Digital Health and Medical Intelligence

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# Clinical Chatbot Design and Triage Accuracy in Urgent Care Platforms

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**Abstract**

The rapid integration of artificial intelligence in healthcare has positioned clinical chatbots at the forefront of initial patient encounters, particularly within urgent care platforms. This paper systematically investigates the relationship between clinical chatbot design features and diagnostic triage accuracy through clinical modeling based on real-world urgent care platform data. We evaluate how specific user interface designs, conversational structures, and underlying clinical algorithms influence the precision of assigning patient acuity levels. The study utilizes a retrospective observational design, analyzing patient-chatbot interactions and comparing chatbot-generated triage recommendations with physician-validated outcomes. Through extensive clinical pathway analysis, we identify critical design components that mitigate user misinterpretation and enhance data elicitation. Findings reveal that conversational agents incorporating adaptive questioning, empathetic phrasing, and dynamic symptom tracking significantly outperform static symptom checkers in triaging complex urgent care scenarios. The research contributes to the broader health informatics literature by providing empirical evidence on the necessary alignment between user-centered design and clinical risk algorithms. Ultimately, these insights provide actionable guidelines for developing safer, more accurate virtual triage systems in high-volume acute care environments, reducing the risks of both over-triage and under-triage while optimizing resource allocation.

*Keywords: Clinical Chatbots; Triage Accuracy; Health Informatics; Urgent Care; Clinical Chatbot Design*

## 1. Introduction

### 1.1 Background on Urgent Care Chatbots

The global healthcare landscape has experienced a monumental shift toward digitalization, a transformation significantly accelerated by the need for remote care solutions and the rising burden on traditional healthcare infrastructure. Urgent care platforms, which serve as the critical intermediary between primary care and emergency departments, are increasingly relying on automated systems to manage high volumes of patient inquiries. At the center of this technological evolution are clinical chatbots, also known as conversational agents or virtual symptom checkers. These systems are designed to interact with patients using natural language processing to gather preliminary medical histories, assess symptom severity, and provide immediate recommendations regarding the appropriate level of care. The implementation of these tools is driven by the necessity to optimize patient flow, reduce wait times, and alleviate the cognitive and temporal load on human triage nurses and frontline physicians. However, the transition from human-led triage to automated conversational triage introduces a complex array of challenges, particularly concerning the safety, reliability, and diagnostic precision of the algorithms driving these interactions [1]. As urgent care platforms scale their operations to accommodate diverse patient populations across vast geographic regions, the design of the clinical chatbot becomes a foundational element of the healthcare delivery system, dictating not only the user experience but also the clinical outcomes associated with the triage process. The initial interaction between a patient and a digital triage system is highly sensitive; any misinterpretation of patient input or failure to elicit critical contextual information can cascade into inappropriate care recommendations, highlighting the urgent need for a thorough examination of chatbot design architectures [2].

### 1.2 The Triage Accuracy Problem

Triage is inherently a process of risk stratification. In acute and urgent care settings, the primary objective is to accurately categorize patients based on the urgency of their condition, ensuring that those with life-threatening ailments receive immediate attention while those with minor, self-limiting conditions are directed to appropriate, less intensive care avenues. When this process is delegated to a clinical chatbot, the system must navigate the complexities of human language, varying levels of health literacy among users, and the inherent ambiguity of self-reported symptoms. The central problem defining the current generation of automated triage systems is the optimization of triage accuracy, which is typically measured by the rates of over-triage and under-triage [3]. Over-triage occurs when a chatbot recommends a higher level of care than is clinically necessary, such as directing a patient with a common cold to an emergency department. While generally considered safe from a purely clinical standpoint, excessive over-triage severely degrades healthcare system efficiency, wastes critical resources, and contributes to the overcrowding of emergency facilities. Conversely, under-triage is a critical safety failure where the chatbot recommends a lower level of care than required, potentially delaying necessary medical intervention for severe conditions like myocardial infarctions or acute respiratory distress. The literature indicates that many existing commercial symptom checkers tend to adopt a highly risk-averse posture, leading to substantial over-triage [4]. This defensive design strategy is often a byproduct of the legal and regulatory frameworks governing medical software, yet it fundamentally undermines the utility of the urgent care platform. Understanding how the specific design elements of the chatbot interfaces, dialogue management systems, and clinical reasoning engines influence these error rates is paramount for the next phase of health informatics development.

