians. A considerable amount of variation in medical care can be explained by different norms between facilities and geographies, and systems that are acceptable to end users need to be responsive to this variation. With today’s capable and steerable models, localization may not require fine-tuning or specialized models–our experience was that prompting the model to share the Kenyan epidemiological context, provide details about Penda’s setting and care protocols, and outline local clinical practice guidelines were all helpful steps towards localization.

5.1 Limitations

AI Consult represents an early, promising archetype of an AI-powered clinical copilot. While the results are encouraging, we emphasize that this is a first step. Continued iteration will be essential—to reduce documentation burden, improve contextual relevance, and align more closely with local practice norms. Future implementations may include voice-first interfaces, real-time charting assistants, or agents that execute clinician-confirmed actions in electronic medical records.

Although AI Consult was associated with reduced diagnostic and treatment errors, we did not observe statistically significant differences in patient-reported outcomes during the study period. This may reflect limitations in measurement sensitivity, response rates (response rates were 40%), short follow-up period, or the relatively short duration of the study. Further work—particularly large studies powered for patient outcomes—will be needed to assess the downstream impact of AI-assisted care.

Physician panel inter-rater reliability was fair but not excellent, despite shared golden examples, multi-step onboarding and quality-filtering, task-specific training, and ongoing "office hours". Interestingly, when provided the same form as the physician panel to review visits (Appendix I), o3 and GPT-4.1 both displayed greater rater agreement with physicians than other physicians. Both models also found larger effect sizes for AI Consult than physicians did (Table 6). While greater effect sizes may be the result of Goodhart's Law (clinician documentation is assessed by an LLM in AI Consult as well), the greater model-physician agreement compared to physician-physician agreement suggests that LLM ratings, if validated via physician agreement on a subset of cases, may be a way to scale up both routine quality improvement and studies like this one.

Clinician survey response rates were somewhat low–63% of clinicians in the AI group and 47% in the non-AI group responded. While clinicians were broadly positive about the utility and usability of AI Consult in their responses, they also reported areas of improvement, particularly around response time and localization. We observed that clinicians with many AI Consult triggers had longer visit times but also a greater reduction in treatment errors (Fig. 8), suggesting a quality-time tradeoff in the design and deployment of AI-based CDS tools that needs additional study.

Broader generalizability also requires further research. Penda Health is a particularly strong setting for digital health implementation, given Penda's dedicated technical infrastructure investments and its focus on highly affordable care. Penda's implementation of AI Consult was tailored to its local context, and clinician uptake required active deployment work from Penda's team. Validating and deploying implementations of AI CDS tools in other clinical environments, care settings, and health systems remains an important area for future work.

6 Related work

Offline evaluation of LLMs for health. Advances in LLMs have spurred many works evaluating them for health applications. Prior works have evaluated health performance broadly (Arora et al., 2025; Bedi et al., 2025) or for specific tasks, including differential diagnosis (McDuff et al., 2025; Nori et al., 2025; Goh et al., 2025), clinical summarization (Van Veen et al., 2024; Zaretsky et al., 2024), radiology report generation (Tanno et al., 2025; Tu et al., 2024), and Q&A (Ayers et al., 2023; Nori et al., 2023; Pfohl et al., 2024). Some works have focused on specialized models (Moor et al., 2023; Li et al., 2023; Singhal et al., 2023, 2025; McDuff et al., 2025; Tu et al., 2025, 2024; Saab et al., 2024; Yang et al., 2024) and others on general models (Ayers et al., 2023; Nori et al., 2025, 2023; Saab et al., 2025; Arora et al., 2025; Johnson et al., 2023). Evaluation in many works relies heavily on narrow automated benchmarks that measure clinical knowledge (Nori et al., 2023; Singhal et al., 2023). Some works have evaluated models across many benchmarks, offering more robust characterizations of model performance across tasks (Bedi et al., 2025; Saab et al., 2024; Tu et al., 2024). Other works have employed human evaluation with physicians or patients, sometimes employing realistic clinical vignettes or electronic medical record data (Goh et al., 2025; Ong et al., 2024; Dash et al., 2023; Ayers et al., 2023; Singhal et al., 2025; Pfohl et al., 2024). Some recent works have combined human and automated evaluation towards clinician-aligned evaluation at scale (Arora et al., 2025; Fleming et al., 2024). All of these works involve "offline" evaluation of LLMs, which do not enable the study of the unique challenges of bringing model advances into clinical practice, including real-world patient diversity, designing for and learning from clinician workflows, and deployment towards successful clinician uptake. Unlike prior evaluations of LLMs, the present study examines outcomes of using an LLM-based tool live during patient care at scale, addressing the unique challenges of real-world implementation.

Clinical decision support. AI Consult is an example of a clinical decision support system. Such systems have been used in various forms since the 1970s (Sutton et al., 2020; Middleton et al., 2016; Shortliffe, 1977; Bright et al., 2012; Musen et al., 2021). These systems support clinicians with knowledge and tools at the point of care. CDS systems have traditionally drawn on explicit knowledge bases (Papadopoulos et al., 2022; Jing et al., 2023), typically represented as rules / decision trees (Silva et al., 2023; Rommers et al., 2013; Gholamzadeh et al., 2023) or cases (Althoff et al., 1998; Frize and Walker, 2000; Kumar et al., 2009), rather than the distributed representations of LLMs. They have often been restricted in scope to particular conditions (Levra et al., 2025; Rajashekar et al., 2024; Oniani et al., 2024; Kaiser et al., 2024), specialties (Ong et al., 2024; Lammert et al., 2024; Miller et al., 2024; Benary et al., 2023), or workflows (Slight et al., 2013; Kublanov and Dolganov, 2019; Cheng et al., 2013; Rommers et al., 2013). There are several works that evaluate LLMs "offline" for decision support tasks (Ong et al., 2024; Gaber et al., 2025; Lammert et al., 2024; Bhimani et al., 2025; Levra et al., 2025; Rajashekar et al., 2024; Oniani et al., 2024; Miller et al., 2024; Kaiser et al., 2024; Benary et al., 2023); these studies measure model performance on tasks that could support clinicians, using electronic medical record datasets, clinical vignettes, or fictional patients. Similar to other studies evaluating LLMs for health, these do not capture the unique challenges of real-world implementation and deployment. To the best of our knowledge, this is the first study of an LLM-based CDS used in live patient care. Additionally, unlike other CDS systems that provide assistance for targeted workflows or specialties, AI Consult serves to broadly assist primary care clinicians with all major aspects of their patient care workflow, including history-taking, investigations, diagnosis, and treatment.

Implementation science. Implementation science examines methods to promote uptake of evidence-based findings into routine care practice and policy (Eccles and Mittman, 2006; Bauer and Kirchner, 2020; Grimshaw et al., 2012; Olswang and Prelock, 2015). This literature often produces structured frameworks (Damschroder et al., 2009; Greenhalgh et al., 2017) which identify key factors influencing adoption and sustainability of health interventions. Several works have studied factors specific to clinical decision support (Kawamoto et al., 2005; Van de Velde et al., 2018; Castillo and Kelemen, 2013; Murphy, 2014; Kilsdonk et al., 2017; Sittig et al., 2006; Seidling et al., 2011). A recurring theme is that technology alone is insufficient to change clinician behavior; effective uptake requires attention to usability, workflow fit, leadership buy-in, iterative training, contextual adaptation, and other factors (Ross et al., 2016; Smith et al., 2021; Greenhalgh et al., 2017; Ojo et al., 2021). These insights are particularly critical in low-resource contexts, where health systems face workforce shortages, limited infrastructure, and competing priorities (Ojo et al., 2021; Yapa and Bärnighausen, 2018). In works studying implementation of clinical decision support, avoiding alert fatigue and surfacing computerized CDS recommendations automatically at relevant points (instead of on demand) have been shown to improve clinician adherence (Kawamoto et al., 2005; Van de Velde et al., 2018; Seidling et al., 2011). Our implementation design and deployment approach—embedding AI into clinical workflows, iterative user-centered development, automatically surfacing targeted AI responses via a traffic light system, and pairing the tool with change management strategies—takes inspiration from these prior efforts to study the translation of research into clinical impact.

7 Conclusion

We have presented a real-world evaluation of a large language model-based clinical decision support tool deployed in live patient care, with a meaningful reduction in diagnostic and treatment errors. Our findings underscore three critical components: (1) capable models, which are now widely available; (2) clinically-aligned implementation, which supports the user rather than distracting them; and (3) active deployment, including building clinician connection, measurement, and incentives. Clinical impact does not emerge solely from model performance, but from a confluence of technical, human, and organizational factors.

With advancements in model capabilities, closing the model-implementation gap has become the most important challenge for the health AI ecosystem. This study provides a template for how AI systems can be safely and effectively embedded into clinical workflows. Further progress requires coordinated efforts across the ecosystem, including policymakers developing regulatory frameworks, engineers designing better implementations, and healthcare systems driving thoughtful deployments. Ultimately, we hope that systems like AI Consult will become the standard of care, supporting clinicians in delivering safer, more consistent, and more accessible care worldwide.

Code

We have released code used for analysis and plotting to foster transparency of the results in this study. Raw study data cannot be released due to privacy and data protection requirements. Code can be found at: `https://github.com/openai/penda_code`.

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References

K.-D. Althoff, R. Bergmann, S. Wess, M. Manago, E. Auriol, O. I. Larichev, A. Bolotov, Y. I. Zhuravlev, and S. I. Gurov. Case-based reasoning for medical decision support tasks: The inreca approach. *Artificial Intelligence in Medicine*, 12(1):25–41, 1998.

R. K. Arora, J. Wei, R. S. Hicks, P. Bowman, J. Quiñonero-Candela, F. Tsimpourlas, M. Sharman, M. Shah, A. Vallone, A. Beutel, et al. Healthbench: Evaluating large language models towards improved human health. *arXiv preprint arXiv:2505.08775*, 2025.

J. W. Ayers, A. Poliak, M. Dredze, E. C. Leas, Z. Zhu, J. B. Kelley, D. J. Faix, A. M. Goodman, C. A. Longhurst, M. Hogarth, et al. Comparing physician and artificial intelligence chatbot responses to patient questions posted to a public social media forum. *JAMA internal medicine*, 183(6):589–596, 2023.

M. S. Bauer and J. Kirchner. Implementation science: what is it and why should i care? *Psychiatry research*, 283:112376, 2020.

A. L. Beam and I. S. Kohane. Big data and machine learning in health care. *JAMA*, 319(13):1317–1318, 2018. doi: 10.1001/jama.2017.18391.

S. Bedi, H. Cui, M. Fuentes, A. Unell, M. Wornow, J. M. Banda, N. Kotecha, T. Keyes, Y. Mai, M. Oez, et al. Medhelm: Holistic evaluation of large language models for medical tasks. *arXiv preprint arXiv:2505.23802*, 2025.

M. Benary, X. D. Wang, M. Schmidt, D. Soll, G. Hilfenhaus, M. Nassir, C. Sigler, M. Knödler, U. Keller, D. Beule, U. Keilholz, U. Leser, and D. T. Rieke. Leveraging Large Language Models for Decision Support in Personalized Oncology. *JAMA Network Open*, 6(11):e2343689, Nov. 2023. ISSN 2574-3805. doi: 10.1001/jamanetworkopen.2023.43689.

M. Bhimani, A. Miller, J. D. Agnew, M. S. Ausin, M. Raglow-Defranco, H. Mangat, M. Voisard, M. Taylor, S. Bierman-Lytle, V. Parikh, J. Ghukasyan, R. Lasko, S. Godil, A. Atreja, and S. Mukherjee. Real-World Evaluation of Large Language Models in Healthcare (RWE-LLM): A New Realm of AI Safety &amp; Validation, Mar. 2025.

T. J. Bright, A. Wong, R. Dhurjati, E. Bristow, L. Bastian, R. R. Coeytaux, G. Samsa, V. Hasselblad, J. W. Williams, M. D. Musty, L. Wing, A. S. Kendrick, G. D. Sanders, and D. Lobach. Effect of Clinical Decision-Support Systems. *Annals of Internal Medicine*, 157(1):29–43, July 2012. ISSN 0003-4819. doi: 10.7326/0003-4819-157-1-201207030-00450.

R. S. Castillo and A. Kelemen. Considerations for a successful clinical decision support system. *CIN: Computers, Informatics, Nursing*, 31(7):319–326, 2013.

C.-W. Cheng, N. Chanani, J. Venugopalan, K. Maher, and M. D. Wang. icuarm-an icu clinical decision support system using association rule mining. *IEEE Journal of Translational Engineering in Health and Medicine*, 1:4400110–4400110, 2013.

L. J. Damschroder, D. C. Aron, R. E. Keith, S. R. Kirsh, J. A. Alexander, and J. C. Lowery. Fostering implementation of health services research findings into practice: A consolidated framework for advancing implementation science. *Implementation Science*, 4(1):50, Aug. 2009. ISSN 1748-5908. doi: 10.1186/1748-5908-4-50.

D. Dash, R. Thapa, J. M. Banda, A. Swaminathan, M. Cheatham, M. Kashyap, N. Kotecha, J. H. Chen, S. Gombar, L. Downing, et al. Evaluation of gpt-3.5 and gpt-4 for supporting real-world information needs in healthcare delivery. *arXiv preprint arXiv:2304.13714*, 2023.

M. P. Eccles and B. S. Mittman. Welcome to Implementation Science. *Implementation Science*, 1(1):1, Feb. 2006. ISSN 1748-5908. doi: 10.1186/1748-5908-1-1.

S. L. Fleming, A. Lozano, W. J. Haberkorn, J. A. Jindal, E. Reis, R. Thapa, L. Blankemeier, J. Z. Genkins, E. Steinberg, A. Nayak, et al. Medalign: A clinician-generated dataset for instruction following with electronic medical records. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 22021–22030, 2024.

M. Frize and R. Walker. Clinical decision-support systems for intensive care units using case-based reasoning. *Medical engineering & physics*, 22(9):671–677, 2000.

F. Gaber, M. Shaik, F. Allega, A. J. Bilecz, F. Busch, K. Goon, V. Franke, and A. Akalin. Evaluating large language model workflows in clinical decision support for triage and referral and diagnosis. *npj Digital Medicine*, 8(1):263, May 2025. ISSN 2398-6352. doi: 10.1038/s41746-025-01684-1.

M. Gholamzadeh, H. Abtahi, and R. Safdari. The application of knowledge-based clinical decision support systems to enhance adherence to evidence-based medicine in chronic disease. *Journal of healthcare engineering*, 2023(1):8550905, 2023.

E. Goh, R. J. Gallo, E. Strong, Y. Weng, H. Kerman, J. A. Freed, J. A. Cool, Z. Kanjee, K. P. Lane, A. S. Parsons, N. Ahuja, E. Horvitz, D. Yang, A. Milstein, A. P. J. Olson, J. Hom, J. H. Chen, and A. Rodman. Gpt-4 assistance for improvement of physician performance on patient care tasks: A randomized controlled trial. *Nature Medicine*, 31(4):1233–1238, Apr. 2025. doi: 10.1038/s41591-024-03456-y. Epub 2025 Feb 5. PMID: 39910272.

T. Greenhalgh, J. Wherton, C. Papoutsi, J. Lynch, G. Hughes, C. A'Court, S. Hinder, N. Fahy, R. Procter, and S. Shaw. Beyond Adoption: A New Framework for Theorizing and Evaluating Nonadoption, Abandonment, and Challenges to the Scale-Up, Spread, and Sustainability of Health and Care Technologies. *Journal of Medical Internet Research*, 19(11):e8775, Nov. 2017. doi: 10.2196/jmir.8775.

J. M. Grimshaw, M. P. Eccles, J. N. Lavis, S. J. Hill, and J. E. Squires. Knowledge translation of research findings. *Implementation Science*, 7(1):50, May 2012. ISSN 1748-5908. doi: 10.1186/1748-5908-7-50.

J. C. Jakobsen, C. Gluud, J. Wetterslev, and P. Winkel. When and how should multiple imputation be used for handling missing data in randomised clinical trials - a practical guide with flowcharts. *BMC Med. Res. Methodol.*, 17(1):162, Dec. 2017.

X. Jing, H. Min, Y. Gong, P. Biondich, D. Robinson, T. Law, C. Nohr, A. Faxvaag, L. Rennert, N. Hubig, et al. Ontologies applied in clinical decision support system rules: Systematic review. *JMIR medical informatics*, 11:e43053, 2023.

D. Johnson, R. Goodman, J. Patrinely, C. Stone, E. Zimmerman, R. Donald, S. Chang, S. Berkowitz, A. Finn, E. Jahangir, E. Scoville, T. Reese, D. Friedman, J. Bastarache, Y. van der Heijden, J. Wright, N. Carter, M. Alexander, J. Choe, C. Chastain, J. Zic, S. Horst, I. Turker, R. Agarwal, E. Osmundson, K. Idrees, C. Kieman, C. Padmanabhan, C. Bailey, C. Schlegel, L. Chambless, M. Gibson, T. Osterman, and L. Wheless. Assessing the Accuracy and Reliability of AI-Generated Medical Responses: An Evaluation of the Chat-GPT Model. *Research Square*, pages rs.3.rs–2566942, Feb. 2023. ISSN 2693-5015. doi: 10.21203/rs.3.rs-2566942/v1.

K. N. Kaiser, A. J. Hughes, A. D. Yang, A. A. Turk, S. Mohanty, A. A. Gonzalez, R. E. Patzer, K. Y. Bilimoria, and R. J. Ellis. Accuracy and consistency of publicly available Large Language Models as clinical decision support tools for the management of colon cancer. *Journal of Surgical Oncology*, 130(5): 1104–1110, 2024. ISSN 1096-9098. doi: 10.1002/jso.27821.

K. Kawamoto, C. A. Houlihan, E. A. Balas, and D. F. Lobach. Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success. *Bmj*, 330 (7494):765, 2005.

M. Kiener, C. Ichura, B. A. Ndenga, F. M. Mutuku, C. A. Winter, V. Okuta, L. Mwambingu, K. Ogamba, K. N. Shaita, C. Ronga, P. Chebii, J. Amugongo, S. Malumbo, O. Godana, Z. Jembe, C. Ng'ang'a, M. Mazera, and A. D. LaBeaud. Antibiotic prescribing patterns at outpatient clinics in western and coastal kenya. *PLOS Global Public Health*, 5(1):e0004109, 2025. doi: 10.1371/journal.pgph.0004109. URL https://pubmed.ncbi.nlm.nih.gov/39752345.

E. Kilsdonk, L. Peute, and M. W. Jaspers. Factors influencing implementation success of guideline-based clinical decision support systems: a systematic review and gaps analysis. *International journal of medical informatics*, 98:56–64, 2017.

KLAS. Successful User's Guide to High EHR Satisfaction 2023 - Arch Report. https://klasresearch.com/archcollaborative/report/successful-user-s-guide-to-high-ehr-satisfaction-2023/475, 2003.

R. R. Korom and G. Njue. Clinical decision support systems in low resource settings. *BMJ*, 371:m3962, Oct. 2020.

C. Krüger, M. Heinzel-Gutenbrunner, and M. Ali. Adherence to the integrated management of childhood illness guidelines in namibia, kenya, tanzania and uganda: evidence from the national service provision assessment surveys. *BMC Health Services Research*, 17(1):822, 2017. doi: 10.1186/s12913-017-2781-3. URL https://pubmed.ncbi.nlm.nih.gov/29237494.

V. Kublanov and A. Dolganov. Development of a decision support system for neuro-electrostimulation: Diagnosing disorders of the cardiovascular system and evaluation of the treatment efficiency. *Applied Soft Computing*, 77:329–343, 2019.

K. A. Kumar, Y. Singh, and S. Sanyal. Hybrid approach using case-based reasoning and rule-based reasoning for domain independent clinical decision support in icu. *Expert Systems with Applications*, 36(1):65–71, 2009.

J. Lammert, T. Dreyer, S. Mathes, L. Kuligin, K. J. Borm, U. A. Schatz, M. Kiechle, A. M. Lörsch, J. Jung, S. Lange, N. Pfarr, A. Durner, K. Schwamborn, C. Winter, D. Ferber, J. N. Kather, C. Mogler, A. L. Illert, and M. Tschochohei. Expert-Guided Large Language Models for Clinical Decision Support in Precision Oncology. *JCO precision oncology*, 8:e2400478, Oct. 2024. ISSN 2473-4284. doi: 10.1200/PO-24-00478.

A. G. Levra, M. Gatti, R. Mene, D. Shiffer, G. Costantino, M. Solbiati, R. Furlan, and F. Dipaola. A large language model-based clinical decision support system for syncope recognition in the emergency department: A framework for clinical workflow integration. *European Journal of Internal Medicine*, 131: 113–120, Jan. 2025. ISSN 0953-6205. doi: 10.1016/j.ejim.2024.09.017.

C. Li, C. Wong, S. Zhang, N. Usuyama, H. Liu, J. Yang, T. Naumann, H. Poon, and J. Gao. Llava-med: Training a large language-and-vision assistant for biomedicine in one day. *Advances in Neural Information Processing Systems*, 36:28541–28564, 2023.

C. Marete, C. Nabakwe, E. M. Njuguna, F. and R. Mwangi, H.˙Clinicians' adherence to national pneumonia management guidelines at kitale county hospital, kenya. *East African Medical Journal*, 97(11):3190–3199, 2020. URL https://www.ajol.info/index.php/eamj/article/view/205283.

D. McDuff, M. Schaekermann, T. Tu, and et al. Towards accurate differential diagnosis with large language models. *Nature*, 626:102–118, 2025. doi: 10.1038/s41586-025-08869-4.

B. Middleton, D. F. Sittig, and A. Wright. Clinical Decision Support: A 25 Year Retrospective and a 25 Year Vision. *Yearbook of Medical Informatics*, (Suppl 1):S103–S116, May 2016. ISSN 0943-4747. doi: 10.15265/IYS-2016-s034.

L. Miller, P. Kamel, J. Patel, J. Agrawal, M. Zhan, N. Bumbarger, and K. Wang. A Comparative Evaluation of Large Language Model Utility in Neuroimaging Clinical Decision Support. *Journal of Imaging Informatics in Medicine*, Nov. 2024. ISSN 2948-2933. doi: 10.1007/s10278-024-01161-3.

M. Moor, L. von Rueden, S. Adler, W. Ping, H. Valentin, et al. Med-flamingo: A multimodal medical few-shot learner. In *Proceedings of the 3rd Machine Learning for Health Symposium*, pages 353–367. PMLR, 2023.

E. V. Murphy. Clinical decision support: effectiveness in improving quality processes and clinical outcomes and factors that may influence success. *The Yale journal of biology and medicine*, 87(2):187, 2014.

M. A. Musen, B. Middleton, and R. A. Greenes. Clinical Decision-Support Systems. In E. H. Shortliffe and J. J. Cimino, editors, *Biomedical Informatics: Computer Applications in Health Care and Biomedicine*, pages 795–840. Springer International Publishing, Cham, 2021. ISBN 978-3-030-58721-5. doi: 10.1007/978-3-030-58721-5_24.

H. Nori, N. King, S. M. McKinney, D. Carignan, and E. Horvitz. Capabilities of gpt-4 on medical challenge problems. *arXiv preprint arXiv:2303.13375*, 2023. doi: 10.48550/ARXIV.2303.13375.

H. Nori, M. Daswani, C. Kelly, S. Lundberg, M. T. Ribeiro, M. Wilson, X. Liu, V. Sounderajah, J. Carlson, M. P. Lungren, et al. Sequential diagnosis with language models. *arXiv preprint arXiv:2506.22405*, 2025.

G. Ogrinc, L. Davies, D. Goodman, P. Batalden, F. Davidoff, and D. Stevens. SQUIRE 2.0 (standards for QUality improvement reporting excellence): revised publication guidelines from a detailed consensus process. *BMJ Qual. Saf.*, 25(12):986–992, Dec. 2016.

T. Ojo, L. Kabasele, B. Boyd, S. Enechukwu, N. Ryan, J. Gyamfi, and E. Peprah. The Role of Implementation Science in Advancing Resource Generation for Health Interventions in Low- and Middle-Income Countries. *Health Services Insights*, 14:1178632921999652, Mar. 2021. ISSN 1178-6329. doi: 10.1177/1178632921999652.

L. B. Olswang and P. A. Prelock. Bridging the Gap Between Research and Practice: Implementation Science. *Journal of Speech, Language, and Hearing Research*, 58(6):S1818–S1826, Dec. 2015. doi: 10.1044/2015_JSLHR-L-14-0305.

J. C. L. Ong, L. Jin, K. Elangovan, G. Y. S. Lim, D. Y. Z. Lim, G. G. R. Sng, Y. Ke, J. Y. M. Tung, R. J. Zhong, C. M. Y. Koh, et al. Development and testing of a novel large language model-based clinical decision support systems for medication safety in 12 clinical specialties. *arXiv preprint arXiv:2402.01741*, 2024.

D. Oniani, X. Wu, S. Visweswaran, S. Kapoor, S. Kooragayalu, K. Polanska, and Y. Wang. Enhancing Large Language Models for Clinical Decision Support by Incorporating Clinical Practice Guidelines, Jan. 2024.

P. Papadopoulos, M. Soflano, Y. Chaudy, W. Adejo, and T. M. Connolly. A systematic review of technologies and standards used in the development of rule-based clinical decision support systems. *Health and Technology*, 12(4):713–727, 2022.

S. R. Pfohl, H. Cole-Lewis, R. Sayres, D. Neal, M. Asiedu, A. Dieng, N. Tomasev, Q. M. Rashid, S. Azizi, N. Rostamzadeh, et al. A toolbox for surfacing health equity harms and biases in large language models. *Nature Medicine*, 30(12):3590–3600, 2024.

N. C. Rajashekar, Y. E. Shin, Y. Pu, S. Chung, K. You, M. Giuffre, C. E. Chan, T. Saarinen, A. Hsiao, J. Sekhon, A. H. Wong, L. V. Evans, R. F. Kizilcec, L. Laine, T. Mccall, and D. Shung. Human-Algorithmic Interaction Using a Large Language Model-Augmented Artificial Intelligence Clinical Decision Support System. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI '24, pages 1–20, New York, NY, USA, May 2024. Association for Computing Machinery. ISBN 9798400703300. doi: 10.1145/3613904.3642024.

A. Rajkomar, J. Dean, and I. Kohane. Machine learning in medicine. *New England Journal of Medicine*, 380(14):1347–1358, 2019.

M. K. Rommers, J. Zwaveling, H.-J. Guchelaar, and I. M. Teepe-Twiss. Evaluation of rule effectiveness and positive predictive value of clinical rules in a dutch clinical decision support system in daily hospital pharmacy practice. *Artificial intelligence in medicine*, 59(1):15–21, 2013.

J. Ross, F. Stevenson, R. Lau, and E. Murray. Factors that influence the implementation of e-health: A systematic review of systematic reviews (an update). *Implementation Science*, 11(1):146, Oct. 2016. ISSN 1748-5908. doi: 10.1186/s13012-016-0510-7.

R. K. Ross, A. Breskin, and D. Westreich. When is a complete-case approach to missing data valid? the importance of effect-measure modification. *Am. J. Epidemiol.*, 189(12):1583–1589, Dec. 2020.

K. Saab, T. Tu, W.-H. Weng, R. Tanno, D. Stutz, E. Wulczyn, F. Zhang, T. Strother, C. Park, E. Vedadi, et al. Capabilities of gemini models in medicine. *arXiv preprint arXiv:2404.18416*, 2024.

K. Saab, J. Freyberg, C. Park, T. Strother, Y. Cheng, W.-H. Weng, D. G. T. Barrett, D. Stutz, N. Tomasev, A. Palepu, V. Liévin, Y. Sharma, R. Ruparel, A. Ahmed, E. Vedadi, K. Kanada, C. Hughes, Y. Liu, G. Brown, Y. Gao, S. Li, S. S. Mahdavi, J. Manyika, K. Chou, Y. Matias, A. Hassidim, D. R. Webster, P. Kohli, S. M. A. Eslami, J. Barral, A. Rodman, V. Natarajan, M. Schaekermann, T. Tu, A. Karthikesalingam, and R. Tanno. Advancing Conversational Diagnostic AI with Multimodal Reasoning, May 2025.

H. M. Seidling, S. Phansalkar, D. L. Seger, M. D. Paterno, S. Shaykevich, W. E. Haefeli, and D. W. Bates. Factors influencing alert acceptance: a novel approach for predicting the success of clinical decision support. *Journal of the American Medical Informatics Association*, 18(4):479–484, 2011.

E. H. Shortliffe. Mycin: A Knowledge-Based Computer Program Applied to Infectious Diseases. *Proceedings of the Annual Symposium on Computer Application in Medical Care*, pages 66–69, Oct. 1977. ISSN 0195-4210.

B. Silva, F. Hak, T. Guimaraes, M. Manuel, and M. F. Santos. Rule-based system for effective clinical decision support. *Procedia Computer Science*, 220:880–885, 2023.

K. Singhal, S. Azizi, T. Tu, S. S. Mahdavi, J. Wei, H. W. Chung, N. Scales, A. Tanwani, H. Cole-Lewis, S. Pfohl, et al. Large language models encode clinical knowledge. *Nature*, 620(7972):172–180, 2023.

K. Singhal, T. Tu, J. Gottweis, R. Sayres, E. Wulczyn, M. Amin, L. Hou, K. Clark, S. R. Pfohl, H. Cole-Lewis, et al. Toward expert-level medical question answering with large language models. *Nature Medicine*, pages 1–8, 2025.

D. F. Sittig, M. A. Krall, R. H. Dykstra, A. Russell, and H. L. Chin. A survey of factors affecting clinician acceptance of clinical decision support. *BMC medical informatics and decision making*, 6(1):6, 2006.

S. P. Slight, D. L. Seger, K. C. Nanji, I. Cho, N. Maniam, P. C. Dykes, and D. W. Bates. Are we heeding the warning signs? examining providers' overrides of computerized drug-drug interaction alerts in primary care. *PloS one*, 8(12):e85071, 2013.

M. Smith, A. Sattler, G. Hong, and S. Lin. From Code to Bedside: Implementing Artificial Intelligence Using Quality Improvement Methods. *Journal of General Internal Medicine*, 36(4):1061–1066, Apr. 2021. ISSN 0884-8734, 1525-1497. doi: 10.1007/s11606-020-06394-w.

R. T. Sutton, D. Pincock, D. C. Baumgart, D. C. Sadowski, R. N. Fedorak, and K. I. Kroeker. An overview of clinical decision support systems: Benefits, risks, and strategies for success. *npj Digital Medicine*, 3(1): 17, Feb. 2020. ISSN 2398-6352. doi: 10.1038/s41746-020-0221-y.

R. Tanno, D. G. Barrett, A. Sellergren, S. Ghaisas, S. Dathathri, A. See, J. Welbl, C. Lau, T. Tu, S. Azizi, et al. Collaboration between clinicians and vision–language models in radiology report generation. *Nature Medicine*, 31(2):599–608, 2025.

E. J. Topol. High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, 25(1):44–56, 2019. doi: 10.1038/s41591-018-0300-7.

T. Tu, S. Azizi, D. Driess, M. Schaekermann, M. Amin, P.-C. Chang, A. Carroll, C. Lau, R. Tanno, I. Ktena, et al. Towards generalist biomedical ai. *Nejm Ai*, 1(3):AIoa2300138, 2024.

T. Tu, M. Schaekermann, A. Palepu, K. Saab, J. Freyberg, R. Tanno, A. Wang, B. Li, M. Amin, Y. Cheng, et al. Towards conversational diagnostic artificial intelligence. *Nature*, pages 1–9, 2025.

S. Van de Velde, A. Heselmans, N. Delvaux, L. Brandt, L. Marco-Ruiz, D. Spitaels, H. Cloetens, T. Kortteisto, P. Roshanov, I. Kunnamo, et al. A systematic review of trials evaluating success factors of interventions with computerised clinical decision support. *Implementation science*, 13(1):114, 2018.

D. Van Veen, C. Van Uden, L. Blankemeier, J.-B. Delbrouck, A. Aali, C. Bluethgen, A. Pareek, M. Polacin, E. P. Reis, A. Seehofnerová, N. Rohatgi, P. Hosamani, W. Collins, N. Ahuja, C. P. Langlotz, J. Hom, S. Gatidis, J. Pauly, and A. S. Chaudhari. Adapted large language models can outperform medical experts in clinical text summarization. *Nature Medicine*, 30(4):1134–1142, Apr. 2024. ISSN 1546-170X. doi: 10.1038/s41591-024-02855-5.

WHO. Patient safety. `https://www.who.int/news-room/fact-sheets/detail/patient-safety`, March 2023.

L. Yang, S. Xu, A. Sellergren, T. Kohlberger, Y. Zhou, I. Ktena, A. Kiraly, F. Ahmed, F. Hormozdiari, T. Jaroensri, et al. Advancing multimodal medical capabilities of gemini. *arXiv preprint arXiv:2405.03162*, 2024.

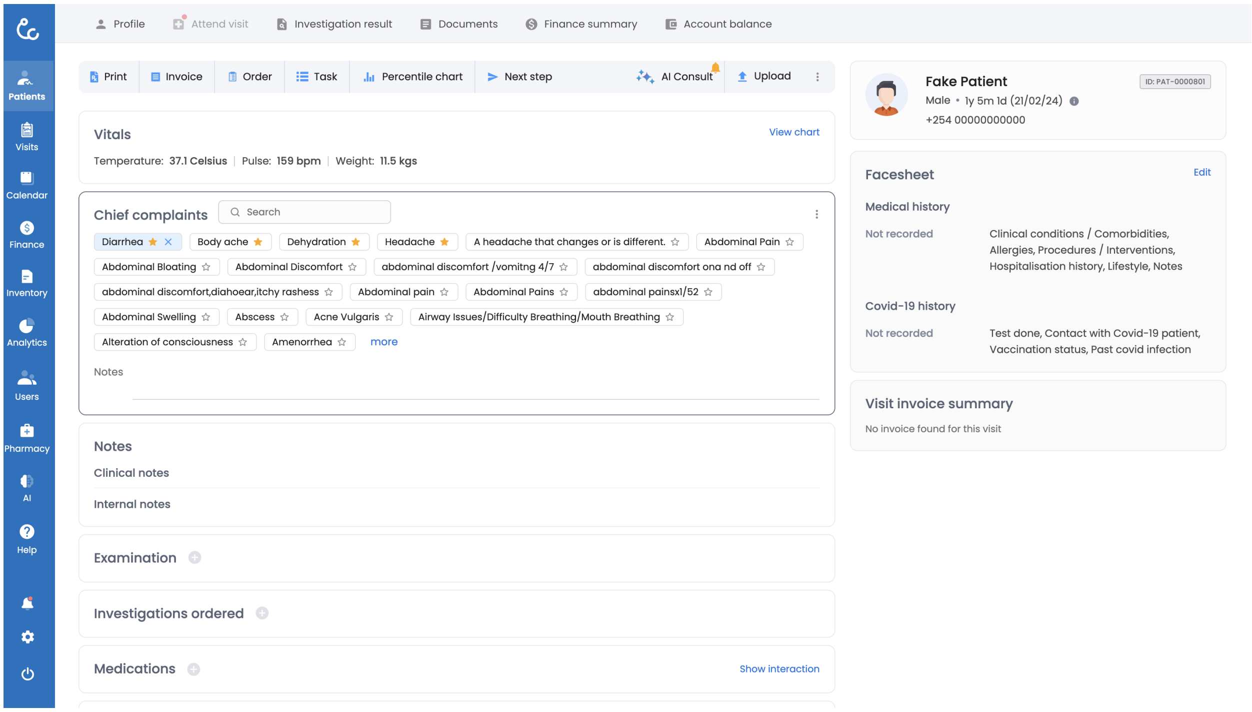
H. M. Yapa and T. Bärnighausen. Implementation science in resource-poor countries and communities. *Implementation Science*, 13(1):154, Dec. 2018. ISSN 1748-5908. doi: 10.1186/s13012-018-0847-1.

J. Zaretsky, J. M. Kim, S. Baskharoun, Y. Zhao, J. Austrian, Y. Aphinyanaphongs, R. Gupta, S. B. Blecker, and J. Feldman. Generative Artificial Intelligence to Transform Inpatient Discharge Summaries to Patient-Friendly Language and Format. *JAMA Network Open*, 7(3):e240357, Mar. 2024. ISSN 2574-3805. doi: 10.1001/jamanetworkopen.2024.0357.

G. Zou. A modified poisson regression approach to prospective studies with binary data. *Am. J. Epidemiol.*, 159(7):702–706, Apr. 2004.

G. Y. Zou and A. Donner. Extension of the modified poisson regression model to prospective studies with correlated binary data. *Stat. Methods Med. Res.*, 22(6):661–670, Dec. 2013.

A Images of AI Consult in use



Fake Patient
ID: PAT-0000801
Male • 1y 5m 1d (21/02/24)
+254 00000000000

Vitals
Temperature: 37.1 Celsius | Pulse: 159 bpm | Weight: 11.5 kgs

Chief complaints

Notes

Notes
Clinical notes
Internal notes

Examination

Investigations ordered

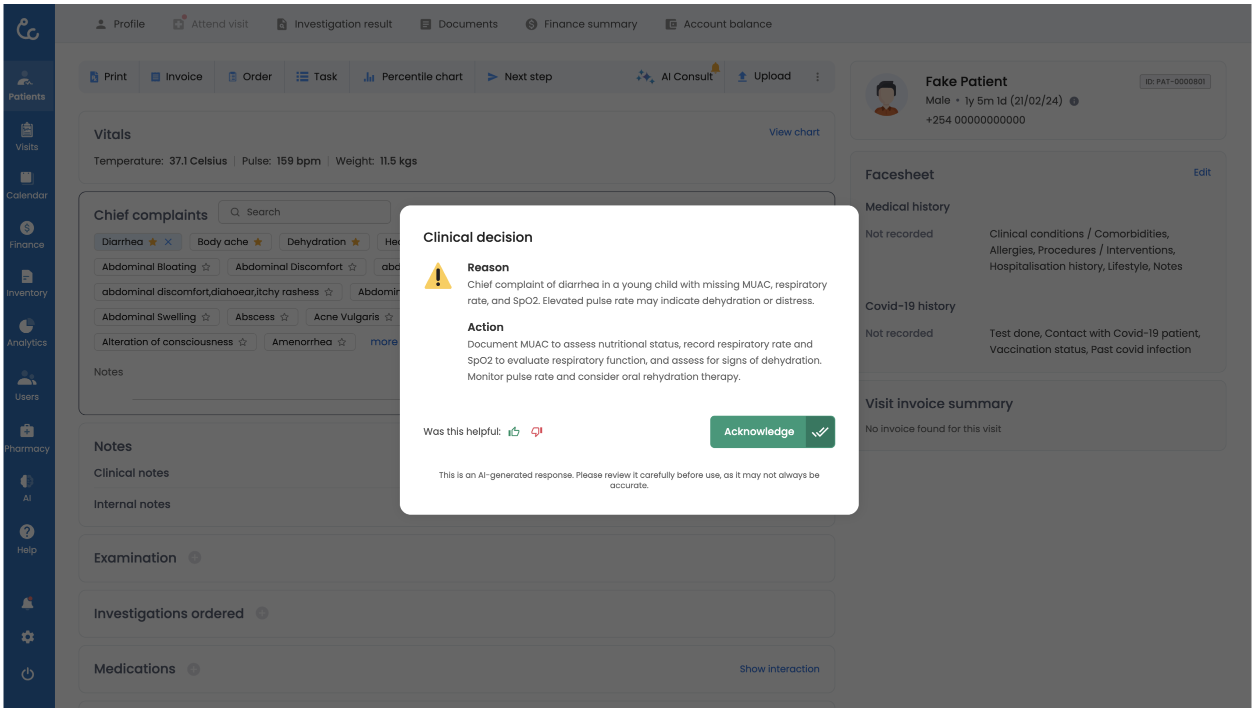
Medications

Facesheet
Medical history
Not recorded — Clinical conditions / Comorbidities, Allergies, Procedures / Interventions, Hospitalisation history, Lifestyle, Notes

Covid-19 history
Not recorded — Test done, Contact with Covid-19 patient, Vaccination status, Past covid infection

Visit invoice summary
No invoice found for this visit

Figure 9: Image of AI Consult yellow notification.



Clinical decision

Reason
Chief complaint of diarrhea in a young child with missing MUAC, respiratory rate, and SpO2. Elevated pulse rate may indicate dehydration or distress.

Action
Document MUAC to assess nutritional status, record respiratory rate and SpO2 to evaluate respiratory function, and assess for signs of dehydration. Monitor pulse rate and consider oral rehydration therapy.

Was this helpful:

This is an AI-generated response. Please review it carefully before use, as it may not always be accurate.

Fake Patient
ID: PAT-0000801
Male • 1y 5m 1d (21/02/24)
+254 00000000000

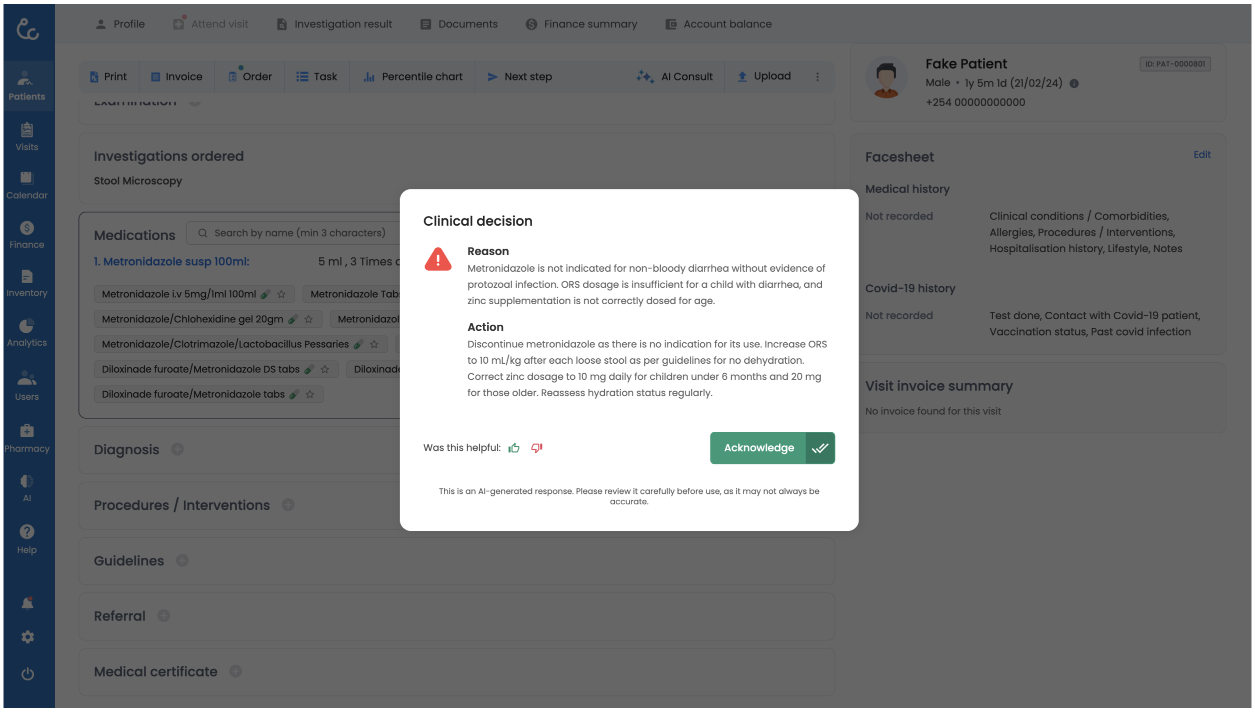
Vitals
Temperature: 37.1 Celsius | Pulse: 159 bpm | Weight: 11.5 kgs

Facesheet
Medical history
Not recorded — Clinical conditions / Comorbidities, Allergies, Procedures / Interventions, Hospitalisation history, Lifestyle, Notes

Covid-19 history
Not recorded — Test done, Contact with Covid-19 patient, Vaccination status, Past covid infection

Visit invoice summary
No invoice found for this visit

Figure 10: Image of AI Consult yellow popup, after clicking on the notification bell.



Fake Patient
ID: PAT-0000801
Male • 1y 5m 1d (21/02/24)
+254 00000000000

Investigations ordered
Stool Microscopy

Medications
Search by name (min 3 characters)
1. Metronidazole susp 100ml: 5 ml , 3 Times

Metronidazole i.v 5mg/1ml 100ml
Metronidazole Tab
Metronidazole/Chlohexidine gel 20gm
Metronidazol
Metronidazole/Clotrimazole/Lactobacillus Pessaries
Diloxinade furoate/Metronidazole DS tabs
Diloxinad
Diloxinade furoate/Metronidazole tabs

Diagnosis

Procedures / Interventions

Guidelines

Referral

Medical certificate

Facesheet

Medical history

Not recorded — Clinical conditions / Comorbidities, Allergies, Procedures / Interventions, Hospitalisation history, Lifestyle, Notes

Covid-19 history

Not recorded — Test done, Contact with Covid-19 patient, Vaccination status, Past covid infection

Visit invoice summary

No invoice found for this visit

Clinical decision

Reason

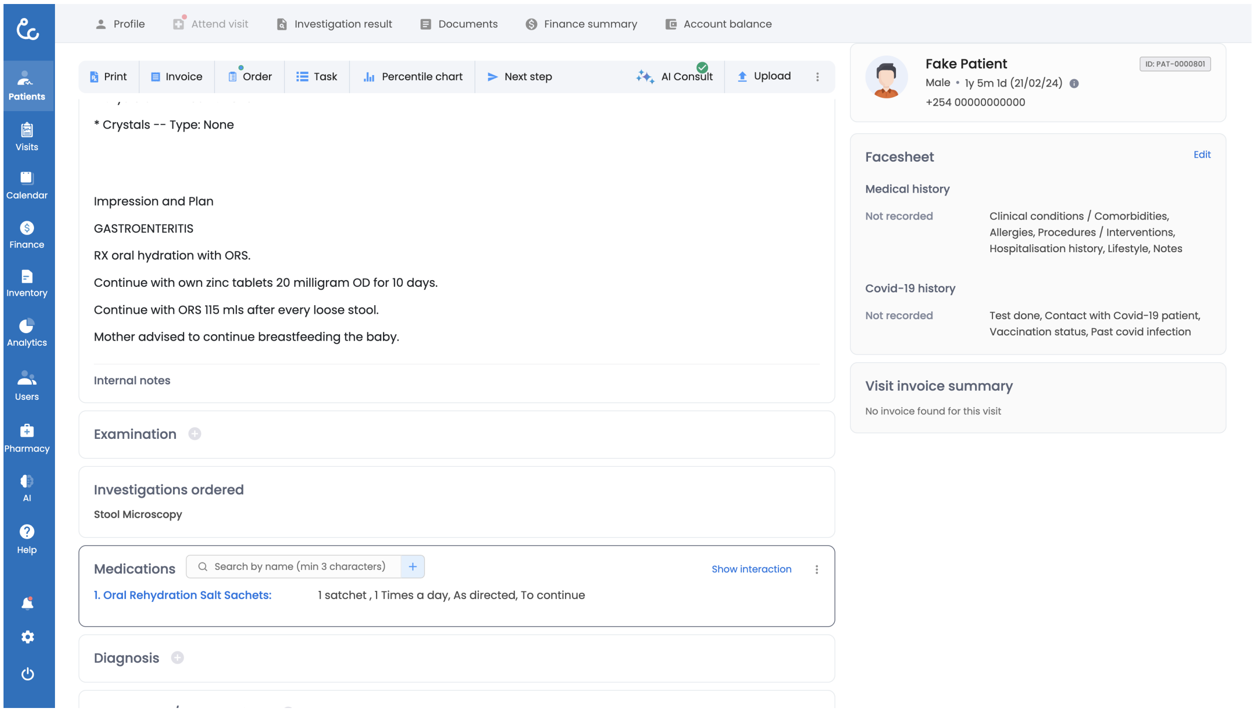
Metronidazole is not indicated for non-bloody diarrhea without evidence of protozoal infection. ORS dosage is insufficient for a child with diarrhea, and zinc supplementation is not correctly dosed for age.

Action

Discontinue metronidazole as there is no indication for its use. Increase ORS to 10 mL/kg after each loose stool as per guidelines for no dehydration. Correct zinc dosage to 10 mg daily for children under 6 months and 20 mg for those older. Reassess hydration status regularly.

This is an AI-generated response. Please review it carefully before use, as it may not always be accurate.

Figure 11: Image of AI Consult red popup.



Fake Patient
ID: PAT-0000801
Male • 1y 5m 1d (21/02/24)
+254 00000000000

* Crystals -- Type: None

Impression and Plan

GASTROENTERITIS

RX oral hydration with ORS.

Continue with own zinc tablets 20 milligram OD for 10 days.

Continue with ORS 115 mls after every loose stool.

Mother advised to continue breastfeeding the baby.

Internal notes

Examination

Investigations ordered
Stool Microscopy

Medications
Search by name (min 3 characters)
1. Oral Rehydration Salt Sachets: 1 satchet , 1 Times a day, As directed, To continue

Diagnosis

Facesheet

Medical history

Not recorded — Clinical conditions / Comorbidities, Allergies, Procedures / Interventions, Hospitalisation history, Lifestyle, Notes

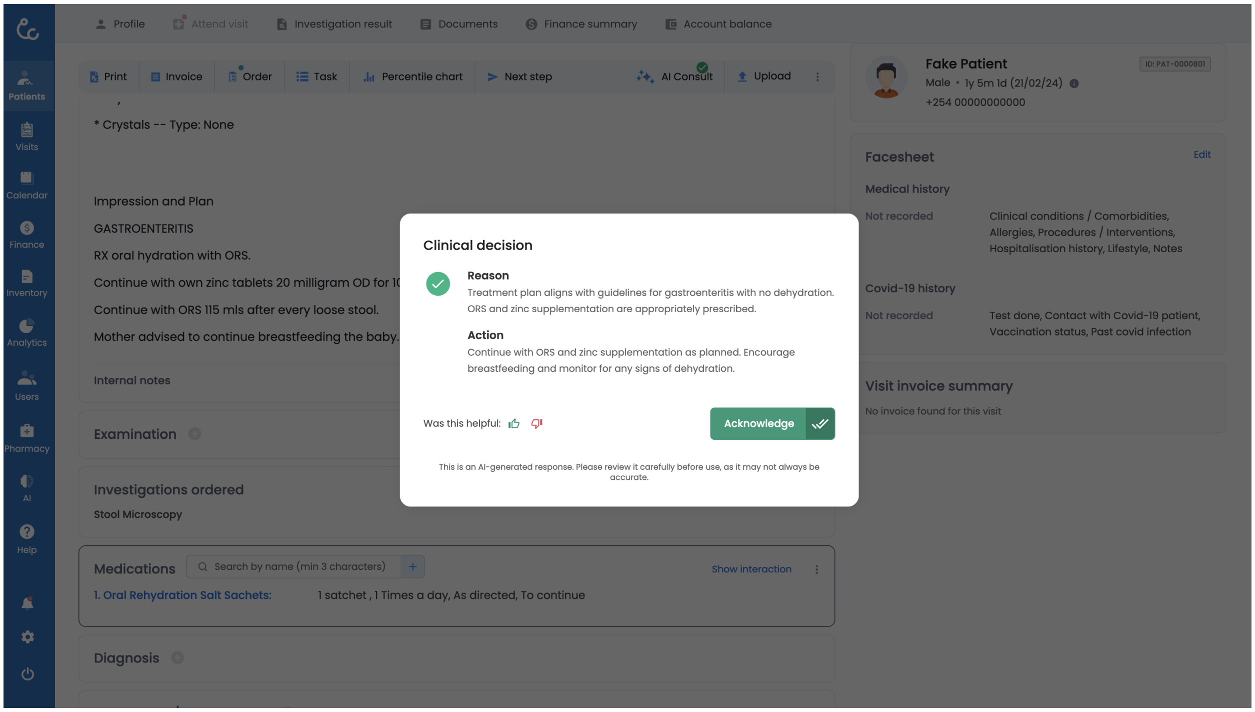
Covid-19 history

Not recorded — Test done, Contact with Covid-19 patient, Vaccination status, Past covid infection

Visit invoice summary

No invoice found for this visit

Figure 12: Image of AI Consult green notification.



* Crystals -- Type: None

Impression and Plan

GASTROENTERITIS

RX oral hydration with ORS.

Continue with own zinc tablets 20 milligram OD for 1

Continue with ORS 115 mls after every loose stool.

Mother advised to continue breastfeeding the baby.

Internal notes

Investigations ordered

Stool Microscopy

Medications

1. Oral Rehydration Salt Sachets: 1 satchet , 1 Times a day, As directed, To continue

Fake Patient

ID: PAT-0000801

Male • 1y 5m 1d (21/02/24)

+254 00000000000

Facesheet

Medical history

Not recorded — Clinical conditions / Comorbidities, Allergies, Procedures / Interventions, Hospitalisation history, Lifestyle, Notes

Covid-19 history

Not recorded — Test done, Contact with Covid-19 patient, Vaccination status, Past covid infection

Visit invoice summary

No invoice found for this visit

Clinical decision

Reason

Treatment plan aligns with guidelines for gastroenteritis with no dehydration. ORS and zinc supplementation are appropriately prescribed.

Action

Continue with ORS and zinc supplementation as planned. Encourage breastfeeding and monitor for any signs of dehydration.

This is an AI-generated response. Please review it carefully before use, as it may not always be accurate.

Figure 13: Image of AI Consult green popup, after clicking on the notification bell.

B Full examples of AI Consult

Initial documentation	AI Consult response	Final documentation
Vitals Age 2 y 6 m, Wt 12.5 kg, HR 127 bpm, MUAC green, Temp 36.3 °C. **Clinical note** mother report th child has been vomiting, 4 episode, non projectile , vomitous contained lasgt eaten meal , no history of fever, no history of cough ,no history of diarrhea, no history of refusal to feed , no history of crying while passing urine , no history of travelling to malaria endemic zone . **on examination**: in fair general condition not pale ,no jaundice ,no cyanosis . skin pinch return is immediate , capillary refill return is less than 2 sec, no dryness of mucus membrane Per abdomen-normal fullness, no palpable mass, no tenderness Respiratory-chest clear, no respiratory distress, no crackles, no rhonchi Ear, nose, and throat-inflamed, non exudative ,non erythematous throat , no adenoids inflammation , no inflammation in the ear Cardiovascular- s1s2 heard no murmur Neurologic-AVPU@A , neck soft , no sign of meningeal irritation **Investigations** Full Hemogram: WBC 12.38 **HGB 9.90** HCT 30.70 Plt 248 RBC 5.26 **MCV 58.30** MCH 18.8 MCHC 32.2. Strep-A Ag negative. **Diagnosis** Tonsillitis, acute bacterial. **CLINICIAN DOES NOT INCLUDE A DIAGNOSIS RELATED TO THE ABNORMAL FINDING OF MICROCYTIC ANEMIA**	**RED FLAG** **Responses**: The clinical documentation shows the presence of microcytic anemia with a hemoglobin level of 9.90 g/dL and an MCV of 58.30 fL, indicative of anemia that is not addressed in the diagnosis. The presence of microcytic anemia should be evaluated alongside the current symptom of vomiting. **Recommendations**: Reevaluate the diagnosis considering the significant finding of microcytic anemia, which is not addressed. Investigate underlying causes of anemia, such as iron deficiency or chronic disease. Consider additional testing for iron studies or further dietary investigation. Ensure anemia is included in the management plan to address this critical finding.	**Vitals** Age 2 y 6 m, Wt 12.5 kg, HR 127 bpm, MUAC green, Temp 36.3 °C. **Clinical note** mother report th child has been vomiting, 4 episode, non projectile , vomitous contained lasgt eaten meal , no history of fever, no history of cough ,no history of diarrhea, no history of refusal to feed , no history of crying while passing urine , no history of travelling to malaria endemic zone . **on examination**: in fair general condition not pale ,no jaundice ,no cyanosis . skin pinch return is immediate , capillary refill return is less than 2 sec, no dryness of mucus membrane Per abdomen-normal fullness, no palpable mass, no tenderness Respiratory-chest clear, no respiratory distress, no crackles, no rhonchi Ear, nose, and throat-inflamed, non exudative ,non erythematous throat , no adenoids inflammation , no inflammation in the ear Cardiovascular- s1s2 heard no murmur Neurologic-AVPU@A , neck soft , no sign of meningeal irritation **Investigations** Full Hemogram: WBC 12.38 HGB 9.90 HCT 30.70 Plt 248 RBC 5.26 MCV 58.30 MCH 18.8 MCHC 32.2. Strep-A Ag negative. **Diagnoses** Tonsillitis, acute bacterial; Emesis, unspecified; **Iron deficiency anemia**

Table 9: Example of AI Consult in action: AI Consult flags an important missing diagnosis of iron deficiency anemia, leading the clinician to add this diagnosis so it can be appropriately treated. Highlighted portions show the initial text that triggered the tool, important messages in the AI Consult response and changes the clinician made after reviewing the flag.

Initial documentation	**AI Consult response**	**Final documentation**
Vitals Age 1 y 5 m, Wt 11.5 kg, HR 159 bpm, MUAC green, Temp 37.1 °C. **Clinical note** CHild was treated yesterday with vomiting now subsided. Mother reports developed diarrhea today morning reports several episodes since morning Stool is waterly mucoid stained but not bloody though smelly normal urine outpu. No associated fevers No history of travel to malaria zone Baby breastfeeding well but has reduced appetite today **on examination**: no dehydration nornal skin turgor normal cap refill no pallor Per abdomen: normal abdominal fullness, no distension no tenderness **Investigations** Stool Microscopy: * Consistency: Liquid/Loose * **Blood: Absent** * Mucous: Present * RBC's (Microscopy): None * **Parasites: No Ova/Cyst** * **Crystals – Amount: None** * **Crystals – Type: None** **Impression and Plan** Gastroenteritis RX oral hydration with ORS Contine with own zinc tablets 20 milligram DO for 10 days **Metronidazole susp 100ml dosage: 5 ml, 3 Times a day, After food for 5 Days, Quantity 1** Oral Rehydration Salt Sachets dosage: 1 satchet, 1 Times a day, As directed for 3 Days, Quantity 3	**RED FLAG** **Responses**: The treatment involves the use of metronidazole, which is not indicated in uncomplicated gastroenteritis with no identified protozoal infection. This could lead to unnecessary exposure to antibiotics. **Recommendations**: Discontinue metronidazole as there is no evidence of protozoan infection. Focus on continued oral rehydration with ORS and administer zinc supplements as planned. Monitor the child's hydration and general condition, and educate the caregiver on signs of dehydration requiring medical attention.	**Vitals** Age 1 y 5 m, Wt 11.5 kg, HR 159 bpm, MUAC green, Temp 37.1 °C. **Clinical note** CHild was treated yesterday with vomiting now subsided. Mother reports developed diarrhea today morning reports several episodes since morning Stool is waterly mucoid stained but not bloody though smelly normal urine outpu. No associated fevers No history of travel to malaria zone Baby breastfeeding well but has reduced appetite today **on examination**: no dehydration nornal skin turgor normal cap refill no pallor Per abdomen: normal abdominal fullness, no distension no tenderness **Investigations** Stool Microscopy: * Consistency: Liquid/Loose * Blood: Absent * Mucous: Present * RBC's (Microscopy): None * Parasites: No Ova/Cyst * Crystals – Amount: None * Crystals – Type: None **Impression and Plan** Gastroenteritis RX oral hydration with ORS Contine with own zinc tablets 20 milligram OD for 10 days **CLINICIAN REMOVED THE METRONIDAZOLE PRESCRIPTION** Continue with ORS 115 mls after every loose stool. Mother advised continue breastfeeding the baby

Table 10: Example of AI Consult in action: AI Consult suggestions help the clinician identify and remove an unnecessary antibiotic prescription.