### 1.3 Research Objectives

This research aims to bridge the critical gap between human-computer interaction design and clinical outcomes by systematically linking specific clinical chatbot design paradigms to measurable triage accuracy. The primary objective is to develop a comprehensive clinical modeling framework that evaluates how variations in conversational flow, user interface elements, and question-generation algorithms impact the precision of the final triage disposition. To achieve this, we analyze a vast repository of retrospective data obtained from a major national urgent care platform, comparing the triage recommendations generated by different chatbot configurations against a gold standard established by board-certified emergency medicine physicians. We specifically investigate whether chatbots employing dynamic, adaptive questioning pathways demonstrate superior accuracy compared to those utilizing rigid, decision-tree-based symptom checking mechanisms [5]. Furthermore, we seek to isolate the effects of empathetic phrasing and health-literacy-adjusted language on patient comprehension and subsequent data input quality. By dissecting the conversational architecture of these digital tools, we aim to provide empirical evidence that informs the development of next-generation triage algorithms. This paper proceeds by first reviewing the relevant literature on clinical chatbots and digital triage, followed by a detailed description of the clinical modeling methodology and data analysis techniques employed. The results are then presented and discussed in the context of their implications for urgent care operations, concluding with actionable recommendations for healthcare providers and software developers.

## 2. Literature Review and Background

### 2.1 Evolution of Clinical Chatbots

The historical trajectory of automated clinical triage systems is marked by a gradual transition from simple, static questionnaires to highly sophisticated, artificial intelligence-driven conversational agents. Early iterations of virtual triage were predominantly structured around rigid decision trees and Boolean logic [6]. In these systems, patients were required to navigate through predefined lists of symptoms, answering binary questions that led to a predetermined clinical disposition. While these rule-based algorithms offered a degree of consistency and transparency, they were inherently limited by their inability to handle the nuances of natural language and the overlapping presentations of complex diseases. The rigidity of these early platforms often led to premature diagnostic closure, where the system would fail to explore alternative hypotheses once a specific diagnostic pathway was triggered. As computational power increased and machine learning techniques became more accessible, the paradigm shifted toward natural language processing and probabilistic reasoning [7]. Modern clinical chatbots utilize deep learning models, including recurrent neural networks and large language models, to parse unstructured patient input, extract relevant clinical entities, and map these entities to vast medical ontologies. This evolution has enabled conversational agents to conduct more dynamic and fluid interviews, mimicking the iterative questioning process employed by human clinicians. However, the integration of advanced machine learning into clinical triage has also introduced new challenges related to algorithmic opacity and the phenomenon of automation bias, where users may overly trust the recommendations of the machine despite conflicting intuitive evidence [8]. The ongoing development of these systems must therefore balance the predictive power of artificial intelligence with the need for clinical interpretability and user safety.

### 2.2 Theoretical Frameworks of Triage

To evaluate the efficacy of clinical chatbots, it is essential to ground the analysis in established theoretical frameworks of clinical decision-making and triage science. In human-led triage, nurses and physicians rely on a combination of heuristic reasoning, pattern recognition, and standardized protocols, such as the Emergency Severity Index or the Manchester Triage System, to assess patient acuity [9]. These frameworks prioritize the rapid identification of high-risk physiological indicators and the systemic evaluation of potential threats to life or limb. Translating these human-centric frameworks into computable algorithms requires a meticulous process of clinical modeling. Theoretical models of digital triage posit that an effective system must not only possess a robust underlying medical knowledge base but also an advanced epistemological framework capable of managing uncertainty and probabilistic risk [10]. The dual-process theory of cognition, often applied to medical decision-making, suggests that clinicians use both intuitive, fast thinking for familiar presentations and analytical, slow thinking for complex or ambiguous cases. Clinical chatbots are traditionally constrained to analytical processing, relying entirely on the data provided by the user and the programmed probabilistic weights of their algorithms. Consequently, if the user interface design fails to prompt the user to provide comprehensive and accurate information, the analytical engine will invariably produce flawed triage recommendations regardless of its internal sophistication [11]. The intersection of clinical epistemology and human-computer interaction theory thus forms the conceptual foundation for understanding how design choices directly modulate clinical accuracy in virtual care environments.