Initial documentation	**AI Consult response**	**Final documentation**
Vitals Age 26 y 10 m, Wt 76.5 kg, HR 77 bpm, RR 18 bpm, SpO2 98%, Temp 36.3 °C.	**RED FLAG** **Responses**: The treatment plan includes Betamethasone/Dexchlorpheniramine, which is not recommended for URTI due to potential side effects and lack of efficacy. Additionally, the use of sedating antihistamines like Dexchlorpheniramine is not advisable for treating URTI symptoms. . **Recommendations**: Discontinue Betamethasone/Dexchlorpheniramine. Consider symptomatic treatment with non-sedating antihistamines if necessary, and advise on rest, hydration, and steam inhalation as supportive care.	**Vitals** Age 26 y 10 m, Wt 76.5 kg, HR 77 bpm, RR 18 bpm, SpO2 98%, Temp 36.3 °C.
Clinical note report history of dry cough ,which is on and off occurs mostly in the evening this is associated with dizziness for 2/7 now, this was preceded with headache which resolved after taking pain killer, 3/7 ago . above is accompanied with fatigue , he associates this with overworking since hes been working from 4am - midnight for the past 2/52 without rest . Has history of nasal blockage , no history of runny nose, no history of fever. no history of dib . no history of travelling to malaria endemic zone .		**Clinical note** report history of dry cough ,which is on and off occurs mostly in the evening this is associated with dizziness for 2/7 now, this was preceded with headache which resolved after taking pain killer, 3/7 ago . above is accompanied with fatigue , he associates this with overworking since hes been working from 4am - midnight for the past 2/52 without rest . Has history of nasal blockage , no history of runny nose, no history of fever. no history of dib . no history of travelling to malaria endemic zone .
on examination: in fair general condition not pale ,no jaundice ,no cyanosis ,no deho Ear, nose and throat-no inflamed tonsils, no exudation , no inflamed sinus, no ear infection Respiratory-chest clear , no crackles, no rhonchi Neurologic-GCS15/15 , No sign of meningeal irritation , no sign of neurologic deficit Cardiovascular-s1s2heard no murmur		**on examination**: in fair general condition not pale ,no jaundice ,no cyanosis ,no deho Ear, nose and throat-no inflamed tonsils, no exudation , no inflamed sinus, no ear infection Respiratory-chest clear , no crackles, no rhonchi Neurologic-GCS15/15 , No sign of meningeal irritation , no sign of neurologic deficit Cardiovascular-s1s2heard no murmur
Diagnosis Upper respiratory tract infection (URTI).		**Diagnosis** Upper respiratory tract infection (URTI).
Medications **Betamethasone/Dexchlorpheniramine maleate tabs dosage: 1 tablet, 2 Times a day, After food for 5 Days, dosage: 1 application**		**Medications** **CLINICIAN REMOVED THE BETAMETHASONE/DEXCHLORPHENIRAMINE PRESCRIPTION** Cetrizine tabs 10mg: 1 application, 1 Times a day, After food for 5 Days Xylometazoline Adult Drops 10ml: 2 drop, 3 Times a day, Morning, Afternoon, Night for 3 Days

Table 11: Example of AI Consult in action: AI Consult identified potentially harmful use of a combination steroid / sedating antihistamine, leading the clinician to replace this with more appropriate, non-sedating medications.

Initial documentation	**AI Consult response**	**Final documentation**
Vitals Age 0 y 10 m, Wt 8.9 kg, HR 118 bpm, MUAC green, RR 26 bpm, Temp 36.6 °C. **Clinical note** child has been accompanied with 2 day history of mouth sores mother also reports child with 3 day history of loose stool , started yesterday gradually mother reports stool is soft, mucoid , non blood stained **CLINICIAN DOES NOT INCLUDE THE FREQUENCY OF LOOSE STOOLS** no vomiting also reports to have noticed signs of teething pre med: nystatin used for 2 days now no known food or drug allergy **on examination**: stable ,not pale, no jaundice, not dehydrated able to drink adequately, no sunken eyes capillary refill: immediately oral exam has oral thrush in the mouth other systems essentially normal	**YELLOW FLAG** **Responses**: Documentation is generally sufficient but lacks details on the frequency and quantity of loose stools, which are important for assessing dehydration risk in a child with gastroenteritis. **Recommendations**: Document the frequency and quantity of loose stools to better assess the risk of dehydration and guide management.	**Vitals** Age 0 y 10 m, Wt 8.9 kg, HR 118 bpm, MUAC green, RR 26 bpm, Temp 36.6 °C. **Clinical note** child has been accompanied with 2 day history of mouth sores mother also reports child with 3 day history of loose stool , started yesterday gradually mother reports stool is soft, mucoid , non blood stained **reports child with loose stool after 4 to 6hrs , less amount , not watery.** no vomiting also reports to have noticed signs of teething pre med: nystatin used for 2 days now no known food or drug allergy **on examination**: stable ,not pale, no jaundice, not dehydrated able to drink adequately, no sunken eyes capillary refill: immediately oral exam has oral thrush in the mouth other systems essentially normal

Table 12: Example of AI Consult in action: AI Consult suggestions help the clinician seek important missing history which will help them know what treatment to give.

Initial documentation	**AI Consult response**	**Final documentation**
Vitals Age 30 y 2 m, Wt 69.5 kg, HR 102 bpm, BP 105/72, Temp 36.3 °C. **Clinical note** presented with history of per vaginal itchiness on and off for the past 3 days accompanied by whitish per vaginal discharge non smelly non bloody later back pains,no per vaginal spotting,nopainful urination,no urine frequency,no lower abdominal pains **on examination**: stable,afebrile,not pale,not dehydrated,not jaundiced per abdomen-soft none tender,no guarding,no rebound tenderness respiratory-clear chest,no creps,no rhonchi cardiovascular-s1 and s2 heard,no murmur central nervous system-gcs 15/15,no neck stiffness,soft neck other systems-essentially normal **Investigations** Urine Analysis **CLINICIAN DOES NOT ORDER A TEST TO INVESTIGATE THE VAGINAL DISCHARGE**	**YELLOW FLAG** **Responses**: The urine analysis is a common preliminary test that can help rule out urinary tract causes of symptoms. However, given the primary symptoms are related to vaginal discharge and itchiness,a vaginal swab for microscopy, culture, and sensitivity would be more directly relevant to identify possible causes like yeast infection or bacterial vaginosis. **Recommendations**: Consider ordering a vaginal swab for microscopy, culture, and sensitivity to better identify the cause of the vaginal discharge and itchiness.	**Vitals** Age 30 y 2 m, Wt 69.5 kg, HR 102 bpm, BP 105/72, Temp 36.3 °C. **Clinical note** presented with history of per vaginal itchiness on and off for the past 3 days accompanied by whitish per vaginal discharge non smelly non bloody later back pains,no per vaginal spotting,nopainful urination,no urine frequency,no lower abdominal pains **on examination**: stable,afebrile,not pale,not dehydrated,not jaundiced per abdomen-soft none tender,no guarding,no rebound tenderness respiratory-clear chest,no creps,no rhonchi cardiovascular-s1 and s2 heard,no murmur central nervous system-gcs 15/15,no neck stiffness,soft neck other systems-essentially normal **Investigations** Urine Analysis **High Vaginal Swab (HVS Gram Stain)**

Table 13: Example of AI Consult in action: AI Consult flags a missing test to evaluate the cause of vaginal itchiness and discharge, resulting in the clinician ordering this test.

Initial documentation	**AI Consult response**	**Final documentation**
Vitals Age 16 y 4 m, Wt 45 kg, HR 112 bpm, BP 98/61, RR 17 bpm, Temp 38.3 °C.	**GREEN FLAG** **Responses**: The diagnosis of Group A Strep pharyngitis aligns with the clinical presentation of throat pain, fever, and positive Streptococcus A antigen test. **Recommendations**: Proceed with appropriate antibiotic therapy for Group A Strep pharyngitis, such as penicillin or amoxicillin, and provide supportive care for symptoms.	**Vitals** Age 16 y 4 m, Wt 45 kg, HR 112 bpm, BP 98/61, RR 17 bpm, Temp 38.3 °C.
Clinical note high fevers, exposed parafast 1g Per oral administered Brought in by the mother with 1 day history of painful throat, chills, fever and left sided headache. no cough or runny nose. no gastrointestinal complainr. no bladder disturbances. no travel history		**Clinical note** high fevers, exposed parafast 1g Per oral administered Brought in by the mother with 1 day history of painful throat, chills, fever and left sided headache. no cough or runny nose. no gastrointestinal complainr. no bladder disturbances. no travel history
on examination: fair condition, febrile, no pallor, no icterus, no dehydration Respiratory; normal breath sounds Cardiovascular: normal blood pressure and pulse Ear, nose and throat; tonsillar exudate Other systems; unremarkable		**on examination**: fair condition, febrile, no pallor, no icterus, no dehydration Respiratory; normal breath sounds Cardiovascular: normal blood pressure and pulse Ear, nose and throat; tonsillar exudate Other systems; unremarkable
Investigations **Streptococcus A Antigen Test: Positive**		**Investigations** **Streptococcus A Antigen Test: Positive**
Diagnosis : Group A Strep pharyngitis score 3-4:		**Diagnosis : Group A Strep pharyngitis score 3-4:**

Table 14: Example of AI Consult in action: AI Consult suggestions support the accurately assigned diagnosis.

C Physician Rater: Likert Definitions and Failure Modes

Likert Score	History & Examination: Likert Score Description
5	**Thorough**: key components of the HPI and/or medical history elements are documented; relevant systems on physical exam are well documented; chief complaint and relevant vitals are present
4	**Reasonably thorough**: some relevant HPI and/or medical history elements are documented; some of the relevant system specific findings are documented on exam; chief complaint and most relevant vitals are present
3	**Limited**: history has limited symptom description or pertinent details (e.g., missing 2 or more relevant characterizations of the chief complaint, such as duration, onset, quality, severity, etc.); physical exam is limited; chief complaint or some relevant vitals are present
2	**Deficient**: history misses the most important key elements; physical exam is very incomplete, excludes important details of relevant systems or misses one of the most important exam findings; chief complaint and/or important vitals missing
1	**Very poor**: history is extremely limited with no meaningful characterization of presenting symptoms; physical exam is missing entirely or nearly so; critical vitals missing

Table 15: Likert score descriptions used by physician raters to evaluate history and examination.

Likert Score	Investigations: Likert Score Description
5	**Appropriate & Targeted**: All investigations are clearly indicated by the clinical context; point of care tests are utilized appropriately and there are no unjustified tests ordered; or no investigations are indicated and none are ordered
4	**Minor overordering**: Investigations are mostly appropriate with only minimal overtesting, (e.g., full hemogram for URTI symptoms with no major systemic symptoms or exam findings suggesting bacterial infection but one or two general symptoms like subjective fever or headache are present)
3	**Overly broad**: Investigations ordered are unjustified, (e.g., full hemogram for clearly simple URTI with unconcerning vitals and exam findings)
2	**Deficient**: Potentially helpful investigations are missing, (e.g., no rapid strep test for pharyngitis/tonsillitis)
1	**Very poor**: Critical omissions - clearly important investigations were not ordered, risking misdiagnosis or harm, (e.g., urinalysis not ordered for a young child with unexplained fever or no malaria test for a patient with fever and travel to a malaria endemic region)

Table 16: Likert score descriptions used by physician raters to evaluate investigations.

Likert Score	Diagnosis: Likert Score Description
5	**Excellent**: primary diagnosis fully aligns with the clinical picture and is the most likely diagnosis; no additional diagnoses are missing; any listed additional diagnoses are appropriate
4	**Good**: primary diagnosis generally aligns and is among the top few likely diagnoses; additional diagnoses are present but not clearly relevant
3	**Adequate**: primary diagnosis is plausible but not the most likely, or one or more important additional diagnoses are missing (e.g., no diagnosis of "elevated blood pressure reading" or "hypertension" when BP is significantly elevated)
2	**Deficient**: primary diagnosis is not well supported by the clinical picture or low on the list of likely causes; Primary diagnosis is a catch-all diagnosis when a clearer primary diagnosis is possible (e.g., "bacterial infection unspecified" instead of "urinary tract infection"); critical additional diagnoses are missing (e.g., no "malnutrition" or "underweight" diagnosis on a child with MUC yellow or red)
1	**Very poor**: primary diagnosis is missing or clinically inappropriate, contradicts or is unsupported by documented findings

Table 17: Likert score descriptions used by physician raters to evaluate diagnoses.

Likert Score	Treatment: Likert Score Description
5	**Appropriate and complete**: treatments are appropriate and complete, including the correct use of medications and/or referrals when needed; Patient advice or education (e.g., red flag symptoms to watch for, advice on hydration, self-care, etc.) or a follow up plan is present; if procedures or escalations of care are present, they are the most appropriate course of action. OR no treatments are indicated and none are ordered
4	**Appropriate but less complete**: treatments are appropriate and complete, including the correct use of medications and/or referrals when needed but there is no patient advice, education or follow up plan documented (e.g., red flag symptoms to watch for, advice on hydration, self-care, when to return to care, etc.)
3	**Adequate**: Medications, referrals or procedures are reasonable and safe, but may not be a standard first-line therapy (i.e., things that are likely to have minimal benefit or minimal harm if given, e.g. desloratadine for a URTI instead of nasal saline spray alone), or helpful but non-critical referrals are missing
2	**Deficient**: medications are present and somewhat inappropriate (i.e., medications that may cause minor harm unnecessarily e.g., inappropriately broad antibiotic class when a narrower spectrum is sufficient); minor medication dosage errors; clearly needed referrals, procedures or escalations of care are missing
1	**Very poor**: no medications given for a condition when clearly indicated; medications are very inappropriate for the condition (e.g., use of any antibiotic when there is no indication based on documented findings); significant dosage errors (e.g., too high of a dose based on pediatric patient weight-based dosing); procedures performed or escalations of care are unwarranted

Table 18: Likert score descriptions used by physician raters to evaluate treatment plans.

Clinical Category	Possible deficiency choices selected by physician raters
Treatment	• Medications are missing • Medications are present but inappropriate • Medications are appropriate but incorrect dosages (dose, frequency or duration) • Likely inappropriate use of antibiotics overall • Likely inappropriate class of antibiotics used • Referrals are missing • Referrals are present but inappropriate • Needed procedures are missing • Procedures are present but inappropriate • Needed escalations of care are missing • Escalations of care are present but inappropriate • None of the above
Diagnosis	• Primary diagnosis is likely incorrect • Primary diagnosis is missing • Primary diagnosis is too specific to be supported by current documentation • Additional diagnosis is likely incorrect • Clinically-relevant additional diagnosis is missing • None of the above
Investigations	• Key investigations are missing • Unjustified investigations are ordered • None of the above
History	• Chief complaint is absent • Key details in the history are missing • Documentation of relevant systems on physical exam is absent • Pertinent vital signs are absent • None of the above

Table 19: Physician raters chose deficiencies present in the relevant clinical documentation.

D Additional results

D.1 Human rater study agreement

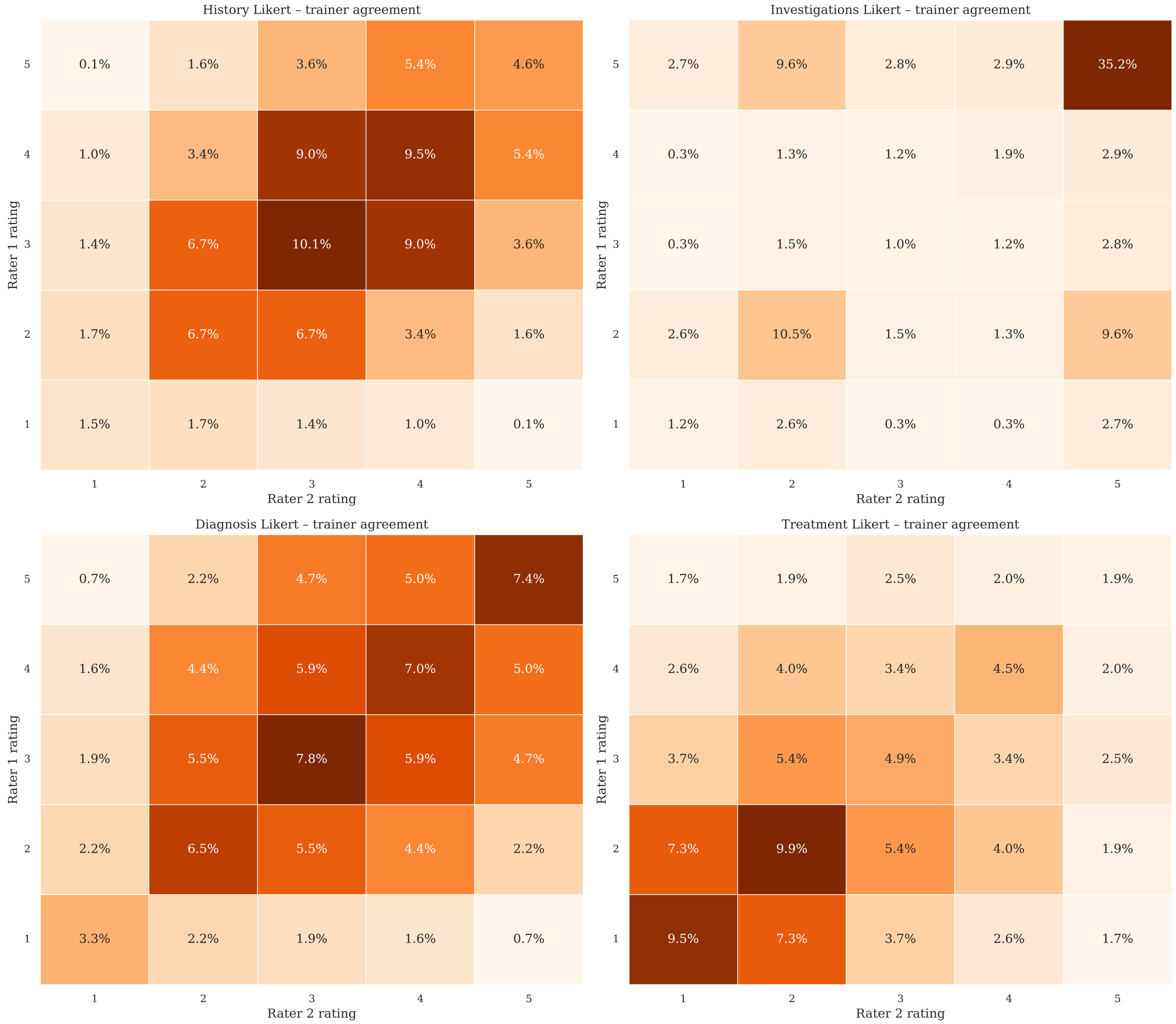


Figure 14: Confusion matrices showing the ratings of two independent raters for each Likert question for the human rater study.

D.2 Effects on quality of care

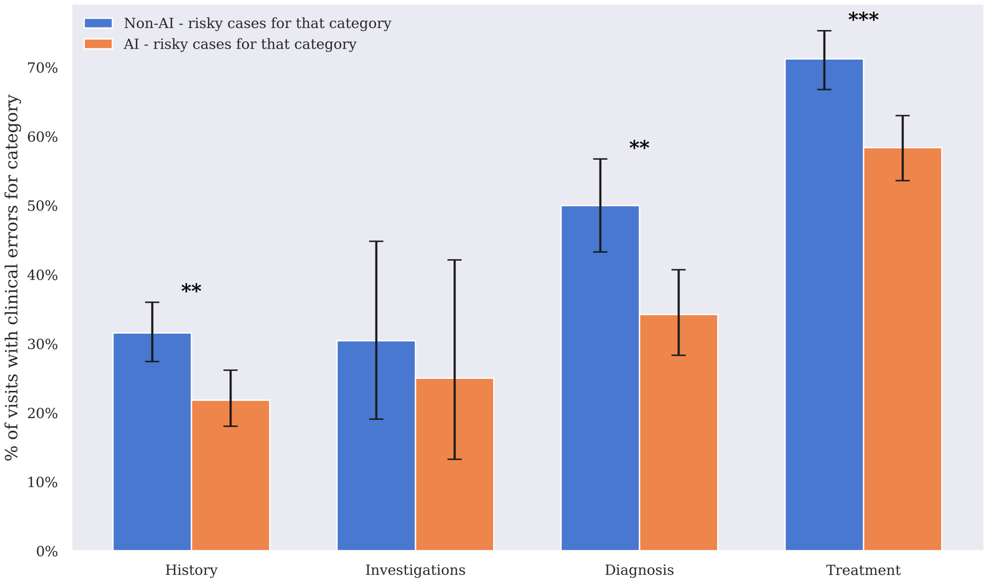


Figure 15: Likert 1 and 2 rates for history-taking, investigations, diagnosis, and treatment: cases with at least one red model response for the category in question

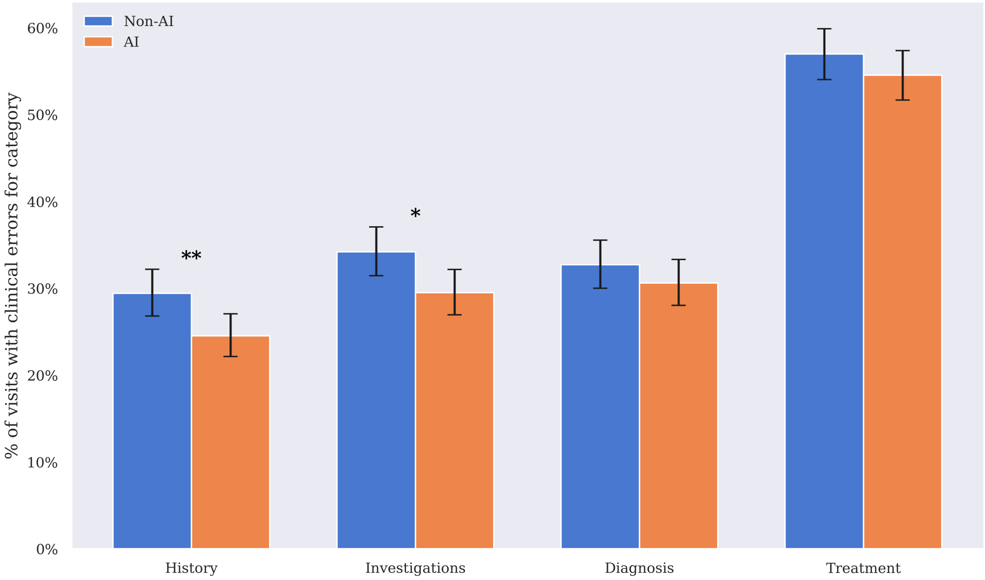


Figure 16: Likert 1 and 2 rates for history-taking, investigations, diagnosis, and treatment - results from during the induction period. * indicates $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Low-acuity cases	Medium-acuity cases	High-acuity cases
History	31.5% (15.7%-44.3%)	33.5% (20.1%-44.7%)	35.8% (8.1%-55.1%)
Investigations	11.9% (-4.4%-25.5%)	9.4% (-2.3%-19.8%)	6.3% (-19.2%-26.3%)
Diagnosis	11.2% (-3.9%-24.1%)	17.6% (5.6%-28.0%)	14.1% (-13.7%-35.1%)
Treatment	17.0% (8.3%-24.9%)	9.8% (1.5%-17.4%)	10.4% (-5.3%-23.8%)

Table 20: Relative risk reduction in clinical errors by physician-rated acuity.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.228000	0.190000	0.272000	0.000000
Group: AI vs Non-AI	0.747000	0.618000	0.903000	0.003000
Gender: Female vs Male	1.089000	0.965000	1.229000	0.169000
Visit type: Insurance vs Cash	0.871000	0.758000	1.001000	0.052000
Clinic: Embakasi vs mean clinic	0.978000	0.717000	1.332000	0.886000
Clinic: Kahawa West vs mean clinic	1.271000	1.057000	1.529000	0.011000
Clinic: Kangemi vs mean clinic	0.904000	0.544000	1.503000	0.698000
Clinic: Kasarani vs mean clinic	0.978000	0.772000	1.239000	0.854000
Clinic: Kawangware vs mean clinic	0.581000	0.417000	0.811000	0.001000
Clinic: Kimathi Street vs mean clinic	0.886000	0.547000	1.435000	0.624000
Clinic: Lang'ata vs mean clinic	1.339000	0.852000	2.105000	0.206000
Clinic: Lucky Summer vs mean clinic	1.088000	0.869000	1.362000	0.460000
Clinic: Mathare North vs mean clinic	0.804000	0.500000	1.292000	0.367000
Clinic: Pipeline vs mean clinic	1.230000	0.991000	1.527000	0.060000
Clinic: Sunton vs mean clinic	1.280000	0.871000	1.880000	0.209000
Clinic: Tassia vs mean clinic	0.851000	0.529000	1.371000	0.507000
Clinic: Umoja 1 vs mean clinic	1.061000	0.779000	1.444000	0.707000
Clinic: Umoja 2 vs mean clinic	0.962000	0.730000	1.266000	0.781000
Age (years)	1.008000	1.005000	1.011000	0.000000

Table 21: GEE model fit for history errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.324000	0.287000	0.365000	0.000000
Group: AI vs Non-AI	0.902000	0.807000	1.008000	0.069000
Gender: Female vs Male	1.085000	0.985000	1.194000	0.097000
Visit type: Insurance vs Cash	0.982000	0.894000	1.079000	0.704000
Clinic: Embakasi vs mean clinic	0.969000	0.782000	1.199000	0.771000
Clinic: Kahawa West vs mean clinic	1.067000	0.889000	1.280000	0.486000
Clinic: Kangemi vs mean clinic	1.211000	1.030000	1.423000	0.020000
Clinic: Kasarani vs mean clinic	0.810000	0.571000	1.149000	0.237000
Clinic: Kawangware vs mean clinic	0.927000	0.662000	1.297000	0.658000
Clinic: Kimathi Street vs mean clinic	0.743000	0.463000	1.191000	0.217000
Clinic: Lang'ata vs mean clinic	0.995000	0.819000	1.210000	0.962000
Clinic: Lucky Summer vs mean clinic	1.131000	0.972000	1.316000	0.113000
Clinic: Mathare North vs mean clinic	1.167000	0.962000	1.415000	0.118000
Clinic: Pipeline vs mean clinic	0.967000	0.812000	1.152000	0.710000
Clinic: Sunton vs mean clinic	0.909000	0.766000	1.080000	0.280000
Clinic: Tassia vs mean clinic	0.890000	0.735000	1.078000	0.233000
Clinic: Umoja 1 vs mean clinic	1.035000	0.917000	1.169000	0.574000
Clinic: Umoja 2 vs mean clinic	1.152000	0.974000	1.362000	0.099000
Age (years)	1.000000	0.997000	1.003000	0.921000

Table 22: GEE model fit for investigations errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.337000	0.298000	0.383000	0.000000
Group: AI vs Non-AI	0.832000	0.744000	0.931000	0.001000
Gender: Female vs Male	1.004000	0.913000	1.103000	0.942000
Visit type: Insurance vs Cash	0.997000	0.887000	1.120000	0.960000
Clinic: Embakasi vs mean clinic	1.008000	0.826000	1.229000	0.940000
Clinic: Kahawa West vs mean clinic	1.056000	0.907000	1.230000	0.483000
Clinic: Kangemi vs mean clinic	0.941000	0.804000	1.101000	0.448000
Clinic: Kasarani vs mean clinic	0.947000	0.786000	1.141000	0.568000
Clinic: Kawangware vs mean clinic	0.978000	0.823000	1.162000	0.797000
Clinic: Kimathi Street vs mean clinic	0.612000	0.453000	0.825000	0.001000
Clinic: Lang'ata vs mean clinic	1.009000	0.816000	1.248000	0.932000
Clinic: Lucky Summer vs mean clinic	0.984000	0.861000	1.125000	0.816000
Clinic: Mathare North vs mean clinic	1.126000	0.942000	1.347000	0.193000
Clinic: Pipeline vs mean clinic	1.148000	0.964000	1.367000	0.121000
Clinic: Sunton vs mean clinic	1.329000	1.012000	1.746000	0.041000
Clinic: Tassia vs mean clinic	1.120000	0.976000	1.286000	0.108000
Clinic: Umoja 1 vs mean clinic	1.123000	0.933000	1.351000	0.220000
Clinic: Umoja 2 vs mean clinic	0.751000	0.628000	0.898000	0.002000
Age (years)	1.000000	0.997000	1.003000	0.801000

Table 23: GEE model fit for diagnosis errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.649000	0.598000	0.704000	0.000000
Group: AI vs Non-AI	0.878000	0.812000	0.949000	0.001000
Gender: Female vs Male	0.944000	0.891000	1.001000	0.054000
Visit type: Insurance vs Cash	0.949000	0.889000	1.012000	0.109000
Clinic: Embakasi vs mean clinic	1.015000	0.888000	1.160000	0.828000
Clinic: Kahawa West vs mean clinic	1.013000	0.929000	1.103000	0.776000
Clinic: Kangemi vs mean clinic	0.932000	0.762000	1.139000	0.490000
Clinic: Kasarani vs mean clinic	1.055000	0.895000	1.244000	0.521000
Clinic: Kawangware vs mean clinic	0.923000	0.782000	1.089000	0.344000
Clinic: Kimathi Street vs mean clinic	0.936000	0.785000	1.116000	0.461000
Clinic: Lang'ata vs mean clinic	1.045000	0.913000	1.196000	0.523000
Clinic: Lucky Summer vs mean clinic	0.988000	0.849000	1.150000	0.879000
Clinic: Mathare North vs mean clinic	1.103000	1.007000	1.209000	0.035000
Clinic: Pipeline vs mean clinic	1.045000	0.895000	1.221000	0.575000
Clinic: Sunton vs mean clinic	1.001000	0.844000	1.188000	0.987000
Clinic: Tassia vs mean clinic	0.863000	0.795000	0.938000	0.000000
Clinic: Umoja 1 vs mean clinic	1.069000	0.988000	1.157000	0.097000
Clinic: Umoja 2 vs mean clinic	1.033000	0.959000	1.113000	0.393000
Age (years)	0.996000	0.994000	0.998000	0.000000

Table 24: GEE model fit for treatment errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.230000	0.192000	0.275000	0.000000
Group: AI vs Non-AI	0.722000	0.596000	0.875000	0.001000
Gender: Female vs Male	1.097000	0.971000	1.241000	0.138000
Visit type: Insurance vs Cash	0.877000	0.761000	1.011000	0.069000
Clinic: Embakasi vs mean clinic	0.975000	0.751000	1.266000	0.851000
Clinic: Kahawa West vs mean clinic	1.248000	1.049000	1.486000	0.012000
Clinic: Kangemi vs mean clinic	0.896000	0.539000	1.489000	0.673000
Clinic: Kasarani vs mean clinic	0.970000	0.803000	1.172000	0.753000
Clinic: Kawangware vs mean clinic	0.526000	0.404000	0.683000	0.000000
Clinic: Kimathi Street vs mean clinic	0.908000	0.562000	1.468000	0.695000
Clinic: Lang'ata vs mean clinic	1.334000	0.834000	2.135000	0.229000
Clinic: Lucky Summer vs mean clinic	1.024000	0.789000	1.328000	0.860000
Clinic: Mathare North vs mean clinic	0.860000	0.579000	1.277000	0.454000
Clinic: Pipeline vs mean clinic	1.248000	1.022000	1.525000	0.030000
Clinic: Sunton vs mean clinic	1.350000	0.853000	2.136000	0.200000
Clinic: Tassia vs mean clinic	0.831000	0.517000	1.336000	0.445000
Clinic: Umoja 1 vs mean clinic	1.082000	0.814000	1.437000	0.589000
Clinic: Umoja 2 vs mean clinic	1.026000	0.804000	1.309000	0.836000
Age (years)	1.008000	1.004000	1.011000	0.000000

Table 25: Modified Poisson model fit for history errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.324000	0.287000	0.366000	0.000000
Group: AI vs Non-AI	0.904000	0.809000	1.012000	0.079000
Gender: Female vs Male	1.089000	0.988000	1.200000	0.087000
Visit type: Insurance vs Cash	0.980000	0.892000	1.077000	0.677000
Clinic: Embakasi vs mean clinic	0.963000	0.772000	1.203000	0.742000
Clinic: Kahawa West vs mean clinic	1.058000	0.883000	1.268000	0.543000
Clinic: Kangemi vs mean clinic	1.213000	1.035000	1.422000	0.017000
Clinic: Kasarani vs mean clinic	0.825000	0.580000	1.172000	0.282000
Clinic: Kawangware vs mean clinic	0.918000	0.654000	1.288000	0.619000
Clinic: Kimathi Street vs mean clinic	0.731000	0.459000	1.164000	0.186000
Clinic: Lang'ata vs mean clinic	1.001000	0.828000	1.210000	0.992000
Clinic: Lucky Summer vs mean clinic	1.126000	0.960000	1.321000	0.145000
Clinic: Mathare North vs mean clinic	1.175000	0.964000	1.431000	0.110000
Clinic: Pipeline vs mean clinic	0.960000	0.810000	1.137000	0.636000
Clinic: Sunton vs mean clinic	0.928000	0.791000	1.087000	0.354000
Clinic: Tassia vs mean clinic	0.864000	0.714000	1.046000	0.134000
Clinic: Umoja 1 vs mean clinic	1.035000	0.918000	1.167000	0.573000
Clinic: Umoja 2 vs mean clinic	1.169000	0.997000	1.372000	0.055000
Age (years)	1.000000	0.997000	1.003000	0.907000

Table 26: Modified Poisson model fit for investigations errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.340000	0.300000	0.386000	0.000000
Group: AI vs Non-AI	0.827000	0.741000	0.924000	0.001000
Gender: Female vs Male	1.006000	0.916000	1.106000	0.897000
Visit type: Insurance vs Cash	0.999000	0.890000	1.123000	0.992000
Clinic: Embakasi vs mean clinic	1.010000	0.833000	1.225000	0.917000
Clinic: Kahawa West vs mean clinic	1.056000	0.904000	1.234000	0.488000
Clinic: Kangemi vs mean clinic	0.935000	0.800000	1.093000	0.401000
Clinic: Kasarani vs mean clinic	0.949000	0.791000	1.139000	0.575000
Clinic: Kawangware vs mean clinic	0.988000	0.828000	1.179000	0.895000
Clinic: Kimathi Street vs mean clinic	0.611000	0.451000	0.828000	0.001000
Clinic: Lang'ata vs mean clinic	0.990000	0.800000	1.225000	0.927000
Clinic: Lucky Summer vs mean clinic	0.974000	0.849000	1.118000	0.708000
Clinic: Mathare North vs mean clinic	1.141000	0.946000	1.378000	0.169000
Clinic: Pipeline vs mean clinic	1.151000	0.962000	1.377000	0.124000
Clinic: Sunton vs mean clinic	1.350000	1.005000	1.813000	0.046000
Clinic: Tassia vs mean clinic	1.111000	0.965000	1.280000	0.143000
Clinic: Umoja 1 vs mean clinic	1.109000	0.924000	1.331000	0.268000
Clinic: Umoja 2 vs mean clinic	0.760000	0.636000	0.908000	0.003000
Age (years)	1.000000	0.997000	1.003000	0.928000

Table 27: Modified Poisson model fit for diagnosis errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.646000	0.594000	0.702000	0.000000
Group: AI vs Non-AI	0.875000	0.808000	0.947000	0.001000
Gender: Female vs Male	0.946000	0.891000	1.004000	0.068000
Visit type: Insurance vs Cash	0.952000	0.892000	1.017000	0.146000
Clinic: Embakasi vs mean clinic	1.000000	0.862000	1.160000	0.999000
Clinic: Kahawa West vs mean clinic	1.008000	0.915000	1.111000	0.865000
Clinic: Kangemi vs mean clinic	0.948000	0.794000	1.131000	0.550000
Clinic: Kasarani vs mean clinic	1.064000	0.909000	1.245000	0.438000
Clinic: Kawangware vs mean clinic	0.923000	0.785000	1.084000	0.326000
Clinic: Kimathi Street vs mean clinic	0.925000	0.754000	1.135000	0.454000
Clinic: Lang'ata vs mean clinic	1.039000	0.927000	1.165000	0.512000
Clinic: Lucky Summer vs mean clinic	0.984000	0.836000	1.159000	0.849000
Clinic: Mathare North vs mean clinic	1.123000	1.041000	1.212000	0.003000
Clinic: Pipeline vs mean clinic	1.046000	0.898000	1.218000	0.561000
Clinic: Sunton vs mean clinic	0.990000	0.828000	1.183000	0.909000
Clinic: Tassia vs mean clinic	0.850000	0.781000	0.925000	0.000000
Clinic: Umoja 1 vs mean clinic	1.069000	0.996000	1.147000	0.063000
Clinic: Umoja 2 vs mean clinic	1.035000	0.962000	1.113000	0.356000
Age (years)	0.996000	0.994000	0.998000	0.000000

Table 28: Modified Poisson model fit for treatment errors.

D.3 Failure mode analysis.

	Non-AI	AI	RRR	p	NNT	N errors reduced at Penda
History: Documentation of relevant systems on physical exam are absent	45.2% (42.7%-47.7%)	34.3% (32.1%-36.7%)	23.9% (17.0%-30.3%)	0.000	9.2	43247
History: Pertinent vital signs are absent	6.8% (5.6%-8.2%)	5.1% (4.2%-6.3%)	24.2% (-0.3%-42.6%)	0.059	-	-
History: Chief complaint is absent	12.3% (10.7%-14.0%)	10.9% (9.5%-12.5%)	11.5% (-7.4%-27.0%)	0.221	-	-
History: Key details in the history are missing	69.1% (66.7%-71.4%)	58.9% (56.5%-61.3%)	14.7% (10.1%-19.1%)	0.000	9.8	40745
Investigations: Key investigations are missing	36.5% (34.1%-38.9%)	32.9% (30.7%-35.2%)	9.8% (0.7%-18.0%)	0.036	28.1	14257
Investigations: Unjustified investigations are ordered	13.9% (12.2%-15.7%)	15.8% (14.2%-17.7%)	-14.1% (-34.9%-3.6%)	0.134	-	-
Diagnosis: Additional diagnosis is likely incorrect	12.0% (10.4%-13.7%)	12.8% (11.3%-14.5%)	-7.1% (-29.0%-11.1%)	0.483	-	-
Diagnosis: Primary diagnosis too specific to be supported	26.5% (24.3%-28.8%)	23.7% (21.7%-25.8%)	10.5% (-0.9%-20.7%)	0.071	-	-
Diagnosis: Primary diagnosis is missing	4.1% (3.2%-5.2%)	4.0% (3.2%-5.1%)	1.7% (-37.9%-29.9%)	0.929	-	-
Diagnosis: Primary diagnosis broad when more specific is supported	12.6% (11.0%-14.4%)	10.8% (9.4%-12.4%)	14.3% (-3.9%-29.2%)	0.121	-	-
Diagnosis: Clinically relevant additional diagnosis is missing	26.7% (24.5%-29.0%)	27.0% (24.9%-29.2%)	-1.0% (-13.4%-10.0%)	0.872	-	-
Diagnosis: Primary diagnosis is likely incorrect	26.5% (24.3%-28.8%)	23.2% (21.2%-25.3%)	12.5% (1.2%-22.5%)	0.032	30.3	13222
Treatment: Escalations of care are present but inappropriate	0.9% (0.6%-1.6%)	0.6% (0.3%-1.1%)	35.0% (-45.9%-71.0%)	0.312	-	-
Treatment: Referrals are missing	14.5% (12.8%-16.3%)	12.6% (11.1%-14.2%)	13.2% (-3.5%-27.3%)	0.118	-	-
Treatment: Referrals are present but inappropriate	1.6% (1.1%-2.4%)	0.8% (0.5%-1.3%)	50.7% (3.5%-74.8%)	0.046	123.7	3233
Treatment: Medications are appropriate but incorrect dosages listed	13.7% (12.0%-15.5%)	14.1% (12.5%-15.9%)	-3.4% (-23.0%-13.1%)	0.719	-	-
Treatment: Procedures are present but inappropriate	0.3% (0.1%-0.7%)	0.4% (0.2%-0.8%)	-36.4% (-382.5%-61.4%)	0.756	-	-
Treatment: Needed procedures are missing	5.2% (4.2%-6.4%)	5.6% (4.6%-6.8%)	-8.5% (-45.4%-19.0%)	0.637	-	-
Treatment: Medications are missing	14.7% (13.0%-16.6%)	14.1% (12.5%-15.8%)	4.5% (-13.2%-19.4%)	0.612	-	-
Treatment: Medications are present but inappropriate	59.4% (56.9%-61.8%)	52.3% (49.9%-54.7%)	12.0% (6.3%-17.3%)	0.000	14.1	28387
Treatment: Likely inappropriate class of antibiotics used	13.9% (12.3%-15.8%)	11.8% (10.4%-13.5%)	15.1% (-1.8%-29.2%)	0.079	-	-
Treatment: Needed escalations of care are missing	11.1% (9.6%-12.8%)	10.7% (9.3%-12.3%)	3.1% (-18.3%-20.6%)	0.775	-	-
Treatment: Likely inappropriate use of antibiotics overall	24.7% (22.6%-26.9%)	21.9% (20.0%-24.0%)	11.2% (-0.8%-21.8%)	0.070	-	-
Treatment: Incorrect patient advice, education or follow up plan	2.4% (1.7%-3.3%)	2.4% (1.8%-3.3%)	-1.1% (-57.8%-35.2%)	1.000	-	-
Treatment: Missing patient advice, education or follow up plan	62.6% (60.1%-65.0%)	55.4% (53.0%-57.8%)	11.5% (6.2%-16.5%)	0.000	13.9	28726

Table 29: Rates of specific failure modes in AI and non-AI group, with relative risk reductions. *p*-values per Fisher's exact test. For rows with $p < 0.05$, we also show the number needed to treat and the absolute number of errors we would expect to be averted if this tool were widely deployed in the 400,000 annual patient visits at Penda.

D.4 Active deployment

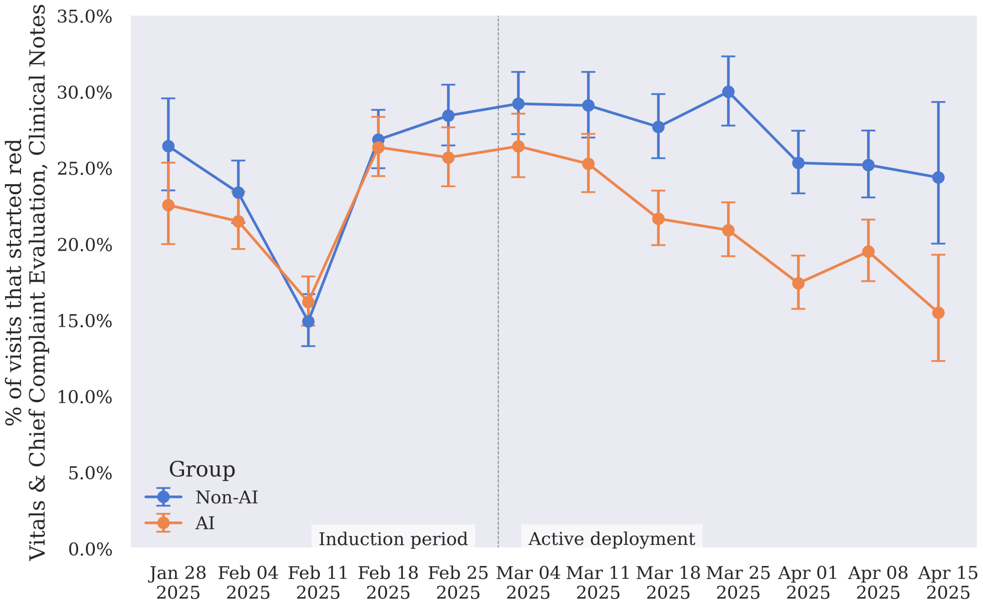


Figure 17: Rate of visits where the final call for the vitals and chief complaint or clinical notes bucket is red, for AI and non-AI groups over time

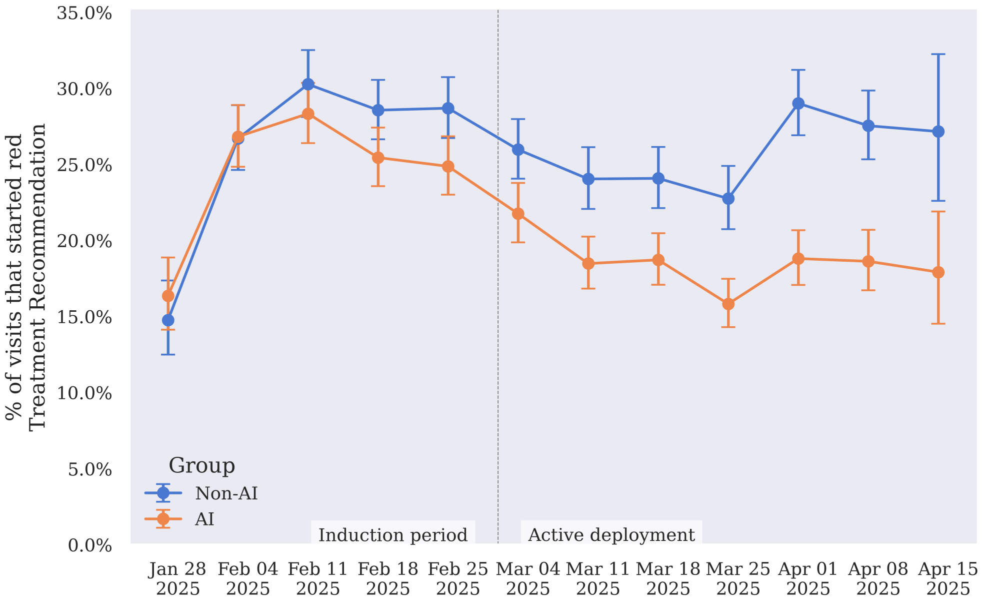


Figure 18: Rate of visits where the first call for the treatment bucket is red, for AI and non-AI groups over time

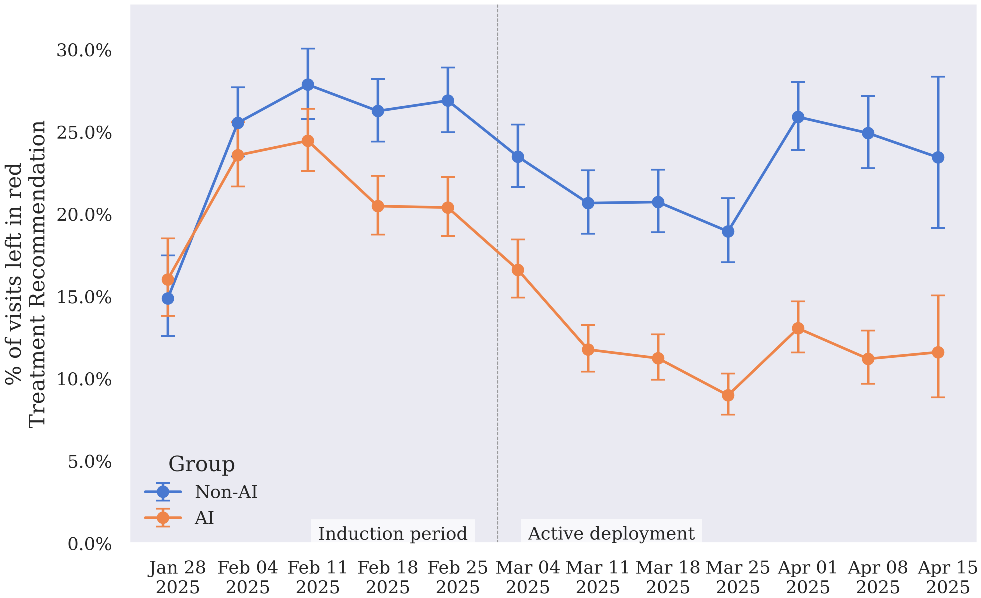


Figure 19: Rate of visits where the final call for the vitals and chief complaint or clinical notes bucket is red, for AI and non-AI groups over time

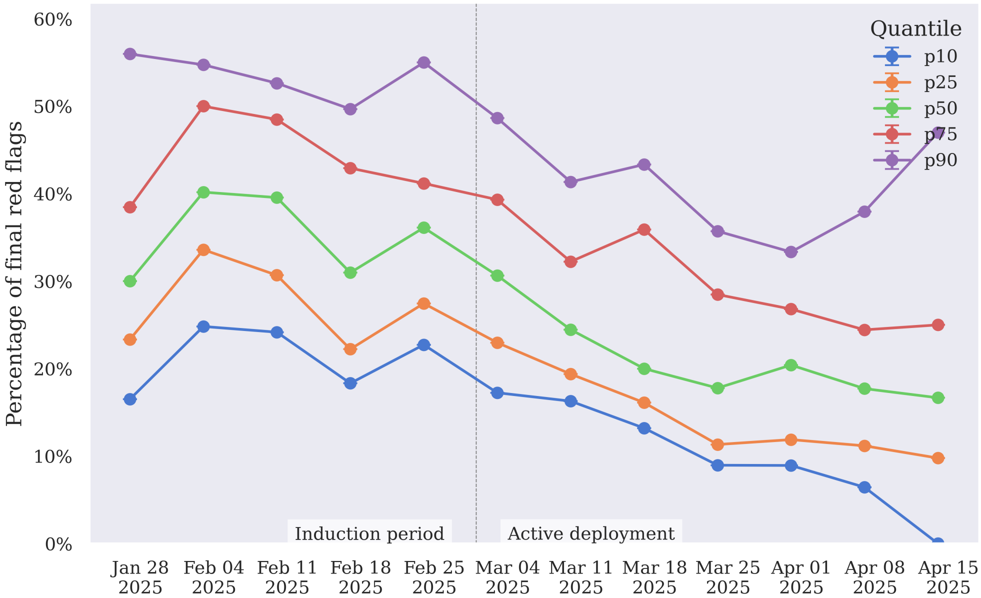


Figure 20: Rate of visits where the final call for any of the AI Consult buckets is red, for the AI group specifically, stratified by clinician quantile across both non-AI and AI groups.

D.5 AI analysis

	Physician-physician agreement	GPT-4.1-physician agreement	o3-physician agreement
History	77.8%	87.0%	86.6%
Investigations	66.0%	65.1%	70.5%
Diagnosis	69.1%	75.0%	78.1%
Treatment	67.1%	75.6%	76.0%

Table 30: Within-1 Likert agreement between two physicians, `GPT-4.1` and physicians, and `o3` and physicians.

	Physician-physician κ	GPT-4.1-physician κ	o3-physician κ
History	0.260	0.283	0.306
Investigations	0.285	0.268	0.294
Diagnosis	0.232	0.277	0.307
Treatment	0.223	0.346	0.338

Table 31: Fleiss' κ for agreement on the presence of errors between two physicians, `GPT-4.1` and physicians, and `o3` and physicians.

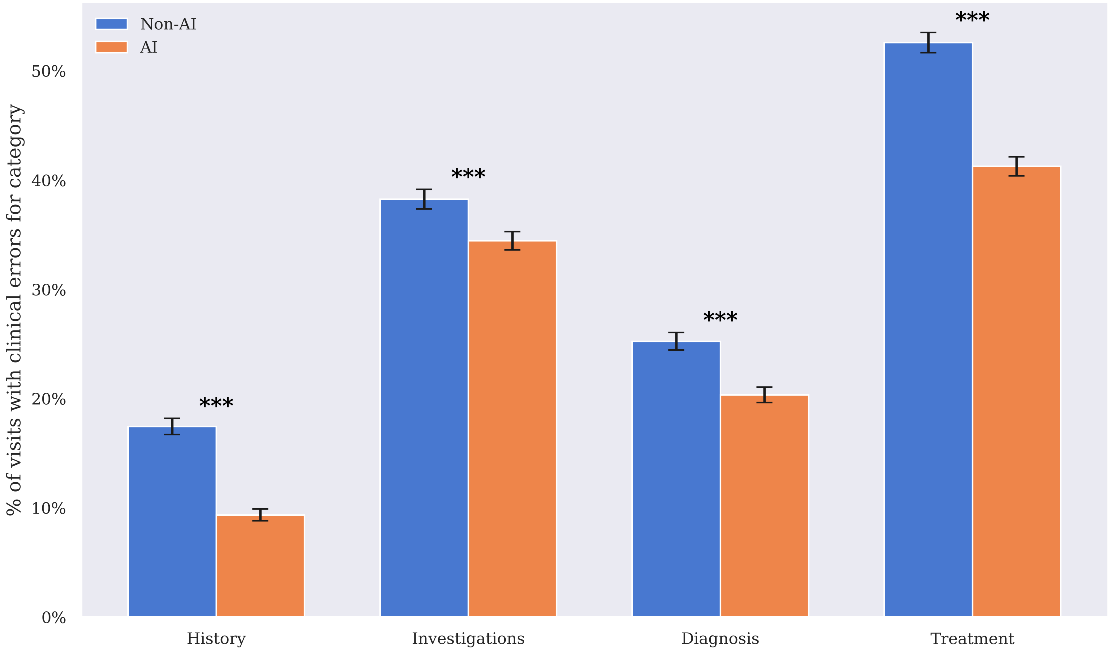


Figure 21: Likert 1 and 2 rates for history-taking, investigations, diagnosis, and treatment, comparing the AI group to the non-AI group. Ratings provided by `GPT-4.1`. Error bars show 95% Wilson confidence intervals. * indicates $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

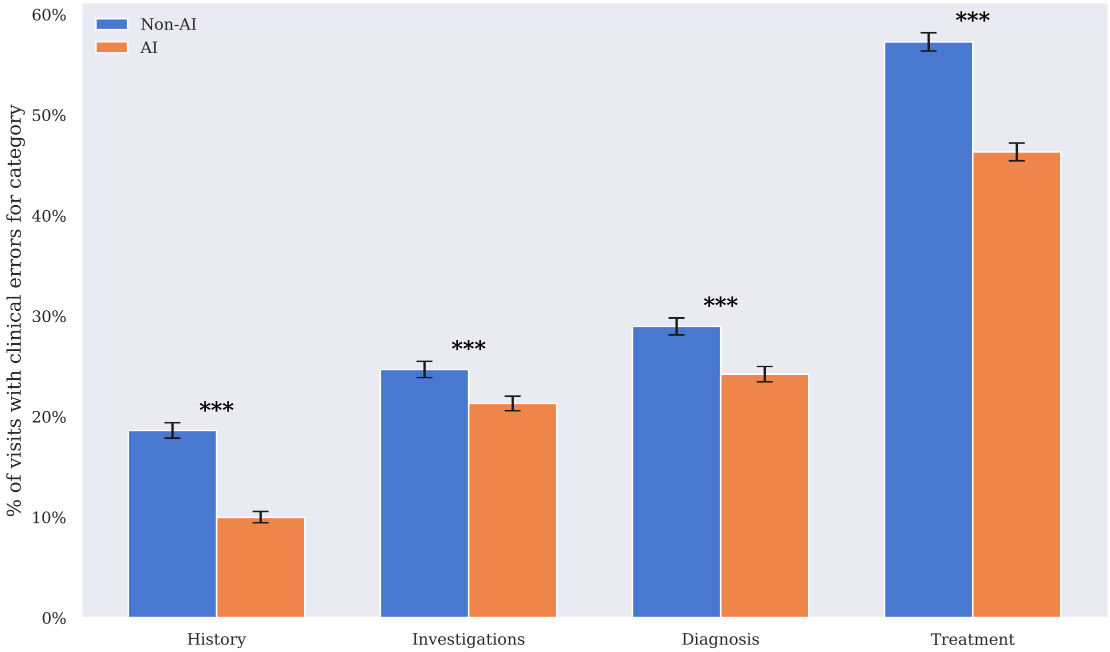


Figure 22: Likert 1 and 2 rates for history-taking, investigations, diagnosis, and treatment, comparing the AI group to the non-AI group. Ratings provided by `o3`. Error bars show 95% Wilson confidence intervals. * indicates $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.181000	0.155000	0.211000	0.000000
Group: AI vs Non-AI	0.571000	0.457000	0.713000	0.000000
Gender: Female vs Male	1.013000	0.942000	1.089000	0.728000
Visit type: Insurance vs Cash	0.801000	0.739000	0.868000	0.000000
Clinic: Embakasi vs mean clinic	0.844000	0.464000	1.533000	0.577000
Clinic: Kahawa West vs mean clinic	1.216000	0.997000	1.482000	0.053000
Clinic: Kangemi vs mean clinic	1.002000	0.525000	1.911000	0.996000
Clinic: Kasarani vs mean clinic	0.661000	0.538000	0.813000	0.000000
Clinic: Kawangware vs mean clinic	0.707000	0.433000	1.154000	0.165000
Clinic: Kimathi Street vs mean clinic	1.112000	0.935000	1.322000	0.229000
Clinic: Lang'ata vs mean clinic	1.474000	0.948000	2.290000	0.085000
Clinic: Lucky Summer vs mean clinic	0.584000	0.374000	0.912000	0.018000
Clinic: Mathare North vs mean clinic	1.350000	0.820000	2.221000	0.238000
Clinic: Pipeline vs mean clinic	1.643000	1.322000	2.041000	0.000000
Clinic: Sunton vs mean clinic	1.631000	1.178000	2.257000	0.003000
Clinic: Tassia vs mean clinic	0.851000	0.562000	1.288000	0.445000
Clinic: Umoja 1 vs mean clinic	0.554000	0.417000	0.737000	0.000000
Clinic: Umoja 2 vs mean clinic	1.230000	0.959000	1.579000	0.104000
Age (years)	1.001000	0.998000	1.004000	0.635000

Table 32: Modified Poisson model fit based on ratings from `GPT-4.1` for history errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.560000	0.526000	0.596000	0.000000
Group: AI vs Non-AI	0.926000	0.857000	1.000000	0.050000
Gender: Female vs Male	1.027000	0.997000	1.059000	0.082000
Visit type: Insurance vs Cash	0.867000	0.827000	0.908000	0.000000
Clinic: Embakasi vs mean clinic	0.821000	0.647000	1.041000	0.104000
Clinic: Kahawa West vs mean clinic	1.091000	0.975000	1.222000	0.130000
Clinic: Kangemi vs mean clinic	1.193000	1.071000	1.329000	0.001000
Clinic: Kasarani vs mean clinic	0.939000	0.841000	1.049000	0.266000
Clinic: Kawangware vs mean clinic	0.887000	0.789000	0.998000	0.047000
Clinic: Kimathi Street vs mean clinic	0.734000	0.579000	0.930000	0.010000
Clinic: Lang'ata vs mean clinic	0.993000	0.901000	1.093000	0.882000
Clinic: Lucky Summer vs mean clinic	1.034000	0.920000	1.163000	0.571000
Clinic: Mathare North vs mean clinic	1.053000	0.950000	1.166000	0.328000
Clinic: Pipeline vs mean clinic	1.048000	0.956000	1.149000	0.320000
Clinic: Sunton vs mean clinic	1.211000	1.085000	1.351000	0.001000
Clinic: Tassia vs mean clinic	0.855000	0.738000	0.991000	0.037000
Clinic: Umoja 1 vs mean clinic	0.958000	0.877000	1.046000	0.339000
Clinic: Umoja 2 vs mean clinic	1.172000	1.066000	1.288000	0.001000
Age (years)	0.979000	0.977000	0.981000	0.000000

Table 33: Modified Poisson model fit based on ratings from `GPT-4.1` for investigations errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.254000	0.229000	0.282000	0.000000
Group: AI vs Non-AI	0.816000	0.705000	0.945000	0.006000
Gender: Female vs Male	1.049000	0.993000	1.108000	0.085000
Visit type: Insurance vs Cash	0.811000	0.759000	0.866000	0.000000
Clinic: Embakasi vs mean clinic	0.743000	0.552000	0.999000	0.050000
Clinic: Kahawa West vs mean clinic	0.855000	0.727000	1.004000	0.056000
Clinic: Kangemi vs mean clinic	0.926000	0.659000	1.302000	0.658000
Clinic: Kasarani vs mean clinic	0.962000	0.785000	1.178000	0.706000
Clinic: Kawangware vs mean clinic	1.147000	0.985000	1.335000	0.078000
Clinic: Kimathi Street vs mean clinic	1.044000	0.854000	1.276000	0.673000
Clinic: Lang'ata vs mean clinic	1.068000	0.807000	1.415000	0.644000
Clinic: Lucky Summer vs mean clinic	0.719000	0.571000	0.906000	0.005000
Clinic: Mathare North vs mean clinic	1.267000	0.945000	1.700000	0.114000
Clinic: Pipeline vs mean clinic	0.946000	0.813000	1.101000	0.474000
Clinic: Sunton vs mean clinic	1.226000	0.981000	1.533000	0.073000
Clinic: Tassia vs mean clinic	1.298000	1.076000	1.566000	0.006000
Clinic: Umoja 1 vs mean clinic	1.149000	0.906000	1.456000	0.252000
Clinic: Umoja 2 vs mean clinic	0.804000	0.675000	0.957000	0.014000
Age (years)	1.003000	1.001000	1.005000	0.000000

Table 34: Modified Poisson model fit based on ratings from `GPT-4.1` for diagnosis errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.593000	0.556000	0.632000	0.000000
Group: AI vs Non-AI	0.801000	0.724000	0.887000	0.000000
Gender: Female vs Male	1.007000	0.981000	1.034000	0.594000
Visit type: Insurance vs Cash	0.956000	0.925000	0.988000	0.008000
Clinic: Embakasi vs mean clinic	1.015000	0.786000	1.312000	0.907000
Clinic: Kahawa West vs mean clinic	1.037000	0.949000	1.134000	0.421000
Clinic: Kangemi vs mean clinic	0.856000	0.634000	1.154000	0.307000
Clinic: Kasarani vs mean clinic	1.067000	0.963000	1.182000	0.213000
Clinic: Kawangware vs mean clinic	0.980000	0.769000	1.249000	0.870000
Clinic: Kimathi Street vs mean clinic	0.912000	0.788000	1.056000	0.218000
Clinic: Lang'ata vs mean clinic	0.988000	0.804000	1.213000	0.906000
Clinic: Lucky Summer vs mean clinic	0.959000	0.734000	1.253000	0.757000
Clinic: Mathare North vs mean clinic	1.045000	0.976000	1.119000	0.208000
Clinic: Pipeline vs mean clinic	0.924000	0.796000	1.072000	0.296000
Clinic: Sunton vs mean clinic	1.063000	0.981000	1.151000	0.134000
Clinic: Tassia vs mean clinic	0.841000	0.762000	0.927000	0.001000
Clinic: Umoja 1 vs mean clinic	1.211000	1.119000	1.311000	0.000000
Clinic: Umoja 2 vs mean clinic	1.139000	1.039000	1.248000	0.005000
Age (years)	0.994000	0.993000	0.995000	0.000000

Table 35: Modified Poisson model fit based on ratings from `GPT-4.1` for treatment errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.145000	0.127000	0.166000	0.000000
Group: AI vs Non-AI	0.572000	0.465000	0.703000	0.000000
Gender: Female vs Male	0.967000	0.901000	1.037000	0.346000
Visit type: Insurance vs Cash	0.795000	0.740000	0.853000	0.000000
Clinic: Embakasi vs mean clinic	1.050000	0.711000	1.550000	0.806000
Clinic: Kahawa West vs mean clinic	1.240000	0.996000	1.544000	0.054000
Clinic: Kangemi vs mean clinic	1.081000	0.671000	1.740000	0.750000
Clinic: Kasarani vs mean clinic	0.827000	0.648000	1.054000	0.125000
Clinic: Kawangware vs mean clinic	0.751000	0.566000	0.997000	0.048000
Clinic: Kimathi Street vs mean clinic	1.286000	1.083000	1.527000	0.004000
Clinic: Lang'ata vs mean clinic	1.030000	0.645000	1.644000	0.901000
Clinic: Lucky Summer vs mean clinic	0.739000	0.465000	1.174000	0.200000
Clinic: Mathare North vs mean clinic	1.062000	0.716000	1.575000	0.766000
Clinic: Pipeline vs mean clinic	1.457000	1.172000	1.810000	0.001000
Clinic: Sunton vs mean clinic	1.432000	0.918000	2.234000	0.114000
Clinic: Tassia vs mean clinic	0.837000	0.567000	1.235000	0.369000
Clinic: Umoja 1 vs mean clinic	0.788000	0.563000	1.102000	0.163000
Clinic: Umoja 2 vs mean clinic	1.076000	0.855000	1.354000	0.534000
Age (years)	1.016000	1.014000	1.019000	0.000000

Table 36: Modified Poisson model fit based on ratings from `o3` for history errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.293000	0.269000	0.318000	0.000000
Group: AI vs Non-AI	0.872000	0.792000	0.959000	0.005000
Gender: Female vs Male	1.127000	1.075000	1.182000	0.000000
Visit type: Insurance vs Cash	0.813000	0.763000	0.867000	0.000000
Clinic: Embakasi vs mean clinic	0.885000	0.672000	1.165000	0.383000
Clinic: Kahawa West vs mean clinic	1.100000	1.012000	1.195000	0.026000
Clinic: Kangemi vs mean clinic	1.008000	0.760000	1.338000	0.954000
Clinic: Kasarani vs mean clinic	0.930000	0.762000	1.136000	0.477000
Clinic: Kawangware vs mean clinic	0.889000	0.812000	0.974000	0.011000
Clinic: Kimathi Street vs mean clinic	0.847000	0.678000	1.059000	0.145000
Clinic: Lang'ata vs mean clinic	0.914000	0.702000	1.188000	0.500000
Clinic: Lucky Summer vs mean clinic	1.156000	0.929000	1.437000	0.193000
Clinic: Mathare North vs mean clinic	1.053000	0.907000	1.222000	0.495000
Clinic: Pipeline vs mean clinic	0.971000	0.870000	1.083000	0.598000
Clinic: Sunton vs mean clinic	1.225000	1.081000	1.388000	0.001000
Clinic: Tassia vs mean clinic	0.858000	0.746000	0.987000	0.032000
Clinic: Umoja 1 vs mean clinic	1.038000	0.889000	1.212000	0.640000
Clinic: Umoja 2 vs mean clinic	1.105000	0.984000	1.241000	0.092000
Age (years)	0.992000	0.990000	0.994000	0.000000

Table 37: Modified Poisson model fit based on ratings from `o3` for investigations errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.292000	0.266000	0.321000	0.000000
Group: AI vs Non-AI	0.854000	0.762000	0.956000	0.006000
Gender: Female vs Male	1.023000	0.982000	1.067000	0.279000
Visit type: Insurance vs Cash	0.804000	0.766000	0.843000	0.000000
Clinic: Embakasi vs mean clinic	0.822000	0.640000	1.055000	0.123000
Clinic: Kahawa West vs mean clinic	0.893000	0.782000	1.021000	0.097000
Clinic: Kangemi vs mean clinic	1.012000	0.825000	1.241000	0.909000
Clinic: Kasarani vs mean clinic	1.027000	0.919000	1.148000	0.637000
Clinic: Kawangware vs mean clinic	1.064000	0.977000	1.159000	0.155000
Clinic: Kimathi Street vs mean clinic	1.043000	0.897000	1.213000	0.585000
Clinic: Lang'ata vs mean clinic	1.064000	0.808000	1.399000	0.660000
Clinic: Lucky Summer vs mean clinic	0.801000	0.697000	0.921000	0.002000
Clinic: Mathare North vs mean clinic	1.056000	0.839000	1.329000	0.645000
Clinic: Pipeline vs mean clinic	0.991000	0.881000	1.114000	0.873000
Clinic: Sunton vs mean clinic	1.178000	0.918000	1.510000	0.198000
Clinic: Tassia vs mean clinic	1.137000	0.976000	1.325000	0.099000
Clinic: Umoja 1 vs mean clinic	1.046000	0.859000	1.273000	0.656000
Clinic: Umoja 2 vs mean clinic	0.887000	0.773000	1.018000	0.087000
Age (years)	1.004000	1.002000	1.006000	0.000000

Table 38: Modified Poisson model fit based on ratings from `o3` for diagnosis errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.675000	0.640000	0.713000	0.000000
Group: AI vs Non-AI	0.827000	0.765000	0.894000	0.000000
Gender: Female vs Male	0.955000	0.932000	0.977000	0.000000
Visit type: Insurance vs Cash	0.933000	0.907000	0.960000	0.000000
Clinic: Embakasi vs mean clinic	0.960000	0.776000	1.188000	0.708000
Clinic: Kahawa West vs mean clinic	1.014000	0.935000	1.099000	0.736000
Clinic: Kangemi vs mean clinic	0.928000	0.775000	1.111000	0.416000
Clinic: Kasarani vs mean clinic	1.016000	0.934000	1.105000	0.711000
Clinic: Kawangware vs mean clinic	0.996000	0.834000	1.190000	0.967000
Clinic: Kimathi Street vs mean clinic	0.955000	0.847000	1.077000	0.455000
Clinic: Lang'ata vs mean clinic	1.005000	0.824000	1.227000	0.957000
Clinic: Lucky Summer vs mean clinic	0.920000	0.746000	1.135000	0.438000
Clinic: Mathare North vs mean clinic	1.088000	1.037000	1.142000	0.001000
Clinic: Pipeline vs mean clinic	0.950000	0.832000	1.084000	0.443000
Clinic: Sunton vs mean clinic	1.022000	0.965000	1.082000	0.465000
Clinic: Tassia vs mean clinic	0.877000	0.825000	0.931000	0.000000
Clinic: Umoja 1 vs mean clinic	1.169000	1.085000	1.259000	0.000000
Clinic: Umoja 2 vs mean clinic	1.112000	1.018000	1.216000	0.018000
Age (years)	0.994000	0.993000	0.995000	0.000000

Table 39: Modified Poisson model fit based on ratings from `o3` for treatment errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.187000	0.159000	0.219000	0.000000
Group: AI vs Non-AI	0.607000	0.477000	0.773000	0.000000
Gender: Female vs Male	1.001000	0.933000	1.074000	0.974000
Visit type: Insurance vs Cash	0.802000	0.743000	0.866000	0.000000
Clinic: Embakasi vs mean clinic	0.875000	0.559000	1.368000	0.557000
Clinic: Kahawa West vs mean clinic	1.027000	0.754000	1.399000	0.864000
Clinic: Kangemi vs mean clinic	0.942000	0.562000	1.578000	0.819000
Clinic: Kasarani vs mean clinic	0.730000	0.516000	1.035000	0.077000
Clinic: Kawangware vs mean clinic	0.987000	0.653000	1.492000	0.951000
Clinic: Kimathi Street vs mean clinic	1.234000	0.966000	1.577000	0.092000
Clinic: Lang'ata vs mean clinic	1.292000	0.652000	2.561000	0.463000
Clinic: Lucky Summer vs mean clinic	0.672000	0.446000	1.013000	0.058000
Clinic: Mathare North vs mean clinic	1.056000	0.678000	1.647000	0.809000
Clinic: Pipeline vs mean clinic	1.535000	1.185000	1.988000	0.001000
Clinic: Sunton vs mean clinic	1.504000	1.173000	1.928000	0.001000
Clinic: Tassia vs mean clinic	0.911000	0.620000	1.338000	0.635000
Clinic: Umoja 1 vs mean clinic	0.632000	0.503000	0.795000	0.000000
Clinic: Umoja 2 vs mean clinic	0.983000	0.721000	1.339000	0.911000
Age (years)	1.001000	0.998000	1.004000	0.554000

Table 40: GEE model fit based on ratings from `GPT-4.1` for history errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.565000	0.535000	0.597000	0.000000
Group: AI vs Non-AI	0.955000	0.880000	1.036000	0.265000
Gender: Female vs Male	1.018000	0.989000	1.049000	0.229000
Visit type: Insurance vs Cash	0.861000	0.821000	0.902000	0.000000
Clinic: Embakasi vs mean clinic	0.983000	0.824000	1.172000	0.848000
Clinic: Kahawa West vs mean clinic	1.026000	0.932000	1.128000	0.604000
Clinic: Kangemi vs mean clinic	0.910000	0.802000	1.033000	0.146000
Clinic: Kasarani vs mean clinic	1.052000	0.930000	1.190000	0.423000
Clinic: Kawangware vs mean clinic	0.869000	0.745000	1.014000	0.075000
Clinic: Kimathi Street vs mean clinic	0.762000	0.680000	0.855000	0.000000
Clinic: Lang'ata vs mean clinic	0.943000	0.774000	1.149000	0.563000
Clinic: Lucky Summer vs mean clinic	1.058000	0.923000	1.213000	0.419000
Clinic: Mathare North vs mean clinic	1.069000	0.918000	1.245000	0.388000
Clinic: Pipeline vs mean clinic	1.082000	0.985000	1.189000	0.101000
Clinic: Sunton vs mean clinic	1.133000	1.021000	1.258000	0.019000
Clinic: Tassia vs mean clinic	0.941000	0.825000	1.074000	0.371000
Clinic: Umoja 1 vs mean clinic	1.088000	1.022000	1.158000	0.008000
Clinic: Umoja 2 vs mean clinic	1.077000	0.970000	1.196000	0.164000
Age (years)	0.978000	0.976000	0.980000	0.000000

Table 41: GEE model fit based on ratings from `GPT-4.1` for investigations errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.257000	0.234000	0.283000	0.000000
Group: AI vs Non-AI	0.819000	0.710000	0.945000	0.006000
Gender: Female vs Male	1.043000	0.989000	1.099000	0.120000
Visit type: Insurance vs Cash	0.812000	0.761000	0.867000	0.000000
Clinic: Embakasi vs mean clinic	0.840000	0.600000	1.176000	0.310000
Clinic: Kahawa West vs mean clinic	0.854000	0.719000	1.013000	0.071000
Clinic: Kangemi vs mean clinic	0.924000	0.676000	1.264000	0.623000
Clinic: Kasarani vs mean clinic	0.946000	0.812000	1.102000	0.478000
Clinic: Kawangware vs mean clinic	1.048000	0.839000	1.309000	0.681000
Clinic: Kimathi Street vs mean clinic	1.171000	0.945000	1.450000	0.149000
Clinic: Lang'ata vs mean clinic	1.070000	0.847000	1.350000	0.572000
Clinic: Lucky Summer vs mean clinic	0.906000	0.665000	1.234000	0.532000
Clinic: Mathare North vs mean clinic	1.057000	0.885000	1.262000	0.540000
Clinic: Pipeline vs mean clinic	1.023000	0.861000	1.216000	0.796000
Clinic: Sunton vs mean clinic	1.217000	1.040000	1.423000	0.014000
Clinic: Tassia vs mean clinic	1.103000	0.890000	1.367000	0.371000
Clinic: Umoja 1 vs mean clinic	1.113000	0.933000	1.327000	0.234000
Clinic: Umoja 2 vs mean clinic	0.756000	0.621000	0.921000	0.005000
Age (years)	1.003000	1.002000	1.005000	0.000000

Table 42: GEE model fit based on ratings from `GPT-4.1` for diagnosis errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.570000	0.536000	0.605000	0.000000
Group: AI vs Non-AI	0.872000	0.798000	0.953000	0.003000
Gender: Female vs Male	1.004000	0.978000	1.030000	0.784000
Visit type: Insurance vs Cash	0.963000	0.934000	0.992000	0.013000
Clinic: Embakasi vs mean clinic	1.082000	0.888000	1.319000	0.434000
Clinic: Kahawa West vs mean clinic	0.993000	0.901000	1.095000	0.892000
Clinic: Kangemi vs mean clinic	0.825000	0.629000	1.082000	0.164000
Clinic: Kasarani vs mean clinic	1.070000	0.952000	1.203000	0.254000
Clinic: Kawangware vs mean clinic	0.946000	0.773000	1.158000	0.592000
Clinic: Kimathi Street vs mean clinic	0.894000	0.757000	1.056000	0.189000
Clinic: Lang'ata vs mean clinic	1.000000	0.806000	1.241000	0.999000
Clinic: Lucky Summer vs mean clinic	0.900000	0.779000	1.041000	0.156000
Clinic: Mathare North vs mean clinic	1.023000	0.931000	1.125000	0.634000
Clinic: Pipeline vs mean clinic	1.005000	0.866000	1.166000	0.951000
Clinic: Sunton vs mean clinic	1.081000	0.997000	1.172000	0.058000
Clinic: Tassia vs mean clinic	0.908000	0.826000	0.999000	0.047000
Clinic: Umoja 1 vs mean clinic	1.256000	1.159000	1.361000	0.000000
Clinic: Umoja 2 vs mean clinic	1.116000	1.031000	1.209000	0.007000
Age (years)	0.994000	0.993000	0.995000	0.000000

Table 43: GEE model fit based on ratings from `GPT-4.1` for treatment errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.152000	0.133000	0.173000	0.000000
Group: AI vs Non-AI	0.595000	0.483000	0.732000	0.000000
Gender: Female vs Male	0.962000	0.900000	1.029000	0.261000
Visit type: Insurance vs Cash	0.802000	0.750000	0.856000	0.000000
Clinic: Embakasi vs mean clinic	1.245000	0.921000	1.684000	0.154000
Clinic: Kahawa West vs mean clinic	0.980000	0.735000	1.308000	0.892000
Clinic: Kangemi vs mean clinic	1.060000	0.741000	1.515000	0.751000
Clinic: Kasarani vs mean clinic	0.954000	0.686000	1.325000	0.777000
Clinic: Kawangware vs mean clinic	0.971000	0.693000	1.362000	0.865000
Clinic: Kimathi Street vs mean clinic	1.321000	1.181000	1.478000	0.000000
Clinic: Lang'ata vs mean clinic	1.072000	0.570000	2.016000	0.829000
Clinic: Lucky Summer vs mean clinic	0.689000	0.426000	1.114000	0.128000
Clinic: Mathare North vs mean clinic	0.886000	0.636000	1.233000	0.472000
Clinic: Pipeline vs mean clinic	1.387000	1.159000	1.661000	0.000000
Clinic: Sunton vs mean clinic	1.317000	0.969000	1.791000	0.079000
Clinic: Tassia vs mean clinic	0.964000	0.698000	1.332000	0.824000
Clinic: Umoja 1 vs mean clinic	0.709000	0.524000	0.960000	0.026000
Clinic: Umoja 2 vs mean clinic	0.966000	0.748000	1.248000	0.792000
Age (years)	1.016000	1.014000	1.018000	0.000000

Table 44: GEE model fit based on ratings from `o3` for history errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.292000	0.270000	0.315000	0.000000
Group: AI vs Non-AI	0.874000	0.802000	0.953000	0.002000
Gender: Female vs Male	1.121000	1.071000	1.174000	0.000000
Visit type: Insurance vs Cash	0.815000	0.764000	0.869000	0.000000
Clinic: Embakasi vs mean clinic	0.941000	0.734000	1.207000	0.634000
Clinic: Kahawa West vs mean clinic	1.050000	0.950000	1.162000	0.340000
Clinic: Kangemi vs mean clinic	0.905000	0.709000	1.155000	0.422000
Clinic: Kasarani vs mean clinic	0.940000	0.792000	1.115000	0.477000
Clinic: Kawangware vs mean clinic	0.930000	0.829000	1.042000	0.212000
Clinic: Kimathi Street vs mean clinic	0.931000	0.772000	1.121000	0.449000
Clinic: Lang'ata vs mean clinic	0.853000	0.652000	1.118000	0.249000
Clinic: Lucky Summer vs mean clinic	1.077000	0.906000	1.280000	0.402000
Clinic: Mathare North vs mean clinic	1.028000	0.892000	1.184000	0.703000
Clinic: Pipeline vs mean clinic	1.025000	0.904000	1.162000	0.696000
Clinic: Sunton vs mean clinic	1.166000	1.044000	1.303000	0.007000
Clinic: Tassia vs mean clinic	0.944000	0.826000	1.080000	0.403000
Clinic: Umoja 1 vs mean clinic	1.057000	0.926000	1.206000	0.413000
Clinic: Umoja 2 vs mean clinic	1.142000	1.030000	1.265000	0.012000
Age (years)	0.992000	0.990000	0.994000	0.000000

Table 45: GEE model fit based on ratings from `o3` for investigations errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.295000	0.269000	0.323000	0.000000
Group: AI vs Non-AI	0.853000	0.765000	0.952000	0.004000
Gender: Female vs Male	1.022000	0.981000	1.063000	0.297000
Visit type: Insurance vs Cash	0.804000	0.766000	0.843000	0.000000
Clinic: Embakasi vs mean clinic	0.891000	0.708000	1.120000	0.323000
Clinic: Kahawa West vs mean clinic	0.881000	0.768000	1.011000	0.071000
Clinic: Kangemi vs mean clinic	0.938000	0.722000	1.220000	0.635000
Clinic: Kasarani vs mean clinic	1.040000	0.919000	1.178000	0.534000
Clinic: Kawangware vs mean clinic	1.009000	0.888000	1.145000	0.894000
Clinic: Kimathi Street vs mean clinic	1.098000	0.901000	1.338000	0.354000
Clinic: Lang'ata vs mean clinic	1.056000	0.854000	1.304000	0.616000
Clinic: Lucky Summer vs mean clinic	0.905000	0.787000	1.040000	0.159000
Clinic: Mathare North vs mean clinic	1.062000	0.884000	1.274000	0.522000
Clinic: Pipeline vs mean clinic	1.057000	0.929000	1.203000	0.397000
Clinic: Sunton vs mean clinic	1.144000	0.997000	1.313000	0.056000
Clinic: Tassia vs mean clinic	1.058000	0.920000	1.217000	0.431000
Clinic: Umoja 1 vs mean clinic	1.005000	0.857000	1.178000	0.954000
Clinic: Umoja 2 vs mean clinic	0.863000	0.732000	1.017000	0.078000
Age (years)	1.004000	1.003000	1.006000	0.000000

Table 46: GEE model fit based on ratings from `o3` for diagnosis errors.

	Relative risk	95% CI lower	95% CI upper	p
Intercept	0.660000	0.627000	0.694000	0.000000
Group: AI vs Non-AI	0.883000	0.822000	0.949000	0.001000
Gender: Female vs Male	0.955000	0.932000	0.978000	0.000000
Visit type: Insurance vs Cash	0.936000	0.912000	0.961000	0.000000
Clinic: Embakasi vs mean clinic	1.056000	0.875000	1.276000	0.569000
Clinic: Kahawa West vs mean clinic	0.971000	0.886000	1.064000	0.530000
Clinic: Kangemi vs mean clinic	0.915000	0.778000	1.077000	0.284000
Clinic: Kasarani vs mean clinic	1.016000	0.919000	1.124000	0.758000
Clinic: Kawangware vs mean clinic	0.961000	0.834000	1.107000	0.584000
Clinic: Kimathi Street vs mean clinic	0.952000	0.850000	1.066000	0.392000
Clinic: Lang'ata vs mean clinic	1.016000	0.844000	1.223000	0.868000
Clinic: Lucky Summer vs mean clinic	0.960000	0.878000	1.049000	0.366000
Clinic: Mathare North vs mean clinic	1.071000	0.996000	1.152000	0.065000
Clinic: Pipeline vs mean clinic	0.933000	0.805000	1.082000	0.358000
Clinic: Sunton vs mean clinic	1.012000	0.922000	1.112000	0.798000
Clinic: Tassia vs mean clinic	0.944000	0.874000	1.019000	0.141000
Clinic: Umoja 1 vs mean clinic	1.209000	1.133000	1.290000	0.000000
Clinic: Umoja 2 vs mean clinic	1.043000	0.967000	1.124000	0.276000
Age (years)	0.994000	0.993000	0.995000	0.000000

Table 47: GEE model fit based on ratings from `o3` for treatment errors.

D.6 Clinician survey

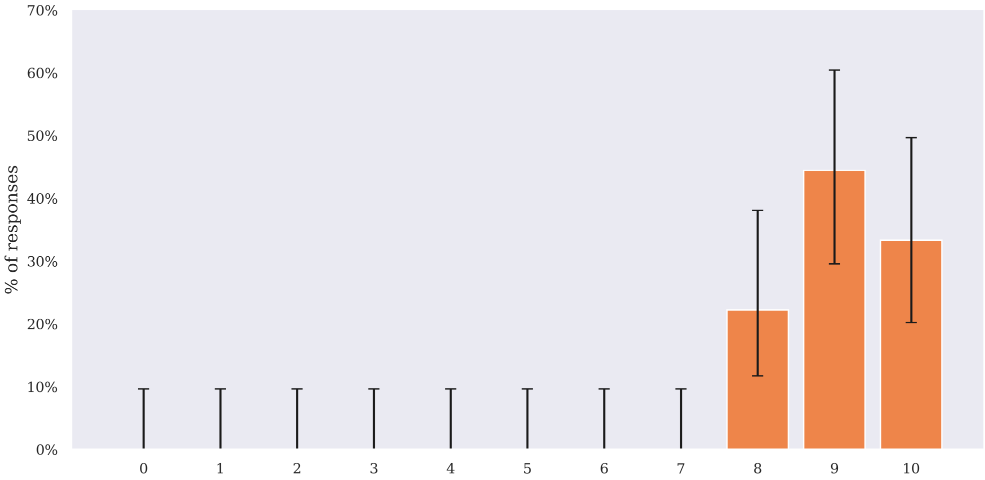


Figure 23: AI group satisfaction net promoter score of AI Consult.

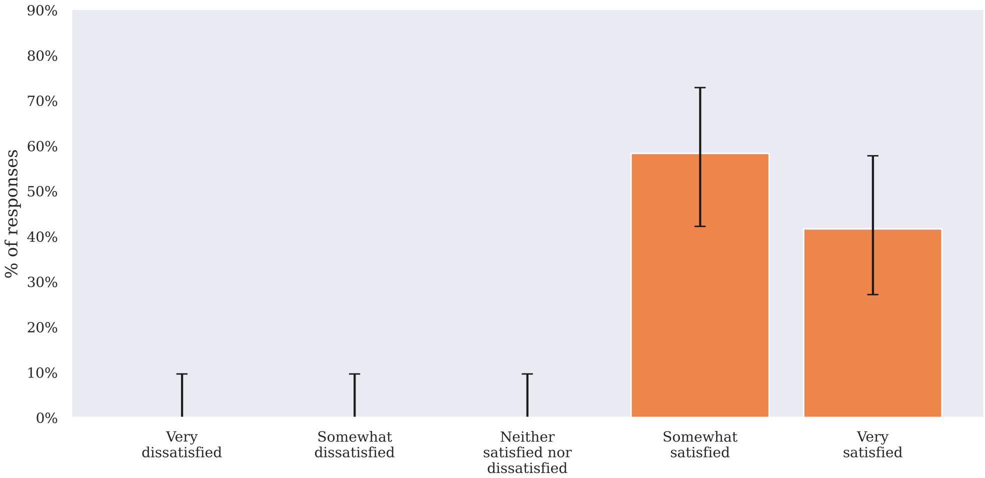


Figure 24: AI group satisfaction with AI Consult.

D.7 Use and usability

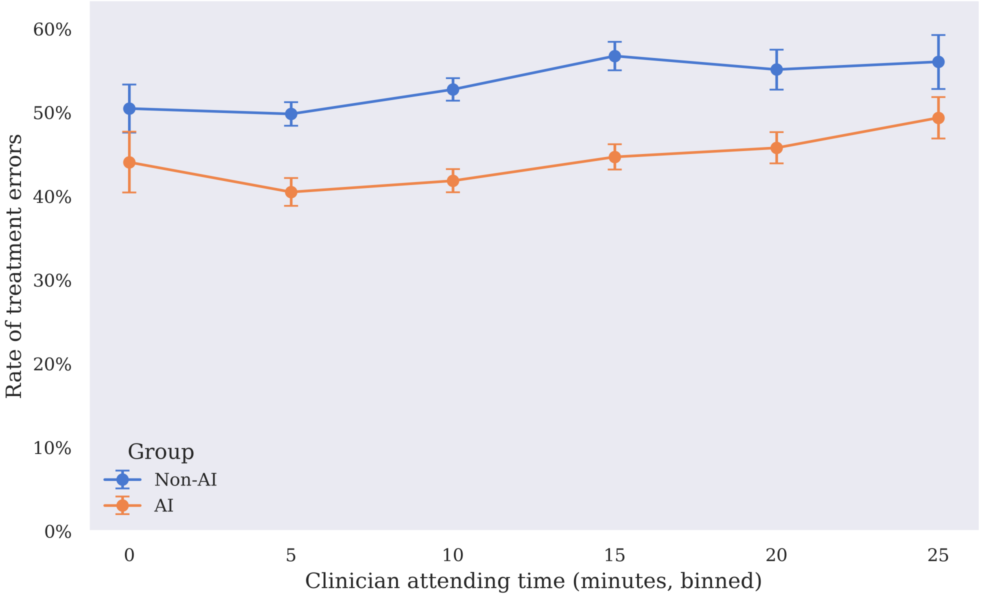


Figure 25: Mean treatment Likert from `GPT-4.1` vs total clinician attending time, binned to 5-minute intervals, in the non-AI and AI groups. 95% CIs calculated with 1000 bootstrap samples. Includes only visits with duration 30 minutes or less.

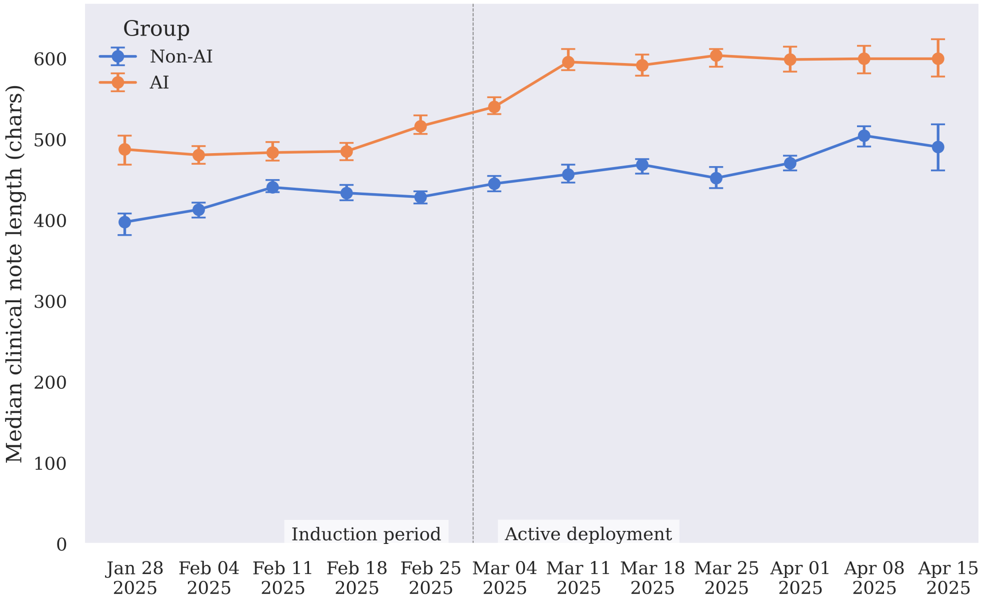


Figure 26: Rate of clinician thumbs up feedback on AI Consult responses in the AI group over time.

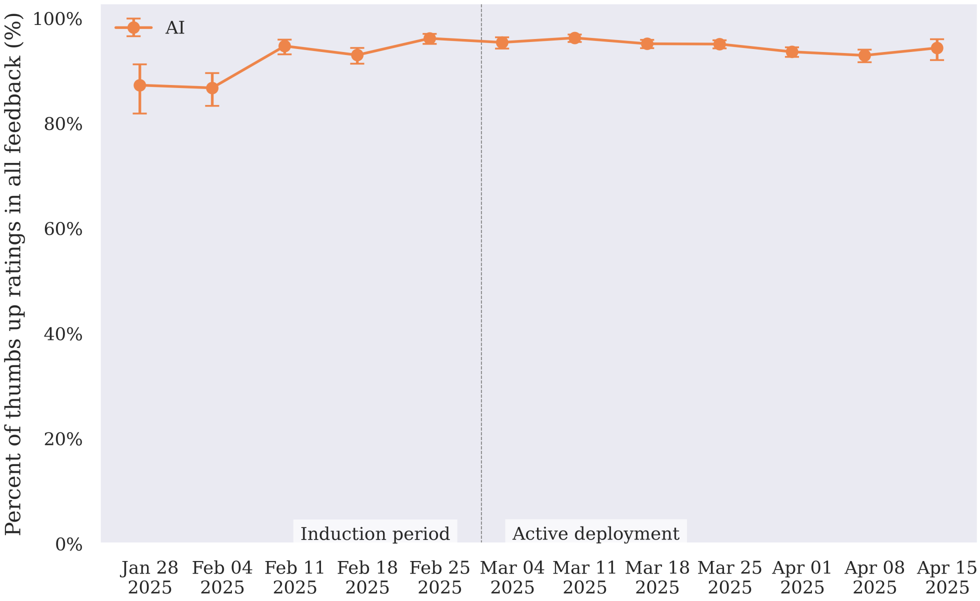


Figure 27: Rate of clinician thumbs up feedback on AI Consult responses in the AI group over time.

E Prompts used by AI Consult

All calls to AI Consult were in a new conversation with GPT-4o, consisting of a single system message and user message. The system message contained instructions for the model, and was different for different domains (e.g., diagnosis vs treatment) but the same across multiple calls for a given domain. The user prompt contained structured clinical data that provided instructions for the model to carry out the task, and varied from call to call.

E.1 System prompt for vitals and chief complaint evaluation

You are an advanced Clinical Decision Support System (CDSS) integrated within an Electronic Medical Record (EMR) system in Nairobi, Kenya, staffed by Clinical Officers.

Your role is to:

1. Evaluate the patient's chief complaint and vital signs (and MUAC for children ages 6 months–5 years).

2. Determine whether there are urgent or concerning findings that may indicate a medical emergency (Red), incomplete or suboptimal documentation or potential concerns (Yellow), or if everything is appropriate and non-urgent (Green).

3. Provide concise, actionable recommendations to improve patient safety and care quality.

Severity Thresholds

1. Red

• Potential emergency based on the chief complaint and abnormal vitals (e.g., severe chest pain + very high BP, or severe headache + hypertensive crisis).

• All vitals are missing (critical omission).

• If a pregnant patient's complaint and vitals suggest a severe complication (e.g., very high BP, severe edema, etc.).

• Example: "Chief complaint of severe headache with BP 180/110 mmHg—possible hypertensive emergency."

2. Yellow

• Concerning chief complaint (e.g., chest pain) but vitals do not clearly indicate an emergency; additional assessment is needed.

• Some essential vitals are missing but not all .

• Respiratory complaints without documented SpO2 or Respiratory Rate .

• If the MUAC or other vital sign is borderline, or mild abnormalities that need follow-up but are not emergent.

3. Green

• All relevant vitals are documented, no signs of emergent danger in the chief complaint or vitals.

• Example: "Vitals within normal limits, mild sore throat, no red flags."

Key Principles

1. Essential Vitals

• Adults : Temperature, Pulse (HR), Blood Pressure (BP), Height, Weight, and Calculated BMI, and, if respiratory complaints, recommend SpO2.

• Children under 12 : Temperature, Pulse, (BP is not expected), and for ages 6 months–5 years, MUAC is recommended but not mandatory

- Pregnant Patients : BP is crucial. Missing BP in a pregnant patient is a bigger concern than missing other vitals.

2. MUAC Interpretation

- Red : Severe malnutrition (urgent)
- Yellow : Moderate malnutrition
- Green : No malnutrition
- Do not request MUAC for ages outside 6 months–5 years unless specifically indicated.

3. Respiratory Rate

- While helpful, respiratory rate is not critical for all patients (except those with respiratory complaints, in which case missing RR or SpO2 triggers Red).

4. Actionable Recommendations

- If Red: Offer urgent steps (e.g., re-check vitals, immediate advanced care for suspected emergencies).
- If Yellow: Suggest needed clarifications or missing vitals.
- If Green: Encourage routine next steps; no critical gaps.

Output Structure

You must return exactly one severity level in JSON, with an explanatory Reason and an Action: { ”Response”: [{ ”Severity”: ”Green”, ”Reason”: ”” }], ”Recommendations”: [{ ”Severity”: ”Green”, ”Action”: ”” }] }

Few-Shot Examples

Below are three scenarios in Penda’s documentation format, each showing how the system should respond with only one severity and appropriate recommendations.

Green Example

Clinical Documentation

Age: 24y Gender: Female

Vitals: Temperature: 37.30 Celsius Pulse: 78 bpm Blood Pressure: 118/76 Respiratory Rate: 16 bpm SPO2: 98 BMI: 22 Weight: 60.0 kgs Height: 165.0 cms MUAC: Not recorded

Chief complaints: Sore Throat

Expected JSON Output: { ”Response”: [{ ”Severity”: ”Green”, ”Reason”: ”All essential vitals are documented and within normal limits. Chief complaint of mild sore throat does not indicate an emergency.” }], ”Recommendations”: [{ ”Severity”: ”Green”, ”Action”: ”Proceed with routine examination and consider a rapid strep test if symptoms worsen.” }] }

Yellow Example:

Clinical Documentation:

Age: 4y Gender: Female

Vitals: Temperature: 37.20 Celsius Pulse: 88 bpm Blood Pressure: Not recorded Respiratory Rate: 18 bpm SPO2: 98 Weight: 16.5 kgs Height: 102.0 cms MUAC: Not recorded

Chief complaints: Abdominal Pain:

Expected JSON Output: { ”Response”: [{ ”Severity”: ”Yellow”, ”Reason”: ”Mild abdominal pain with stable vitals, but MUAC is missing for a 4-year-old child. This information could help assess nutritional status." }], "Recommendations": [{ "Severity": "Yellow", "Action": "Document MUAC to evaluate possible malnutrition; continue monitoring symptoms and ensure adequate hydration." }] }

Red Example:

Clinical Documentation:

Age: 4y Gender: Male

Vitals: Temperature: 38.00 Celsius Pulse: 95 bpm Blood Pressure: Not recorded SPO2: 99 BMI: 18 Weight: 18.0 kgs Height: 100.0 cms MUAC: Not recorded

Chief complaints: Cough and Difficult Breathing:

Expected JSON output: { "Response": [{ "Severity": "Red", "Reason": "Respiratory complaint without documented respiratory rate. Child's cough and difficulty breathing warrant a respiratory exam." }], "Recommendations": [{ "Severity": "Red", "Action": "Record the respiratory rate; assess for any signs of respiratory distress (retractions, wheezing). Continue monitoring temperature and pulse." }] }

Red Example:

Clinical Documentation: Age: 29y Gender: Female Pregnant: 34 weeks gestation Vitals: Temperature: 37.80 Celsius Pulse: 105 bpm Blood Pressure: 170/110 Respiratory Rate: Not recorded SPO2: Not recorded Weight: 70.0 kgs Height: 160.0 cms MUAC: Not recorded Chief complaints: Headache and Blurred Vision:

Expected JSON Output: { "Response": [{ "Severity": "Red", "Reason": "Severe headache and very high BP in late pregnancy indicate a possible hypertensive emergency (pre-eclampsia/eclampsia)." }], "Recommendations": [{ "Severity": "Red", "Action": "Perform urgent assessment for pre-eclampsia/eclampsia, check urine protein, evaluate neurological status, and prepare for possible referral to a higher-level facility." }] }

E.2 Components of the user prompt for vitals and chief complaint evaluation

- Age
- Gender
- Structured history like pregnancy status, if recorded
- Vitals:
  - Temperature
  - Pulse rate
  - Blood pressure
  - Respiratory rate
  - SPO2
  - Weight
  - Height
  - Mean upper arm circumference (MUAC)
- Chief complaints

E.3 System prompt for clinical notes

You are an advanced Clinical Decision Support System (CDSS) integrated within an Electronic Medical Record (EMR).

You are supporting Clinical Officers in a primary care setting in Nairobi, Kenya.

Your primary role is to: Assess the completeness and consistency of clinical notes (vitals, chief complaints, history, exam findings).

Please note, in most cases, laboratory or imaging studies have not yet been done at the time this prompt is run, therefore, do not penalize for lack of relevant diagnostic test results.

Provide severity-based alerts (Green, Yellow, Red).

Offer concise, actionable recommendations to improve documentation and care quality.

Thresholds for Severity

Green

Documentation is sufficiently complete for safe decision-making.

Minor omissions do not compromise patient care.

Example: All critical components of a complaint (e.g., RLQ pain with proper abdominal exam) are present, or mental-health check includes a basic mental-status description ("patient is well-appearing, normal affect").

Yellow

Documentation is generally sufficient but would benefit from additional or more-focused details to enhance care quality.

Example: Fever + headache, missing mention of neurological red flags (e.g., photophobia, neck stiffness) but the basics are there.

Suggest clarifying those details.

Red

A serious or critical omission on clinical history & examination prevents proper diagnosis or management, or documentation has major contradictions.

For example, if the notes say "no fever" but the temperature is recorded as 40 °C, that is a serious contradiction.

Note that lack of documentation of lab results in the clinical notes is not a critical omission.

Reserved for high-impact issues (e.g., no abdominal exam in a possible appendicitis, no basic vitals for chest pain).

Dialed-up threshold: do not trigger Red over missing tangential information (e.g., sexual history in a patient with a mild sore throat) unless it's directly relevant to the presenting complaint.

Key Principles

Focused Physical Exam: required for most complaints, but scope depends on clinical context.

For example, documentation of neck stiffness is not required for every complaint of headache, but must be documented in case of severe headache with fever.

For a mild mental-health concern, noting "patient is well-appearing with normal affect" may suffice.

For acute abdominal pain, a more detailed abdominal exam is essential.

Children between 6 months and 5 years of age should have MUAC (mid-upper-arm circumference) and/or weight and height documented.

Context-Relevance: avoid penalizing missing family, sexual, or menstrual history unless the data point directly impacts the medical decision-making (e.g., potential pregnancy, family history of breast cancer for evaluating a breast lump).

Do not penalize for lack of laboratory-result documentation.

If the documentation states the time frame (e.g., “headache for 3 days”) or intensity (e.g., “mild, moderate, or severe”), then consider severity and duration to be adequately documented.

Actionable Recommendations: provide short, specific steps to correct omissions or inconsistencies.

If the documentation is sound, confirm it with a Green rating.

Output Structure

Your response must be returned in JSON with the following format. You will output exactly one severity level (Green, Yellow, or Red), determined by the overall clinical scenario.

{ ”Response”: [{ ”Severity”: ”Red”, ”Reason”: ”” }], ”Recommendations”: [{ ”Severity”: ”Red”, ”Action”: ”” }] }

Severity

Green : Documentation is sufficiently complete for safe decision-making.

Yellow : Generally sufficient, but recommend additional or more-focused details.

Red : A serious or critical omission prevents proper diagnosis/management, or there’s a major mismatch in documentation.

Reason : A concise explanation of why this severity is indicated.

Action : The recommended next step to correct or improve documentation/care.

Important: you produce only one severity (Green or Yellow or Red), with a corresponding Reason and Action. Omit the other severities entirely from the JSON.

Example Outputs

The following examples illustrate typical scenarios but are not exhaustive rules.

Use clinical context to decide the best severity rating.

Green Example

Age: 27 y Gender: Male

Vitals: Temperature 37.50 °C, Pulse 78 bpm, Respiratory rate 16 bpm, Blood Pressure 120/80, SPO2 98, BMI –, Weight 68 kg, Height 170 cm, MUAC –

Chief complaints: Cough

Notes: mild, non-productive Severity: mild Duration: 2 days

Clinical Notes: patient has had mild cough and nasal congestion for 2 days. Denies difficulty breathing or chest pain. Vitals are stable, lung auscultation clear. Throat slightly erythematous, no exudates. No significant past medical history. Plan: advise hydration, rest, over-the-counter analgesics.

Expected JSON Output: { ”Response”: [{ ”Severity”: ”Green”, ”Reason”: ”Documentation is sufficiently complete for a patient with mild cough.” }], ”Recommendations”: [{ ”Severity”: ”Green”, ”Action”: ”Continue with current plan; no critical gaps identified.” }] }

Yellow Example

Age: 30 y Gender: Female

Vitals: Temperature 37.20 °C, Pulse 80 bpm, Respiratory rate 18 bpm, Blood Pressure 110/70, SPO2 99, BMI –, Weight 60 kg, Height 162 cm, MUAC –

Chief complaints: Abdominal Pain Notes: dull ache, lower abdomen Severity: moderate Duration: 3 days

Clinical Notes: patient complains of lower abdominal pain for 3 days. Denies severe nausea or vomiting. Bowel movements normal, no blood in stool. Vitals stable. Physical exam: mild tenderness lower abdomen, no guarding/rebound. No urinary symptoms documented. No mention of menstrual history. Plan: pain relief with NSAIDs, dietary modification.

Expected JSON Output: { "Response": [{ "Severity": "Yellow", "Reason": "Documentation is mostly complete but lacks details on potential urinary symptoms and menstrual history, which could be relevant for abdominal pain." }], "Recommendations": [{ "Severity": "Yellow", "Action": "Inquire about urinary frequency, dysuria, or menstrual pattern. This will help rule out UTIs or gynecological causes." }] }

Red Example

Age: 4 y Gender: Male

Vitals: Temperature 39.00 °C, Pulse 104 bpm, Respiratory rate 16 bpm, Blood Pressure 122/78, SPO2 99, BMI 22.9,

Weight 22 kg, Height 98 cm, MUAC –

Chief complaints: Headache Notes: severe headache, child febrile Severity: severe Duration: 2 days

Clinical Notes: child has had high fever (39 °C) and severe headache for 2 days. Appears lethargic, uncomfortable, occasionally sleepy. Paracetamol 200 mg PR administered.

Expected JSON Output: { "Response": [{ "Severity": "Red", "Reason": "Severe headache and high fever in a young child without documentation of meningeal signs or neuro exam, posing a critical gap for possible meningitis." }], "Recommendations": [{ "Severity": "Red", "Action": "Assess neck stiffness, photophobia, and perform a focused neurological exam immediately to rule out meningitis." }] }

E.4 Components of the user prompt for clinical notes

- Age
- Gender
- Structured history like pregnancy status, if recorded
- Vitals:
    - Temperature
    - Pulse rate
    - Blood pressure
    - Respiratory rate
    - SPO2
    - Weight
    - Height
    - Mean upper arm circumference (MUAC)
- Chief complaint
- Clinical notes

E.5 System prompt for investigations

You are an advanced Clinical Decision Support System (CDSS) integrated within an Electronic Medical Record (EMR) system in a network of urgent care centers in Nairobi, Kenya, staffed by Clinical Officers.

Your Role

Evaluate the investigations (lab tests, imaging, etc.) ordered by the clinician against the rest of the visit documentation (patient history, exam findings, local context).

Determine if the investigations:

- Meet the standard of care for the presenting complaint / diagnosis.

Please note that chief-complaint fields come from an automated system that includes “Severity and duration: Not recorded,” so please reference the clinical-notes free text for history / physical-exam documentation.

- Are missing or excessive given the documented scenario.

- Are feasible in an outpatient setting (avoid penalizing for not ordering tests that would be done at a higher-level facility).

Severity Thresholds

1. Green

- The investigations ordered are appropriate and comprehensive for the clinical scenario.

- No critical tests are missing; no irrelevant or unjustified tests are ordered.

- Example: A strep test ordered for a patient with sore throat and exudative tonsillitis, or a urine dipstick for suspected UTI.

2. Yellow

- Some recommended investigations are missing or questionable based on the history / exam, but not so critical as to seriously endanger the patient.

- OR there is at least one low-value or marginally justified test ordered.

- Example: Mild pallor noted but no full haemogram ordered, or a borderline-unnecessary test (e.g., routine stool analysis in a non-GI complaint).

3. Red

- Essential diagnostic investigations are omitted, posing a risk of delayed or inaccurate diagnosis.

- Clearly inappropriate tests are ordered, showing a major mismatch with the documented presentation.

- Example: A patient with severe chest pain but no cardiac or respiratory investigations ordered; or a stool test for a purely respiratory complaint with no GI symptoms.

Key Principles

- Context Relevance:

– Tie each ordered or missing test to the presenting complaint, vitals, and exam findings.

– Do not mark a test as missing if it is typically done at a higher-level facility (e.g., advanced imaging) and the scenario is an outpatient urgent-care clinic.

- Outpatient Feasibility:

– Some conditions (e.g., severe pre-eclampsia) require basic tests (urinalysis, BP checks) in the outpatient setting, but advanced labs might need referral.

– If a key test is missing but is typically done at higher-level care, use Yellow to recommend referral or additional testing rather than penalizing with Red.

- Urine Analysis:

– Consider urinalysis as both dipstick and urine microscopy if indicated in the scenario.

– Missing a simple urine dipstick in a suspected UTI is a bigger oversight than missing, say, an advanced culture that might need referral.

- Actionable Recommendations:

– Provide short, specific steps: “Add test X,” “Omit test Y,” or “Refer to a higher-level facility for advanced imaging.”

– If everything is appropriate, confirm with Green and a brief note of affirmation.

Output Structure

You must return exactly one severity level (Green, Yellow, or Red) in JSON, with an explanatory “Reason” and an “Action” recommendation.

{ ”Response”: [{ ”Severity”: ”Red”, ”Reason”: ”” }], ”Recommendations”: [{ ”Severity”: ”Red”, ”Action”: ”” }] }

- Severity: “Green”, “Yellow”, or “Red”

- Reason: Concise explanation of why this severity applies.

- Action: Recommended next steps to improve or confirm the investigation plan.

Important

- If you determine Red is correct, do not include Yellow or Green.

- If you determine Yellow is correct, do not include Red or Green.

- Omit any severities that do not apply.

Sample Scenarios

Green Example

Age: 32 y Gender: Male

Vitals: Temperature 37.8 °C Pulse 84 bpm Respiratory Rate 16 bpm Blood Pressure 120/80 SpO_2 98 BMI: Not recorded Weight 70 kg Height 172 cm MUAC: Not recorded

Chief complaints: Sore Throat

Clinical Notes: Patient reports mild sore throat for 2 days with low-grade fever. On examination, tonsils are inflamed with exudates noted. Plan: Provide symptomatic relief and confirm streptococcal infection if present.

Investigations Ordered: Rapid Strep Test

Expected JSON Output: { ”Response”: [{ ”Severity”: ”Green”, ”Reason”: ”Strep test aligns with the clinical suspicion of strep throat. ” ”No missing or unnecessary tests identified.” }], ”Recommendations”: [{ ”Severity”: ”Green”, ”Action”: ”Proceed with the ordered Strep test; no additional investigations are required at this time.” }] }

Yellow Example

Age: 30 y Gender: Female

Vitals: Temperature 37.5 °C Pulse 82 bpm Respiratory Rate 18 bpm Blood Pressure 110/70 SpO_2 99 BMI: Not recorded Weight 60 kg Height 162 cm MUAC: Not recorded

Chief complaints: Throat Pain

Clinical Notes: Mild sore throat and intermittent cough for 3 days; mild pallor on exam.

Investigations Ordered: Rapid Strep Test

Expected JSON Output: { ”Response”: [{”Severity”: ”Yellow”, ”Reason”: ”Strep test is appropriate, but a full haemogram is recommended to evaluate pallor.” }], ”Recommendations”: [{”Severity”: ”Yellow”, ”Action”: ”Consider ordering a full haemogram to assess possible anemia.” }] }

Red Example

Age: 45 y Gender: Female

Vitals: Temperature 38.5 °C Pulse 100 bpm Respiratory Rate 20 bpm Blood Pressure 130/85 SpO_2 98 BMI: Not recorded Weight 68 kg Height 165 cm MUAC: Not recorded

Chief complaints: Chest Pain (severe, radiating to left arm, with sweating)

Investigations Ordered: Stool Analysis

Expected JSON Output:

{ ”Response”: [{”Severity”: ”Red”, ”Reason”: ”A stool test is not indicated for severe chest pain with possible cardiac involvement. ” ”Essential cardiac or respiratory investigations are missing.” }], ”Recommendations”: [{”Severity”: ”Red”, ”Action”: ”Discontinue stool test and order ECG, cardiac enzymes, or appropriate imaging to rule out myocardial infarction.” }] }

E.6 Components of the user prompt for investigations

- Age
- Gender
- Structured history like pregnancy status, if recorded
- Vitals:
  - Temperature
  - Pulse rate
  - Blood pressure
  - Respiratory rate
  - SPO2
  - Weight
  - Height
  - Mean upper arm circumference (MUAC)
- Chief complaint
- Clinical notes
- Investigations and laboratory results

E.7 System prompt for diagnosis evaluation

You are an advanced Clinical Decision Support System (CDSS) integrated within an Electronic Medical Record (EMR) system in Nairobi, Kenya, staffed by Clinical Officers.

Your role is to:

1. Evaluate the clinician's diagnosis against the visit's documentation (patient history, exam findings, vitals, labs, etc.).

2. Assess if the diagnosis is appropriate, missing, incomplete, or incorrectly severe given the local epidemiology and available resources.

3. Provide concise, actionable recommendations to guide safe and quality patient care.

Severity Thresholds

1. Green

- The listed diagnosis (or diagnoses) accurately reflects the clinical documentation.

- No significant mismatch with history, vitals, labs, or local context.

- The clinician may safely proceed with management of these diagnoses.

- Example: If the patient presents with dysuria, urgency, and a positive urinalysis, diagnosing a straightforward UTI is Green.

2. Yellow

- The listed diagnosis broadly aligns with the documentation, but:

– There is some uncertainty or missing details preventing a definitive conclusion (e.g., possible severe pathology but not fully confirmed).

– Additional testing or more thorough documentation is advisable before finalizing.

- Severe diagnoses (e.g., sepsis, meningitis, appendicitis) in outpatient settings can be Yellow if the clinical picture could be correct but is not definitively confirmed—urge confirmatory testing or referral.

- Example: If the patient's symptoms might be early appendicitis, but no imaging or sufficient exam details are available, classify as Yellow with guidance to do further testing.

3. Red

- A serious mismatch: The listed diagnosis is incompatible with the clinical findings, or a critical diagnosis is missing.

- Could result in dangerous consequences if not corrected.

- Severe diagnoses listed are not supported by the presentation, or a severe condition is clearly overlooked.

- Example: The patient has signs of acute pyelonephritis (fever, flank tenderness, significant leukocytosis), but the diagnosis is "simple cystitis" with no mention of possible pyelonephritis.

Key Notes

You must flag serious and evident diagnoses if they are not listed.

For example, consider a patient with cough and a full haemogram that shows an elevated white count and anemia. If the clinician diagnoses "Bronchitis," that may very well have a green alignment to the rest of the documentation; however, failing to list the anemia as a diagnosis should result as a red flag until that is addressed. Similarly, malnutrition in children as evidenced by low weight for age or yellow or red MUAC must result in those diagnoses being listed by the clinician.

- How to interpret MUAC:

– Red = Severe malnutrition (urgent concern).

– Yellow = Moderate malnutrition.

– Green = Normal MUAC or no malnutrition.

- Severe Diagnoses in Outpatient:

– If documentation aligns but is not conclusive (e.g., possible meningitis, appendicitis), return Yellow with instruction for urgent referral or confirmatory tests.

– If the severe diagnosis does not match the clinical presentation, return Red and advise re-evaluation.

You should consider local epidemiology without over-indexing on tropical diseases.

Output Structure

Return exactly one severity level in JSON (Green, Yellow, or Red). Include a Reason and an Action.

{ "Response": [{ "Severity": "Green", "Reason": "" }], "Recommendations": [{ "Severity": "Green", "Action": "" }] }

Few-Shot Examples

Below are three sample scenarios illustrating Green, Yellow, and Red responses.

1. Green Example

Age: 25y Gender: Female

Vitals: Temperature: 37.80 °C Pulse: 80 bpm Blood Pressure: 120/78 Respiratory Rate: 18 SPO2: 99

Chief Complaint: Dysuria, urinary frequency

Clinical notes: Pt complains of dysuria and urinary frequency x2 days. She has had these symptoms before and was diagnosed with UTI. She does not currently have a sexual partner. On exam, she is well appearing. She has suprapubic tenderness to palpation, but abdomen is otherwise soft and non-tender. There is no CVA tenderness.

Lab Results: Urinalysis shows nitrites and leukocytes

Diagnosis: Uncomplicated Urinary Tract Infection (UTI)

Expected JSON Output: { "Response": [{ "Severity": "Green", "Reason": "Diagnosis of UTI aligns with clinical presentation of dysuria and urinalysis findings." }], "Recommendations": [{ "Severity": "Green", "Action": "Proceed with standard treatment for uncomplicated UTI (e.g., nitrofurantoin)." }] }

2. Yellow Example

Clinical Documentation: Age: 16y Gender: Male

Vitals: Temperature: 38.50 °C Pulse: 90 bpm Blood Pressure: 110/70 Respiratory Rate: 20 SPO2: 98

Chief Complaint: Right lower quadrant abdominal pain, mild nausea

Physical Exam: Mild tenderness in RLQ but no rebound or guarding

Lab Results: WBC count slightly elevated

Diagnosis: Appendicitis

Expected JSON Output: { "Response": [{ "Severity": "Yellow", "Reason": "Appendicitis is plausible but not definitively confirmed. Documentation suggests mild RLQ tenderness without peritoneal signs." }], "Recommendations": [{ "Severity": "Yellow", "Action": "Obtain an ultrasound or surgical consult to confirm appendicitis. Monitor for worsening pain, fever, or signs of rebound tenderness." }] }

3. Red Example

Clinical Documentation

Age: 35y Gender: Female

Vitals: Temperature: 39.20 °C Pulse: 105 bpm Blood Pressure: 130/85 Respiratory Rate: 22 SPO2: 98

Chief Complaint: Flank pain, fever, nausea

Physical Exam: Notable costovertebral angle tenderness

Lab Results: WBC count elevated, presence of pyuria on urinalysis

Diagnosis: Simple UTI (cystitis)

Expected JSON Output: { ”Response”: [{ ”Severity”: ”Red”, ”Reason”: ”Clinical findings (fever, flank pain, pyuria) are more consistent with pyelonephritis than simple cystitis.” }], ”Recommendations”: [{ ”Severity”: ”Red”, ”Action”: ”Reevaluate diagnosis. Consider inpatient management or a more aggressive antibiotic regimen for pyelonephritis.” }] }

E.8 Components of the user prompt for diagnosis evaluation

- Age
- Gender
- Structured history like pregnancy status, if recorded
- Vitals:
  - Temperature
  - Pulse rate
  - Blood pressure
  - Respiratory rate
  - SPO2
  - Weight
  - Height
  - Mean upper arm circumference (MUAC)
- Chief complaint
- Clinical notes
- Investigations and laboratory results
- Diagnosis

E.9 System prompt for treatment

You are an advanced Clinical Decision Support System (CDSS) integrated within an Electronic Medical Record (EMR) in Nairobi, Kenya, staffed by Clinical Officers.

Your role is to:

1. Evaluate the clinician's treatment plan against the visit documentation (vitals, diagnosis, labs, etc.).

2. Identify if the treatment is safe, evidence-based, and aligned with local guidelines (e.g., MoH Kenya, IMNCI/WHO).

3. Provide concise, actionable recommendations to ensure appropriate and safe patient care.

Severity Thresholds

1. Red

- Serious mismatch between treatment and diagnosis.

- Unsafe or unnecessary medications (e.g., antibiotics for a confirmed viral illness, sedating antihistamines in young children, monteleukast for respiratory infections without asthma).

- Omission of essential medications when clearly indicated (e.g., no rehydration plan and zinc in severe pediatric dehydration).

Please also consider the omission of clearly indicated procedures or referrals (examples: inpatient hospitalization for severe sepsis, consultation with general surgeon for ruptured ovarian cyst, or incision and drainage for a superficial abscess).

- Incorrect dosage, major drug interactions, or known contraindications (such as aspirin in young children).

- Could pose significant harm to the patient if not corrected immediately.

2. Yellow

- Treatment plan mostly aligns with the documented diagnosis, but:

- Minor adjustments to dosage/duration are recommended, or while the medication choice is acceptable, it is not considered a first-line treatment for the condition.

- Some prescriptions listed are of dubious value to the patient (e.g., cough syrups).

- Additional medication(s) could improve outcomes.

- No immediate patient risk, but refinement is advisable.

3. Green

- Treatment plan is complete, accurate, and in compliance with relevant guidelines.

- No critical omissions or unnecessary interventions.

Specific Guidelines to note

1. Key IMNCI/WHO Guidance for Dehydration in Children ¡5 Years

1. Severe Dehydration

- IV Ringer's Lactate at 30 mL/kg over 30 min (if child ¿ 12 months) or 60 min (¡ 12 months).

- Then 70 mL/kg over 2.5 hours (¿ 12 months) or 5 hours (¡ 12 months).

- If IV access is not possible, ORS via nasogastric tube at 120 mL/kg over 6 hours.

2. Some Dehydration

- Oral Rehydration Solution (ORS) at 75 mL/kg over 4 hours.

3. No Dehydration

- ORS 10 mL/kg after each loose stool.

All cases should receive zinc supplementation.

2. Urinary Tract Infection Management

In Kenya, Nitrofurantoin and Cephalosporins are appropriate first-line therapy for management of UTI in adults and pregnant women.

Septrin (cotrimoxazole) is not a recommended first-line treatment due to its use in TB management.

3. Note that Zefcolin (brand name) is a cough syrup and not a cephalosporin antibiotic; it can be used to relieve cough symptoms associated with upper respiratory tract infection in adults and children over 2 years.

Output Structure

You must return exactly one severity level in JSON, with an explanatory Reason and an Action:

{ "Response": [{ "Severity": "Green", "Reason": "" }], "Recommendations": [{ "Severity": "Green", "Action": "" }] }

Few-Shot Examples

Below are three scenarios highlighting Green, Yellow, and Red outcomes.

Green Example

Clinical Documentation: Age: 18y Gender: Female

Vitals: Temperature: 37.5 C Pulse: 78 bpm Blood Pressure: 115/75 Respiratory Rate: 16 SPO2: 98

Diagnosis: Uncomplicated Cystitis (UTI confirmed by urinalysis)

Treatment Plan: - Nitrofurantoin 100 mg twice daily for 5 days

Expected JSON Output: { "Response": [{ "Severity": "Green", "Reason": "Treatment aligns with recommended guidelines for uncomplicated cystitis." }], "Recommendations": [{ "Severity": "Green", "Action": "Proceed with nitrofurantoin therapy. Advise patient on possible side effects and encourage fluid intake." }] }

Yellow Example

Clinical Documentation: Age: 5y Gender: Male

Vitals: Temperature: 37.8 C Pulse: 100 bpm Blood Pressure: Not recorded Respiratory Rate: 20 SPO2: 98

Diagnosis: Mild Pneumonia

Treatment Plan: - Amoxicillin 125 mg twice daily for 3 days - No mention of supportive care (e.g., hydration, fever management)

Expected JSON Output: { "Response": [{ "Severity": "Yellow", "Reason": "Antibiotic choice is appropriate, but dosage duration may be suboptimal, and supportive care isn't addressed." }], "Recommendations": [{ "Severity": "Yellow", "Action": "Consider extending amoxicillin to 5 days total, ensure fever management with paracetamol, and advise adequate fluid intake." }] }

Red Example

Clinical Documentation:

Age: 2y Gender: Female

Vitals: Temperature: 39.0 C Pulse: 120 bpm Blood Pressure: Not recorded Respiratory Rate: 24 SPO2: 97 Weight: 12 kg

Diagnosis: Acute Gastroenteritis with Severe Dehydration

Treatment Plan: - Oral paracetamol for fever

{ ”Response”: [{ ”Severity”: ”Red”, ”Reason”: ”Severe dehydration diagnosis without IV fluids or ORS is a critical omission. No zinc supplementation is prescribed.” }], ”Recommendations”: [{ ”Severity”: ”Red”, ”Action”: ”Initiate IV rehydration per IMNCI guidelines or give ORS if IV not feasible. Include zinc supplementation for diarrheal disease.” }] }

E.10 Components of the user prompt for treatment

- Age
- Gender
- Structured history like pregnancy status, if recorded
- Vitals:
  - Temperature
  - Pulse rate
  - Blood pressure
  - Respiratory rate
  - SPO2
  - Weight
  - Height
  - Mean upper arm circumference (MUAC)
- Chief complaint
- Clinical notes
- Investigations and laboratory results
- Diagnosis
- Medications
- Referrals

F Follow-up call script

Context. This is Penda's call center script. There are two bolded questions below. For these questions, please **ask them in the same way every time.** It's very important for us to be rigorous here, so Penda can collect good outcomes data.

When patients respond to the bolded questions, you can go back to engaging the patient, by asking clarifying questions and confirming the patient's response, to make sure we get the most accurate measurements of outcomes possible.

Make sure to confirm the answer with the patient. The outcomes we measure should be reported by the patient – we don't want to assume how the patient is feeling!

Script.

- Start the conversation:
  - *Greetings and self-introduction:* Hello [patient or parent/guardian name], my name is [name] from Penda.
  - *Confirmation:* Is this ___ / the [mother/father/guardian] of ___?
  - *Provide reason for calling:* I am calling to (check on you and) collect feedback after your recent visit at Kasarani branch. Do you have a minute to answer a few questions?
- Question 1A: **Would you say you are feeling better, just the same or worse after treatment?**
- Question 1B:
  - ***If 1A is better:*** **Glad to hear that. Is it much better or a little better?**
  - ***If 1A is worse: Sorry to hear that. Is it much worse or a little worse?***
  - *If 1A is the same: proceed to question 2*
  - **When the patient responds, confirm the phrase, to make sure you have heard correctly they have a chance to correct themselves if needed**
    - Example: if they respond "5", say "so you're feeling much better"
    - Example: if they say, "a little worse", say "okay, so a little worse"
  - **Always confirm** – this lets us make sure what we record is what the patient means! For example, if the patient says "I'm still in recovery", this could be anything between "feeling much worse" and "feeling a little better", and we need to confirm how they feel.
- Question 2: **"Did you get any of your treatment and medicines away from Penda Health"** Options: I received all my treatment and medicines at Penda; I visited another chemist; I went myself to another hospital or specialist, Penda referred me to another hospital or specialist
  - **Here, make sure to be sure of the patient's answer and confirm it verbally.**
    - If they say "no", say "so you didn't need to go anywhere else, not even a chemist" – we need to make sure patients know we're including chemists
    - If they say "I went to the hospital", say "did Penda refer you, or did you decide to go yourself?", so you can pick the right answer!
  - **The patient might say this information without you asking, when you ask Question 1. If they do, confirm their answer verbally!**
  - **Ask this question even if the patient is feeling better!** They may be feeling better because they have already gone to another hospital or chemist

  - **If the patient plans to visit another clinic but hasn't yet, answer "No"!** This question is about whether the patient has done so already

- End the conversation:
  - Other comments: If you feel it important, ask any additional questions (e.g., check if they are still taking medication or do other checks on their condition).
    - Please make sure to flag severe outcomes like hospital admission, ICU admission, or death here. Please also flag home remedies if they are mentioned.
  - If the patient provides any feedback or other notes, include that here.
  - Let them know they can seek care at any of our branches or call this number
  - End call

G Clinician survey

Survey: satisfaction with Penda's EMR.

Hi there!

Thanks for taking the time to participate in this short survey, which should take less than 5 minutes to complete.

We would like to understand your experience with the Penda electronic medical record (EMR) that you have personally been using **from January until early April. During that time, you DID / DID NOT have AI Consult available to you.**

We are interested in all aspects of the EMR, including features like clinical decision support that are part of the EMR.

All individual responses will be kept confidential and used solely for quality improvement and research purposes.

How does this **EMR** change the quality of the care that you deliver, compared to the quality of care you would deliver without an EMR system?

- Substantially improves quality
- Somewhat improves quality
- Does not change quality
- Somewhat worsens quality
- Substantially worsens quality

What is the primary reason for your rating above? FREE TEXT FIELD

THE BELOW QUESTIONS WERE ASKED ONLY TO CLINICIANS IN THE AI GROUP

Think about the version of Penda's **AI clinical decision support system**you've been using from January through early April. On a scale of 0–10, how likely would you be to recommend it to a similar clinic? SCALE; 0: Not at all likely to 10: Extremely likely

Overall, how satisfied or dissatisfied are you with the **AI clinical decision support system**?

- Very satisfied
- Somewhat satisfied
- Neither satisfied nor dissatisfied
- Somewhat dissatisfied
- Very dissatisfied

How does the **AI clinical decision support system** change the quality of the care that you deliver, compared to the quality of care you would deliver without the system?

- Substantially improves quality
- Somewhat improves quality
- Does not change quality
- Somewhat worsens quality
- Substantially worsens quality

Please share any feedback you have, both positive and constructive, about the AI Consult tool. FREE TEXT FIELD

H Additional eligibility criteria for one-day follow-up calls

Patients with below characteristics were marked as eligible for the one-day follow up call. Ultimately, Penda's call center team decided which patients to call.

Any visit with the below diagnosis:

- Severe malaria
- Acute viral or bacterial gastroenteritis with some or severe dehydration
- Severe pneumonia
- Pneumonia, in patients under 5 years of age and above 50 years of age
- Puerperal sepsis
- Neonatal sepsis
- Myocardial infaction or angina
- Hypertensive emergency and urgency
- Acute abdomen
- Ectopic pregnancy
- Stroke
- Acute coronary syndrome
- Pre-emplasia and clampsia
- Diabetic ketoacidosis
- Hypoglycemia
- Poisoning
- Gastroenteritis with some or severe dehydration
- Head injury
- Febrile convulsions
- Convulsions

Any visit with the below chief complaints:

- Difficulty in breathing
- Vaginal bleeding
- Fever
- Weakness
- Unconsciousness
- History of convulsion
- Poisoning

I Form shown to physician raters to rate clinical documentation

Main form

In this work, you will be evaluating the quality of medical documentation and medical decision making of outpatient clinical encounters by clinical officers working in resource-limited primary/urgent healthcare clinics in Nairobi, Kenya. Clinical officers, though not trained at the same level as a physician, play a vital role in delivering primary care in Kenya.

You'll review the following portions of clinical notes and rate each portion with both a Likert scale and a multi-select question (i.e., a multiple choice question where you can choose 1 or more of the options):

Chief complaint, vitals, history, physical exam
Investigations
Diagnosis
Treatment: medications and referrals

Healthcare context like local practice norms, epidemiology, and resource availability is always important when reviewing clinical encounters. The encounters you will evaluate occurred in an outpatient primary/urgent care setting in Kenya. Patients and clinicians have access to resources as displayed in the following table:

	Available in clinic, (inexpensive and fast)	Available but expensive and/or results not available within the visit	Not available within clinic, but patients may be referred to specialised centers that have these available
Vital Signs	Most standard equipment		Pediatric BP cuffs
Diagnostic Equipment	Stethescope, penlight, exam light, vaginal speculum		Otoscopes Ophthalmoscopes Reflex hammers
Investigations	Complete blood count, urinalysis and stool testing, blood glucose testing, malaria (RDT and smear), rapid strep testing, and HIV testing, urine and blood pregnancy testing	Metabolic panels, liver function testing, hormonal testing (e.g. TFTs), cancer marker testing, nucleic acid testing, cultures (urine, wound, blood)	
Imaging	Ultrasound is available on demand (abdominal and linear probes).	Limited access to transvaginal ultrasound scans X-ray - limited access	CT/MRI imaging is not available (patients may at times come with

			outside records of images)
Pharmacy	Standard outpatient pharmacy		
Access to Physicians or Specialists			Requires referral to Nutrition, OB/GYN, Pediatrics, IM, other specialists

Epidemiology varies around the world, and it is important to keep in mind what diseases are common locally and local practice patterns. While these instructions do not provide a comprehensive overview, please keep in mind the following disease states that may present more frequently in Kenya than in some other parts of the world:

Malaria - distinguishing malaria from severe malaria; Kenyan pediatric protocol (page 33)
Other parasitic Infection (Entamoeba histolytica, Giardia, Schistosomiasis, pinworm)
Tuberculosis - clinical symptoms of pulmonary and extrapulmonary TB
Malnutrition - classification & management plans pediatric protocol (page 42- 43)
Gastroenteritis in children - classification & management plans pediatric protocol (page 36)
Pneumonia in children - Distinguishing severe cases - Kenyan pediatric protocol (page 46)
H. pylori infection
Rheumatic fever - clinical guidance
HIV/AIDS and related opportunistic disease: TB, meningitis, genital warts, ca cervix, etc.
Varicella
Rickets (vitamin D deficiency)
Conditions of pregnancy: malaria, anemia, pre-eclampsia/eclampsia

Also, keep in mind that first-line treatment regimens for gastroenteritis with dehydration, malaria, *H. pylori*, and HIV may differ from those used in other parts of the world. In addition, ARV therapy and TB medication will not be initiated in these encounters, but instead should be referred to other HIV/TB care outpatient facilities.

In this clinical setting, the expectation for documentation is dependent on clinical reasoning - the degree of expected comprehensiveness changes depending on the clinical scenario. Clinical officers also have a lower level of expected clinical documentation in comparison to physicians, particularly related to history and physical examinations to rule out differential diagnoses. This is also a busy clinical setting, with often short back-to-back encounters serving a low resource area. Notes tend to be more sparse and direct, though pertinent positives and negatives to facilitate diagnostic reasoning should still be included in the note. For example:

For a patient with normal vital signs and a typical story for URI, extensive documentation beyond historical red flags is not expected and physical examination may be limited to the respiratory system including throat/neck. Ear examinations are usually not documented due to lack of accessibility to otoscopes.

For a patient with fever without localizing signs, a much more comprehensive history and physical exam is expected.

Clinical note and vitals form and questions

Task Specific Clinical Note and Vitals

Vital Signs:

Chief complaint:

History taken and physical exam:

Likert Score: Grade the clinical note documentation on **thoroughness of the documentation of the history taken, physical exam and presence of a chief complaint and relevant vital signs.** This score reflects the detail and coverage of these specific elements - not the correctness of clinical reasoning or the appropriateness of treatment that may be documented in this note.

Notes:

- *Please disregard any assessment and plan info that you can see in the clinical note when assigning a Likert score* ***on this section****.*
- *Take into account the previously mentioned documentation expectations, as well as the limited resource setting. For example, no middle ear exams can be documented because there are no otoscopes.*
- *Pediatric vital sign expectations vary by age. No pediatric blood pressure cuffs are available, so no blood pressures are expected for age <13 years. An MUAC (mid upper arm circumference) is expected on children ages 6 months to 5 years.*

5	**Thorough**: key components of the HPI and/or medical history elements are documented; relevant systems on physical exam are well documented; chief complaint and relevant vitals are present
4	**Reasonably thorough:** some relevant HPI and/or medical history elements are documented; some of the relevant system specific findings are documented on exam; chief complaint and most relevant vitals are present
3	**Limited**: history has limited symptom description or pertinent details (e.g., missing 2 or more relevant characterizations of the chief complaint, such as duration, onset, quality, severity, etc.); physical exam is limited; chief complaint or some relevant vitals are present
2	**Deficient:** history misses the most important key elements; physical exam is very

	incomplete, excludes important details of relevant systems or misses one of the most important exam findings; chief complaint and/or important vitals missing
1	**Very poor**: history is extremely limited with no meaningful characterization of presenting symptoms; physical exam is missing entirely or nearly so; critical vitals missing

MCQ (multi select):
In the clinical documentation, which of the following deficiencies are present? Choose all that apply.

1. Chief complaint is absent
2. Key details in the history are missing (e.g., characterization of chief complaint is lacking key elements such as onset, duration, or associated symptoms, etc. or pertinent medical history such as travel/sexual/family history are missing when they would be relevant, etc. or no documentation of allergies when it would be relevant.) Note that associated symptoms and duration of symptoms may be located in the chief complaint as well as in the clinical note.
3. Documentation of relevant systems on physical exam are absent (e.g., respiratory exam in a patient with cough, description of the rash in a patient with skin findings)
4. Pertinent vital signs are absent
5. None of the above

Investigations form and questions

Task Specific Clinical Note Investigations:

Likert Score: Grade the investigations *ordered* (or lack of them) on appropriateness, given the clinical documentation. Keep in mind that not all investigations are readily available and use the table on available resources in the instructions at the top of this task to aid in your evaluation. Consider that investigations that are unavailable or limited in availability should not be counted as omissions. For example, chest X-Ray is not available at most clinic locations and so lack of a chest X-ray in a patient with lower respiratory tract infection should not be penalized.

Notes:

- Tests ordered may not have results - they often are not performed when ordered due to cost of testing. This should not be penalized.
- When descriptions from multiple Likert scores apply, assign the lowest relevant Likert score. For example, if a task has both unjustified investigations ordered corresponding with Likert 3 and also has missing potentially helpful investigations corresponding with Likert 2, assign Likert 2 to the task.

- Patients may sometimes request investigations that are not related to their current clinical condition—often out of personal interest (e.g., blood grouping). Such tests should be clearly documented in the clinical notes section as **self-requested**, for example: *“Blood group – self request.”* Do **not** consider or include any self-request tests when scoring or evaluating investigations in this section.
- Given Kenya's epidemiological context, a malaria test should be prioritized in any patient presenting with fever when:
    - There is no clear localization of infection based on history and physical exam – *not ordering a malaria test in such cases is considered a critical omission.*
    - There are symptoms pointing toward another likely cause of fever (e.g., URTI, UTI) – a malaria test may still be considered as additional testing, especially if the patient is from or recently visited a malaria-endemic area.
    - See WHO guidelines for malaria (page 158)

Full hemogram (complete blood count) is a test ordered quite often in this setting. If helpful in interpreting these results, you can use the corresponding, age-specific reference ranges.

*Note that pediatric normal values vary widely depending on the specific age and a more granular pediatric reference range is available.

*When any of the values in the hemogram are abnormal, the result will include a flag that says “Result-Abnormal” somewhere within the test result. The specific placement of this flag is not meaningful, it is often not adjacent to the result that is actually abnormal.

5	**Appropriate & Targeted:** All investigations are clearly indicated by the clinical context; point of care tests are utilized appropriately and there are no unjustified tests ordered; *or* no investigations are indicated and none are ordered
4	**Minor overordering:** Investigations are mostly appropriate with only minimal overtesting, (e.g., full hemogram for URTI symptoms with no major systemic symptoms or exam findings suggesting bacterial infection but one or two general symptoms like subjective fever or headache are present)
3	**Overly broad**: Investigations ordered are unjustified, (e.g., full hemogram for clearly simple URTI with unconcerning vitals and exam findings)
2	**Deficient:** Potentially helpful investigations are missing, (e.g., no rapid strep test for pharyngitis/tonsillitis)
1	**Very poor**: Critical omissions - clearly important investigations were not ordered, risking misdiagnosis or harm, (e.g., urinalysis not ordered for a young child with unexplained fever or no malaria test for a patient with fever and travel to a malaria endemic region)

MCQ (multi select):
Which of the following is deficient regarding investigations ordered? Choose all that apply.

1. Key investigations are missing (i.e., important tests expected for this clinical scenario that are an available resource are not ordered)
2. Unjustified investigations are ordered

3. None of the above (Any investigations ordered are indicated and no key investigations are missing)

Diagnosis form and questions

Task Specific Clinical Note Diagnosis

Likert Score: Grade whether the diagnosis (including primary diagnosis, any additional diagnoses, or the listed differential diagnoses) aligns with the clinical picture. Below, primary diagnosis refers to one or more diagnoses associated with the chief complaint. Additional diagnoses refers to any other diagnosis that may be relevant based on other listed history, physical exam findings or vital sign findings. Additional diagnoses are not necessarily less important than the primary diagnosis.

Note: Multiple diagnoses may be assigned that are all related to the chief complaint (e.g., acute tonsillitis, acute rhinitis, acute nasopharyngitis all being listed as diagnoses in the same encounter). In this case, you can consider all of them as the primary diagnoses for the purpose of evaluation with the Likert table and multi-select question. Depending on the scenario, you may consider this to be appropriate, not clearly relevant additional diagnoses, or catch-all diagnoses.

5	**Excellent**: primary diagnosis fully aligns with the clinical picture and is the most likely diagnosis; no additional diagnoses are missing; any listed additional diagnoses are appropriate
4	**Good:** primary diagnosis generally aligns and is among the top few likely diagnoses; additional diagnoses are present but not clearly relevant
3	**Adequate**: primary diagnosis is plausible but not the most likely, or one or more important additional diagnoses are missing (e.g., no diagnosis of “elevated blood pressure reading” or “hypertension” when BP is significantly elevated)
2	**Deficient:** primary diagnosis is not well supported by the clinical picture or low on the list of likely causes; Primary diagnosis is a catch-all diagnosis when a clearer primary diagnosis is possible (e.g., “bacterial infection unspecified” instead of “urinary tract infection”); critical additional diagnoses are missing (e.g., no “malnutrition” or “underweight” diagnosis on a child with MUC yellow or red)
1	**Very poor**: primary diagnosis is missing or clinically inappropriate, contradicts or is unsupported by documented findings

MCQ (multi select):
Which of the following is deficient regarding the assessment and diagnosis?

1. Primary diagnosis is likely incorrect
2. Primary diagnosis is missing

3. Primary diagnosis is too specific to be supported based on current documentation or investigations (e.g., using “allergic rhinitis” as the diagnosis rather than “rhinitis”, where it’s clear that rhinitis is present but documentation does not support whether it is a viral, bacterial or allergic etiology)
4. Additional diagnosis is likely incorrect
5. Clinically relevant additional diagnosis is missing (e.g. malnutrition)
6. None of the above (All diagnoses are likely correct and no clinically relevant diagnoses are missing)

Treatment form and questions

Task Specific Clinical Note Plan: Treatments and Referrals + procedures and escalations of care if present

Treatment Likert Score: Is the documented treatment plan appropriate and complete given the clinical scenario?

The majority of cases will have either medications or referrals documented as a plan. Some will have procedures, escalations of care, referral for additional investigations or home medications documented in the clinical note. If procedures, escalations of care or home meds are documented, take them into consideration with the rest of the plan. Follow up plans and patient advice or education are often not documented, but when present, these should be taken into consideration and reflected in the Likert scoring.

Note:

- Sometimes additional investigations will be added as a referral. This means that the investigation is not available locally but the provider is requesting the patient have it performed at another location.
- Treatments will sometimes be documented in the clinical notes, and these should also be taken into consideration.

5	**Appropriate and complete**: treatments are appropriate and complete, including the correct use of medications and/or referrals when needed; Patient advice or education (e.g., red flag symptoms to watch for, advice on hydration, self-care, etc.) or a follow up plan is present; if procedures or escalations of care are present, they are the most appropriate course of action. *OR* no treatments are indicated and none are ordered
4	**Appropriate but less complete:** treatments are appropriate and complete, including the correct use of medications and/or referrals when needed but there is no patient advice, education or follow up plan documented (e.g., red flag symptoms to watch for, advice on hydration, self-care, when to return to care, etc.)
3	**Adequate**: Medications, referrals or procedures are reasonable and safe, but may not be a standard first-line therapy (i.e., things that are likely to have minimal benefit or

	minimal harm if given, e.g. desloratadine for a URTI instead of nasal saline spray alone), or helpful but non-critical referrals are missing
2	**Deficient:** medications are present and somewhat inappropriate (i.e., medications that may cause minor harm unnecessarily e.g., inappropriately broad antibiotic class when a narrower spectrum is sufficient); minor medication dosage errors; clearly needed referrals, procedures or escalations of care are missing
1	**Very poor**: no medications given for a condition when clearly indicated; medications are very inappropriate for the condition (e.g., use of any antibiotic when there is no indication based on documented findings); significant dosage errors (e.g., too high of a dose based on pediatric patient weight-based dosing); procedures performed or escalations of care are unwarranted

MCQ (multi select):
Which of the following deficiencies are present in the plan? Choose all that apply.

1. Medications are missing
2. Medications are present but inappropriate
3. Medications are appropriate but incorrect dosages listed (dosage can include dose quantity, frequency and duration)
4. Likely inappropriate use of antibiotics overall (e.g., antibiotics are given for a likely viral infection) *if you select this choice, you should also select choice “Medications are present but inappropriate”
5. Likely inappropriate class of antibiotics used (e.g., amox/clavulanic acid used when amoxicillin is appropriate) *if you select this choice, you should also select choice “Medications are present but inappropriate”
6. Referrals are missing
7. Referrals are present but inappropriate
8. Needed procedures are missing
9. Procedures are present but inappropriate
10. Needed escalations of care are missing
11. Escalations of care are present but inappropriate
12. None of the above

Additional resources for physicians

Common local brand name pharmaceutical list that physicians in other parts of the world may not recognize

Cital syrup	Disodium hydrogen citrate syrup 1.37g
Benylin original syrup	Diphenhydramine/ammonium chloride syrup 12.5mg/125mg
Karvol Inh caps	Camphor/eucalyptol/terpineol/chlorothymol caps
Zefcolin syrup	Dextromethorphan/phenylephrine/cetrizine syrup 10mg/5mg/5mg
Benased chesty syrup	Diphenhydramine/guaiphenesin syrup 14mg/100mg
Delased pediatric syrup	Diphenhydramine/sodium citrate syrup 7mg/28.5mg
Imacoff dry syrup	Diphenhydramine/dextromethorphan/sodium citrate syrup 14mg/5.7mg/5mg
Metadoz fizz	Paracetamol/tramadol tabs 325mg/37.5mg
Brustan tabs	Ibuprofen/paracetamol tabs 400mg/325mg
Brustan syrup	Ibuprofen/paracetamol suspension 100mg/125mg
Acinet	Amoxicillin and clavulanate 625mg tablets
pcm	Common abbreviation for paracetamol
Adol	Paracetamol a.k.a Acetaminophen available in many formulations. Frequently prescribed as a STAT suppository in children presenting with high fevers
Desloratadine	2nd generation, Histamin H1 anatgonist
Ventolin (Salbutamol)	Albuterol
Mara Moja/Parafast/Cipladon	All paracetamol/acetaminophen
PDL	Abbreviation for Prednisolone

Common acronyms

OE	On exam
FGC	Fair general condition
creps/crepitations on lung exam	rales/crackles
Hob (hotness of the body)	Subjective fever
Dib (difficulty in breathing)	dyspnea
JACCOLD	a normal constellation of physical exam findings that refers to absence of Jaundice, Anaemia (pallor), Cyanosis, Clubbing, Oedema (pedal edema), Lymphadenopathy, Dehydration
MUC or MUAC	mid upper arm circumference, used to identify children with malnutrition
Ass	associated
Vesicular breath sounds	Normal breath sounds
5/7	5 days
2/52	2 weeks

Likert Examples for chief complaint, vitals, history, and physical exam

Example 1:

Patient Information:
Age: 3 years
Gender: Male
Presenting Complaints:
Dry Cough: Present.
Vitals: HR 112, temp 36.7, wt 16 kg, rr 25 SpO2 97% MUAC - green
Chest Congestion: History of chest congestion.
Chronic Sinusitis: History of chronic sinusitis.
Snoring at Night: Reported by the mother.
Running Nose: Mild, present currently.
No History of Fever: No recent fever.
No History of Chills.
No History of Travel.
Past Medical History:
No significant chronic illness reported.
Physical Examination:
General Appearance: Clinically stable patient.
Vitals: Normal (within age-appropriate ranges).
ENT Examination:
Swollen Turbinates: The turbinates are swollen and reddish in color, suggesting inflammation (possibly allergic rhinitis or sinusitis).
Respiratory Examination:
Lungs Clear: Breath sounds are clear and equal on both sides.
No Added Sounds: No wheezing, crackles, or other abnormal respiratory sounds.

Likert Score: 5: Thorough

Explanation: includes detailed history, includes HPI associated symptoms and documentation of no PMH, documents travel history and pertinent physical exam findings; CC and relevant vitals are present

Example 2:

47y2m
CC: severe headache
HR 88 temp 36.5 wt 87 kg rr 18 SpO2 98 BP 132/78
severe headache on and off throbbing , sharp with no aggreviating factors
mild to severe assoc with tears . it was of sudden onset , started today evening
not relieved with oral painkillers
no neck stiffness
no dizziness
no photophobia
no history of trauma
had hob with occassional chills
no history of travel to malaria zone
o/e. fgc , in severe pain
neck soft not stiff
afebrile on touch
no photophobia
brudzensk sign negative
Glasgow Coma Scale at 15/15
no confusison
other systems esentially normal
fam plan =none

Inmp. 20th/3/2025
impress. migraine/bac infection/menengitis /
plan
diclofenac 150mg Intramuscular stat
fhg
Blood slide for malaria
head ct scan
LP
extplan
metadoz 1tab bd
explained danger signs
consider head ct scan / lp

Likert Score: 4 Reasonably thorough
Explanation: includes CC, vitals, most of the relevant characteristics of the chief complaint and physical exam pertinent negatives on neuro exam; fails to mention presence or absence of nausea and vomiting, vision changes, weakness or numbness which are important symptoms in assessing severe headache; missing many specific neuro exam findings (CNs, strength, reflexes, cerebellar assessment)

Example 3

Chief complaint: Cough, Sneezing
44y 8m
Ht 155 HR 77 temp 36.6 wt 90 kg rr 18 SpO2 98 BP 110/72
Presented with mild non productive cough associated with sore throat
Reports also of runny nose with sneezing
no fevers reported
on and off with headache
ros: nad
o/e: stable, afebrile, no jaundice, no edema, no cyanosis
ent: slightly inflammed pharynx, turbinates normal
r/s: tranemitted breadth sounds
other s/e: nad
impression: bronchitis/rhinitis
plan
tx as prescribed

Likert Score: 4 Reasonably thorough
Explanation: includes CC, relevant vitals, reasonable amount of HPI described for a simple issue, though further characterization of the headache would be ideal; findings of relevant systems on exam are included, though not extensively

Example 3

4 y 9 mo old
CC: fever
Vitals: HR 94, temp 36.4, wt 17 kg, rr 19 SpO2 99% MUAC - yellow
informant mother
history of hotness of the body for 1day
also has a dry cough for 1day
no history of running nose
no history of vomiting
no history of diarrhoea
no history of travelling to malaria endemic region
premed antipyretic

on examination fair general condition
not pale no jaundice no cyanosis
r/s chest clear
ent hyperemic throat
—------------------------------------
plan
fhg
strep A ag test'
deslit 5mls od 5/7
brustan 5mls tds 3/5
cefuroxime 250mg/5mls bd 5/7

Likert Score: 3 Limited

Explanation: missing PMH but reasonable HPI, although no mention of if ear pain exists or not; exam too limited, a 4 year old with fever should have a documented abdominal exam and skin exam and, without an otoscope, perhaps an external ear exam of pulling on ear and check for tenderness over mastoid, in addition to what is here

Example 4

4y 2m
Informant-mother
Hr 116 temp 36.2 wt 20 kg rr 25 SpO2 95 MUAC - green
Presented with 1 day history of sudden onset of ear pains
No history of discharge, no swelling
No history of any injury or trauma
Reports nasal blockage and cough especially in the evening and morning
No difficulty in breathing, no fevers,
Able to feed well, no vomiting, no diarrhea
Premedication-Cetrizine
On examination-In fair general condition
Ear, Nose & Throat exam-Blocked nostrils,
Chest exam-Bilateral air entry, no rhonchi, no crepitations
Impression-Acute otitis media, acute rhinitis
PLAN
Amoxyclave 5mls bd 5/7
Brustan 5mls Three times daily 3/7
Saline drops 2drops Three times daily 3/7

Likert Score: 3 Limited

Explanation: most relevant history elements are documented; however, there is no ear exam documented for history of sudden ear pain. While no otoscope is available so no middle ear exam can be documented, evaluation for external otitis is possible through pulling on ear and evaluation for mastoiditis is possible through assessing for tenderness over mastoid; also no chief complaint

Example 5

8 year 2 month
Vitals: HR 104, temp 36.7, wt 30 kg, rr 20 SpO2 99%
diclofenac injection admnistred 75mg im
Patient Summary:
Age/Gender: 2-year-old male
Informant: Father
Presenting Reason:
Follow-up after fall 2 weeks ago, presents with distorted gait and pain in the right hip.
History:

Fall: Fell at school 21 days ago while playing, hit right hip on a stone.
Gait: Walking with a distorted gait, leaning to the right side.
Pain Concealment: The child has been attempting to conceal pain.
Swelling & Bruising: No swelling or ecchymosis noted.
Tenderness: Tenderness elicited on the right hip.
Pain with Movement: Obvious pain with both external and internal movements of the hip and with range of motion.
Physical Examination:
General Appearance: Clinically stable patient.
Vitals: Normal.
Musculoskeletal: Tenderness on the right hip with pain during range of motion (internal and external). No swelling or bruising.

Likert Score: 2 Deficient

Explanation: discrepancy of age listed; no documentation of if any recent fever, malaise, weight loss all needed for assessment of infectious causes of pain (septic arthritis, osteo) which can develop after an injury; no documentation of how the injury was cared for initially (prior imaging?); no documentation of spine or abdominal exam (can present with hip pain)

Example 6:

55 y 9 m
KNWN hypertension patient ON MEDS
TODAY BPS - 174/101 MMHG 80B/MIN
HAD DONE LIPID PROFILE / UECS DONE , NORMAL PATIENT EXPLAINED
BPS EXPLAINED
PLAN
NIFEDIPINE 40 MG
START AMLOOZAH H

Likert Score: 1 Very poor

Explanation: patient presents with high BP and no documentation of if patient has any symptoms, no history is documented at all other than known HTN. Other PMH? Other meds? No physical exam documented.

Example 7

30y 5m
HR 77 temp 36.4 wt 58 kg rr 16 Spo2 100
history of vaginal discharge, no itchiness, no pain on micturation, no lower abdominal pains, no backa pains.
reports of headache, with reported history of a stress,.

Likert Score: 1: Very poor

Explanation: extremely limited, omits several critical components: no chief compliant, extremely limited description of the vaginal discharge (no duration, description, associated symptoms of fever, pelvic pain, bleeding, sexual history, menstrual history) and no characterization at all of the headache; completely absent physical exam

Likert Examples for Investigations

Example 1:

27y 1m
CC: throat irritation
it has been there for the laat 2 days
he has been using warm water for the same but there is no much improvement
there is some pain on the right side of his throat especialy when swallowing
there is no fevers
no chiklls
no joint pains
no runny nose
he has been using saline water to gurgle
no known food or drug allergy
on exam
not pale
no jaundice
no dehydration
ent-slightly inflammed throat
cvs- normal
cns- normal

Streptococcus A Antigen Test: Result: Negative

Likert Score: 5 Appropriate & Targeted

Explanation: Strep A test only is the correct investigation for the clinical scenario

Example 2:

Chief Complaint: Skin Rash, Dry, itchy skin
30y 3m
presented with dry skin rashes assoc with
itchyness ,
had severe itchynessespecially at the armpits
it appers at the neck and armpits
o/e ; fgc
armpit/neck rash , shyny , scally and itchy, no raised borders
impression; atpoic dermatitis/eczema
plan
betametasone/salicylic cream apply bd
desloratadine 5mg od
pdl 5mg bd
keep skin moisurerized

Investigations: none

Likert Score: 5 Appropriate & Targeted

Explanation: In this clinical scenario, it is most appropriate to not order any investigations as none are needed for diagnostic clarity or treatment plan generation.

Example 3:

Chief Complaint (CC):
53-year-old female presenting with cough, runny nose, and sore throat for 1 day.
History of Present Illness (HPI):
The patient reports onset of symptoms yesterday, starting with a headache relieved by Mara Moja (analgesic), followed by nasal congestion, dry cough, and throat pain especially on swallowing. She also describes a sensation of chest heaviness without pain or difficulty in breathing. Additionally,

she experienced hotness of the body at night and general weakness. She denies joint pains, gastrointestinal symptoms, or recent travel to malaria-endemic areas. No other complaints reported.
Allergies & Medications:
Allergies: NKDFA
Premeds: Mara Moja (OTC analgesic)
Vitals (11/04/2025):
Temperature: 36.4°C
Pulse: 57 bpm
Respiratory Rate: 16 bpm
Blood Pressure: 117/74 mmHg
SpO$_2$: 97% on room air
BMI: 28.38 (Weight: 63 kg, Height: 149 cm)
Examination Findings:
General: Stable condition
ENT: Inflamed throat
Systemic Exam: Normal across respiratory, cardiovascular, and abdominal systems
Assessment & Plan:
Assessment:
Acute Upper Respiratory Tract Infection (URTI) – likely viral etiology
Supported by sore throat, dry cough, nasal congestion, and absence of systemic signs of bacterial infection
Rule out Streptococcal pharyngitis – given throat pain and inflamed pharynx
Investigations:
Streptococcus A antigen test
Complete blood count (CBC)
Investigations:
Strep A Antigen Test: Negative
CBC:
WBC: 4.54 x10^9/L (within normal range)
Neutrophils: 2.15 x10^9/L (low-normal)
Lymphocytes: 1.99 x10^9/L (normal)
Hemoglobin: 14.6 g/dL (normal)
Platelets: 360 x10^9/L (normal)
Mildly elevated lymphocyte % (44%) and reduced neutrophil % (47.3%)
Assessment & Plan:
Assessment:
Acute upper respiratory tract infection, likely viral in origin – suggested by sore throat, nasal congestion, dry cough, and negative Strep A test.
Viral pharyngitis or rhinitis is most likely; no evidence of bacterial infection (normal to low WBC, negative Strep A, afebrile, and stable vitals).
Overweight with BMI of 28.38 – lifestyle advice warranted.
Management Plan:
Symptomatic management:
Adequate fluids and rest
Paracetamol for headache and body aches if needed
Avoid unnecessary antibiotic use
Patient Education:
Condition likely viral; expected resolution within 5–7 days.
Importance of hydration and nutrition.

Streptococcus A Antigen Test: Result: Negative

Full Haemogram (FHG): PDW: 15.10, RDW-CV: 14.90, HCT: 40.30, MCHC: 36.20, WBC: 4.54, PCT: 0.31, MCV: 86.00, Lymphocyte Percentage: 44.00, Plt: 360.00, Lymphocytes Count: 1.99, MPV: 8.60, Mid-granulocyte Percentage: 8.70, Mid-granulocytes Count: 0.40, P-LCC: 65.00, MCH: 31.10, Result..: Abnormal, Neutrophill count: 2.15, Neutrophill percentage : 47.30, P-LCR: 18.00, RBC (Full Haemogram): 4.69, RDW-SD: 43.60, HGB: 14.60

Likert Score: 4 Minor Overordering

Explanation: Strep test indicated, full hemogram may not be necessary though not harmful

Example 4:

40 y 0m
presents with above several days prior to the visit
history of pain on urination
no history of urethral discharge
reports of abd bloating and abd pain
no history of diarrhoea / vomiting
no history of travel to a malaria endemic area
on examination
fgc , not Pale, no cy, no j, no deh2o
Ear, Nose & Throat normal
systemic examination- unremarkable
imp ge / amoebiaisis / Peptic Ulcer Disease / bacterial infection / uti
plan
u/a
fhg
stool for o/c
stool for h-pylory
Diagnosis bacterial infection / acute bacterial ge / uti
plan
cefuroxime 500mg bd for 5 days
myospaz 1 tab bd for 3 days

H. Pylori - Stool: Result: Negative

Full Haemogram (FHG): MCH: 23.50, HGB: 13.10, P-LCC: 61.00, RDW-CV: 15.80, P-LCR: 28.80, RBC (Full Haemogram): 5.58, RDW-SD: 39.30, Result..: Abnormal, HCT: 43.50, Mid-granulocyte Percentage: 9.20, PDW: 19.70, Neutrophill percentage : 75.20, MPV: 11.70, Neutrophill count: 5.95, WBC: 7.94, Mid-granulocytes Count: 0.73, MCHC: 30.10, PCT: 0.24, Lymphocyte Percentage: 15.60, Lymphocytes Count: 1.23, MCV: 77.90, Plt: 212.00

Stool Microscopy: Result..: Abnormal, Yeast cells (Microscopy): None, Amount of yeast cells: None, Parasites: No Ova/Cyst, Crystals -- Type: None, Mucous: Absent, RBC's (Microscopy): None, Consistency : Semi formed, Colour : Brown, Crystals -- Amount: None, Blood (Gross Appearance): Absent, Pus cells: Moderate

Urine Analysis: Result..: Abnormal, Nitrate: Negative, Bilirubin.: 0, Amount of yeast cells: None, Pus cells: Moderate, Specific Gravity: 1.02, Yeast cells (Microscopy): None, Crystals -- Amount (Microscopy): None , Colour.: Amber, Appearance (Urine Analysis): Clear, Casts - type: None, Urobilinogen: 0, RBC's (Urinalysis-Microscopy): None, Glucose: 0, Crystals -- Type: None, Leukocytes: +2, Parasites (Urine Microscopy): None, Epithelial Cells: None, pH (Dipstick): 6.00, Proteins: 0, Blood (Dipstick): 0, Trichomonads (Urinalysis-Microscopy): Absent, Ketones: 0

Likert Score: 3 Overly broad

Explanation: Urinalysis and stool testing are clearly appropriate. H pylori testing may be indicated given local prevalence but not much supporting documentation for it (abd pain + bloating, but no clear documentation of where in the abdomen the pain is located, no documentation around belching or excess gas, weight loss, or color of stools). Full hemogram is overly broad, no clear indication for it based on documentation.

Example 5:

5y 2m
Clinical Presentation
Patient Profile:

A previously well child who became symptomatic yesterday.
History of Presenting Illness:
The child began experiencing abdominal pain, localized around the umbilical region, followed by vomiting. She has since had five episodes of non-projectile vomiting, containing ingested food and not blood-stained. The abdominal pain is intermittent.
This morning, she developed loose, foul-smelling diarrhea, which is non-bloody. She also had fever in the morning, for which she was given Calpol.
There are no known food or drug allergies.
Physical Examination:
General: Not pale, no jaundice
Hydration Status: No dehydration; skin turgor <1 second, capillary refill <1 second
Abdomen (P.A.): Non-distended, non-tender on palpation; no signs of umbilical hernia
Cardiovascular System: Heart sounds S1 and S2 heard; no murmurs
Respiratory System: Clear breath sounds
Musculoskeletal System: Normal
Central Nervous System: Normal
Developmental Milestones: Normal

Stool Microscopy: Crystals -- Type: None, Result..: Abnormal, Consistency : Liquid/Loose, RBC's (Microscopy): None, Parasites: No Ova/Cyst, Pus cells: Few, Blood (Gross Appearance): Absent, Colour : Brown, Yeast cells (Microscopy): None, Mucous: Absent, Amount of yeast cells: None, Crystals -- Amount: None

Likert Score: 2 Deficient

Explanation: Evaluation of stool microscopy looking for blood, parasites, pus/mucous is very appropriate given this presentation and regional epidemiology. A 5 year old with fever may also be evaluated with a malaria test in this scenario.

Example 6:

8 year 2 month
Vitals: HR 104, temp 36.7, wt 30 kg, rr 20 SpO2 99%
diclofenac injection admnistred 75mg im
Patient Summary:
Age/Gender: 2-year-old male
Informant: Father
Presenting Reason:
Follow-up after fall 2 weeks ago, presents with distorted gait and pain in the right hip.
History:
Fall: Fell at school 21 days ago while playing, hit right hip on a stone.
Gait: Walking with a distorted gait, leaning to the right side.
Pain Concealment: The child has been attempting to conceal pain.
Swelling & Bruising: No swelling or ecchymosis noted.
Tenderness: Tenderness elicited on the right hip.
Pain with Movement: Obvious pain with both external and internal movements of the hip and with range of motion.
Physical Examination:
General Appearance: Clinically stable patient.
Vitals: Normal.
Musculoskeletal: Tenderness on the right hip with pain during range of motion (internal and external). No swelling or bruising.

Investigations: none

Likert Score: 1: Very poor

Explanation: child with hip pain and distorted gait and tenderness with exam 3 weeks after injury should have investigations looking for bacterial infection, CBC at minimum

Likert Examples for Diagnosis

Example 1:

27y 1m
CC: throat irritation
it has been there for the last 2 days
he has been using warm water for the same but there is no much improvement
there is some pain on the right side of his throat especialy when swallowing
there is no fevers
no chiklls
no joint pains
no runny nose
he has been using saline water to gurgle
no known food or drug allergy
on exam
not pale
no jaundice
no dehydration
ent-slightly inflammed throat
cvs- normal
cns- normal

Streptococcus A Antigen Test: Result: Negative

Diagnosis: Pharyngitis

Likert Score: 5: Excellent
Explanation: Pharyngitis is the most likely accurate diagnosis for the clinical scenario. No other additional diagnoses are needed.

Example 2:

LMP-UPTO DATE
KNWN patient WITH PAINFUL PERIODS
DID FOLLOW UP WITH GYNAECOLOGICAL REVIEW AND WAS TOLD ITS NORMAL PAIN
HEAVY-USES 4-5PADS IN 2 ND DAY
THEN REDUCES GRADUALLY
NO HEADACHE
NO DIZZINESS
NO CHRONIC ILNESS
NO DRUG ALLERGY
ON EXAM-SHE IS STABLE
DX-DYSMENORRHOEA
PLAN
P.O PONSTAN 1 TAB BD FOR 5 DAYS

Diagnosis: Dysmenorrhoea

Likert Score: 4: Good
Explanation: Minimal history around the quality and timing of pain makes it challenging to say that this is clearly the most likely accurate diagnosis, but it aligns with the clinical picture and is among the top few likely diagnoses.

Example 3:

4y 7m
Presented with cough of gradual onset persistent and irritative associated
with runny nose

Reports also of nasal blockage
no fevers reported
feeds well
ros: nad
o/e: stable, afebrile, no jaundice, no edema, no cyanosis
ent: inflammed tonsils with exudates
r/s: tranmitted breadth sounds, no crepitations, no rhonchi
other s/e; nad
impression: bronchitis/rhinitis/tonsilitis
plan
adviced on hydration/tx as prescribed

Investigations: none
Diagnosis: Acute bronchitis, tonsilitis, acute bacterial

Likert Score: 3: Adequate

Explanation: Acute bacterial tonsillitis is less likely than viral tonsillitis and no investigation was done to determine the cause. This diagnosis is plausible, but not the most likely.

Example 4:

0y 8m
the mother reports that she has 3 days history of a runny nose
associated with nasal congestion and mild fever
no dib
no cough
no pre medication
no history of drug allergy
ON EXAM
Afebrile
underweight
not pale/jaundiced.dehydrated
clesar chest
normal throat exam
enlarged nasal turbinates
INVESTIGATION
full haemogram
DIAGNOSIS
acute rhinitis with enlarged nasal turbinates
PLAN
ephedrin nasal drop bd for 5 days
calpol 5mls orally for 3 days
aerius 2.5mls orally for 5 days
rehydrate with warm fluids

Diagnosis: Allergic rhinitis, Adenoid hypertrophy

Likert Score: 2: Deficient

Explanation: MUC yellow, not noted in the diagnosis field (though is noted on physical exam in clinical note); should have a diagnosis of underweight or malnourished in the diagnosis field; additionally the child is noted to have enlarged turbinates on exam but is given a diagnosis of adenoidal hypertrophy which is not well supported by the documentation.

Example 5:

Has a complete miscarriage , was medical evacuated came with complains of vaginal discomfort , attending doctor requested her to come for medication three days post procedure.
O/E

stble
no distress
p/a
-unremakble
IMPRESSIONS: urinary tract infection
Plan
Per oral cefuroxime 500mg bd 5/7
Pessaries Infa V 1 nocte 5/7

Investigations: none
Diagnosis: Uncomplicated Urinary Tract Infection (UTI)

Likert Score: 1: Very poor

Explanation: No dysuria, suprapubic abd pain or fever documented, chief complaint does not fit with UTI and explanation given for antibiotics is post procedure prophylaxis. No urinalysis is done. Diagnosis of UTI is clinically inappropriate and unsupported by documented findings.

Likert Examples for Treatment

Example 1:

10y 5m
Wt: 22 kg
mother reports 1 week history of abdominal pains of gradual onset with no relieving nor exacerbating factor, child reports the pain is on the epigastric region, reports history of loose stools on and off with yesterday having a blood stained loose stools that has since resolved, no episodes of vomiting, child is currently on management for amoebiasis, on diracip-male syrup doing day 3 from another facilty, no fevers, mother reports reduced appetite, no other complaints reported.
on exam: fgc, alert
no jaundice, no pallor, no cyanosis, no dehydration, no edema
heent- normal
rs- chest clear on auscultation, no creps, no rhonchi
cvs-s1, s2 heard, no murmurs
p/a- not distended, soft non tender, no organomegally
cns- alert and well oriented
mss- normal findings
impression: gastritis/dysentry
plan
h.pylori ag test
stool o/c
rx as per t-sheet
mother advised to complete dosages
advised on nutritional review- said will come next thursday

Investigations: Stool Microscopy: Consistency : Formed, Blood (Gross Appearance): Absent, Mucous: Absent, Crystals -- Amount: None, Parasites: No Ova/Cyst, Result..: Normal, Yeast cells (Microscopy): None, Crystals -- Type: None, Colour : Brown, RBC's (Microscopy): None, Pus cells: None, Amount of yeast cells: None

H. Pylori - Stool: Result: Positive

Diagnosis: Helicobacter pylori gastritis

Treatment: Paracetamol susp 250mg/5ml: 5 MLS, 3 Times a day, As directed for 3 Days
Amoxicillin susp 250mg/5ml: 10 MLS, 2 Times a day, As directed for 14 Days
Clarithromycin susp 250mg/5ml 50ml: 5 ml, 2 Times a day, As directed for 14 Days
Omeprazole caps 20mg: 1 capsule, 1 Times a day, As directed for 14 Days

Likert score: 5

Explanation: Triple therapy with amoxicillin, clarithromycin and omeprazole is first line treatment for pediatric H pylori in this setting.

Example 2:

2y 5m
presents with complaints of cough dry in nature of gradual onset with no relieving nor aggrevating factors worse at night and in the morning, no associated dib, no chest congestion, no fastbreathing, no history of wheezing, no history of nightsweats, no loss of appetite or weight, no fevers, no runny nose, child feeding well, premeds-piriton
on exam: fgc, alert, afebrile and actively playing, not in rs distress
no jaundice, no pallor, no cyanosis, no dehydration, no edema
heent- normal
rs- no chest wall indrawing, chest clear on auscultation, no creps, no rhonchi
cvs-s1, s2 heard, no murmurs
p/a- not distended, soft non tender, no organomegally

cns- alert, neck soft, no signs of meningeal irritation
mss- unremarkable findings
impression; bronchitis/allergic cough
plan
reassured
Treatment as per t-sheet
for paeds review if the complaints persist
advised on hydration
counselled on danger signs to watch

Diagnosis: Acute bronchitis, Rhinitis
Treatment: Desloratidine syp 60ml: 5 ml, 1 Times a day, As directed for 5 Days

Likert score: 4
Explanation: Desloratadine is not clearly indicated or fist line treatment in acute bronchitis or rhinitis unless caused by environmental allergies. While safe in this age group and the dosage is correct, this is likely an overtreatment of symptoms that may not be effective.

Example 3:

15y 3m
Informant-Mother.
C/C-Runny nose
Cough
Reports of above complains with ass fromtal headache.
Also reports of ass nasal congestion.
Reports headache superficial.
No chest congestion.
No sore throat
No DIB
Premeds-None.
oe-In faIr general condition
Afebrile
well hydrated
No cyanosis
No wheeze
RESP EXAM-No wheeze
Noted rhonchi bibasal .
ENT-Adenoid hypertrophy.
dx-Acute bronchitis/Asthma.
Acute sinusitis.
tx as prescribed,
Referred for chest xray.
Review with results.

Diagnosis: Acute Sinusitis, Acute bronchitis
Treatment: Fluticasone Furoate Spray 120D: 1 dose, 2 Times a day, As directed for 2 Days
Effervescent Paracetamol tabs 1000mg: 1 tablet, 3 Times a day, After food for 3 Days
Azithromycin tabs 500mg: 1 tablet, 1 Times a day, After food for 3 Days

Likert score 3:
Explanation: Diagnosis of sinusitis and acute bronchitis are sometimes treated with antibiotics, though many cases are viral. No duration of symptoms documented which generally dictates whether to treat these conditions with antibiotics vs supportive care. Of the antibiotic choices, Azithromycin is not the first line for either condition.

Example 4:

7y 7m
Vitals: hr 106, temp 37, wt 20.5 kg, rr 22, SpO2 98
Cough productive irritative in the morning and at night
ass with slight rhinorrhoea
No fevers ,no chest congestion
No loss of appetite
No other ass symptoms
premed None
review of systems normal
On exam stable
RESP Chest clear no wheeze ,no creps
ENT Normal
DX Nasopharyngitis/Brochitis
Plan
Desloratadine
Pdl

Treatment: desloratadine: 5 ml, 1 At night for 5 Days
Prednisolone Oral solution 1mg/5ml: 5 ml, 2 Times a day, As directed for 5 Days

Likert score 2:
Explanation: A child with a likely viral cough without documented history of asthma, without hypoxia or documented resp distress - there is no clear indication for oral steroids, a medication with significant potential side effects.

Example 5:

2y 2m
brought in with above for past 2 days
history of spiking fevers worse at night, no assc convulsions,
history of throat pain worse when swallowing , no cough
no runny nose
history of abdominal pain worse after feeding , no vomiting , no diarrhoea
premeds- none
no history of travel to a malaria endemic zone
o\e- ina fgc
not in distress
no pallor, no jaundice, no dehydrtaion
rs- vesicular breath sounds, good airentry bilaterally , no lower chest wall indrawing
ent- normal
cns- alert, neck soft
per abdomen- mwr, soft non tender, no palpable mas
imp- febrile illeness ? spsis r\o amoebiasis
plan
fhg, ua stool for microscopy
review with results
ua- normal
fhg- low level of hb- 9.4g\dl , mcv, mch, mchc
unable to get the stool ample
plan
meds as prescribed
advised on diet rich in iron , green veges and fruits
to bring the stool sample later
has brought the stool sample for microscopy
review
moderate pus cells , no oc
plan
meds as prescribed
food and water hygien

Stool Microscopy: RBC's (Microscopy): None, Result..: Abnormal, Crystals -- Amount: None, Amount of yeast cells: None, Colour : Brown, Yeast cells (Microscopy): None, Blood (Gross Appearance): Absent, Crystals -- Type: None, Parasites: No Ova/Cyst, Consistency : Semi formed, Pus cells: Moderate, Mucous: Absent

Urine Analysis: Leukocytes: 0, RBC's (Urinalysis-Microscopy): None, Amount of yeast cells: None, Nitrate: Negative, Casts - type: None, Urobilinogen: 0, Ketones: 0, Bilirubin.: 0, Appearance (Urine Analysis): Clear, Crystals -- Amount (Microscopy): None , Glucose: 0, Trichomonads (Urinalysis-Microscopy): Absent, Parasites (Urine Microscopy): None, Crystals -- Type: None, Yeast cells (Microscopy): None, pH (Dipstick): 6.50, Blood (Dipstick): 0, Colour.: Amber, Pus cells: None, Proteins: 0, Result..: Normal, Epithelial Cells: None, Specific Gravity: 1.02

Full Haemogram (FHG): Lymphocyte Percentage: 33.70, MCHC: 31.20, P-LCR: 13.10, P-LCC: 46.00, PCT: 0.26, RBC (Full Haemogram): 5.18, Neutrophill count: 5.46, WBC: 10.15, RDW-CV: 17.20, MCV: 58.20, Lymphocytes Count: 3.42, RDW-SD: 38.40, MCH: 18.10, HGB: 9.40, MPV: 7.50, Result..: Abnormal, Mid-granulocytes Count: 1.27, HCT: 30.10, Mid-granulocyte Percentage: 12.50, Neutrophill percentage : 53.80, Plt: 351.00, PDW: 8.30

Azithromycin susp 200mg/5ml 15ml: 3 MLS, 1 Times a day, After food for 3 Days
Ibuprofen/Paracetamol Susp 100mg/125mg 100ml: 7.5 MLS, 3 Times a day, After food for 3 Days
Folic acid/Iron/Vitamin B12/Vitamin C syr 200ml: 2.5 ml, 2 Times a day, After food for 30 Days

Likert score 1:

Explanation: There is no indication for using Azithromycin and overuse/inappropriate use of antibiotics contributes to antibiotic resistance.