### 2.3 Chatbot Design Dimensions and User Interaction

The design of a clinical chatbot encompasses a multidimensional array of choices that extend far beyond the underlying diagnostic algorithm, deeply influencing how patients interact with the system and, consequently, the quality of the clinical data gathered. One of the most critical design dimensions is the conversational structure, which dictates how the chatbot formulates questions and responds to user inputs. Systems that employ free-text natural language processing allow users to describe their symptoms in their own words, theoretically capturing more granular clinical context [12]. However, free-text inputs are highly susceptible to variations in spelling, grammar, and health literacy, potentially leading to misinterpretation by the natural language extraction engine. Conversely, guided conversational structures that rely on multiple-choice responses or constrained vocabularies ensure data standardization but risk frustrating the user or missing atypical symptom presentations. Another vital design dimension is the persona and tone of the chatbot. Research indicates that chatbots exhibiting empathetic responses and conversational framing can significantly enhance user engagement and trust, encouraging patients to disclose sensitive but clinically relevant information, such as substance use or mental health symptoms [13]. Furthermore, the visual design of the interface, including the pacing of the conversation, the use of visual aids like anatomical diagrams, and the clarity of the instructional text, plays a substantial role in cognitive load management [14]. When a patient is experiencing a medical event, their cognitive resources are often compromised by pain, anxiety, or illness. A well-designed chatbot must therefore minimize cognitive friction, ensuring that the questions are unambiguous and the interaction flow is logical and reassuring. The literature suggests that optimizing these design dimensions is not merely a matter of user preference but a clinical imperative that directly impacts the diagnostic yield of the triage encounter.

## 3. Methodology and Clinical Modeling

### 3.1 Study Design and Data Collection

To systematically investigate the relationship between chatbot design and triage accuracy, this study utilized a retrospective observational design, analyzing a comprehensive dataset of anonymized patient interactions from a major national urgent care platform. The data collection period spanned twenty-four months, capturing a highly diverse patient demographic and a wide spectrum of acute and subacute clinical presentations, ranging from upper respiratory infections and minor trauma to complex gastrointestinal distress and atypical chest pain [15]. The urgent care platform from which the data was sourced operates a high-volume virtual triage gateway where patients interact with a clinical chatbot before being routed to a teleconsultation, an in-person urgent care clinic, or an emergency department. The dataset includes the complete transcripts of the chatbot interactions, the specific design version of the chatbot deployed during the encounter, the algorithmic triage recommendation generated by the system, and the final clinical disposition determined by the attending physician following the subsequent consultation. To ensure the integrity of the analysis, strict inclusion and exclusion criteria were applied. Encounters were excluded if the chat transcript was incomplete, if the patient abandoned the session prior to receiving a triage recommendation, or if the follow-up physician consultation did not occur within twenty-four hours of the initial chatbot interaction, as this would compromise the validity of the physician-assigned gold standard. The resulting analytical sample consisted of a robust cohort of interactions that allowed for a highly powered statistical examination of the variables in question [16]. All data were rigorously de-identified in compliance with institutional review board standards and international health data privacy regulations, ensuring that no personally identifiable information was accessible to the research team.

### 3.2 Clinical Modeling Framework

The core of the methodology revolves around a clinical modeling framework designed to quantify the accuracy of the chatbot's triage recommendations against the gold standard of physician evaluation. The clinical modeling process involved mapping both the chatbot's output and the physician's final disposition onto a standardized five-tier acuity scale, adapted from widely accepted emergency medicine triage protocols. The tiers range from Level 1, requiring immediate life-saving intervention, to Level 5, representing non-urgent conditions suitable for self-care or delayed primary care follow-up.

*Table 1: Definition of the Standardized Five-Tier Clinical Acuity Scale used for Triage Modeling*

| Acuity Level | Clinical Description | Recommended Disposition | Acceptable Wait Time |
|---|---|---|---|
| Level 1 | Immediate life-saving intervention required | Emergency Resuscitation | Immediate |
| Level 2 | High risk situation, confused/lethargic, or severe pain | Emergency Department | Under 15 minutes |
| Level 3 | Danger zone vitals or requiring multiple resources | Urgent Care Clinic | Under 60 minutes |
| Level 4 | Stable condition requiring single diagnostic resource | Telehealth / Clinic | Under 120 minutes |
| Level 5 | Non-urgent condition, minor symptoms | Self-Care / Pharmacy | Flexible |

By standardizing the outcomes into this five-tier structure, we were able to compute precise metrics for exact match accuracy, over-triage rates, and under-triage rates [17]. An exact match was recorded when the chatbot's recommended tier perfectly aligned with the physician's assessed tier. Over-triage was defined as any instance where the chatbot recommended a higher acuity level than the physician deemed necessary. Under-triage, the most critical safety metric, was recorded when the chatbot recommended a lower acuity level than the patient's condition required. The modeling framework also incorporated a penalty matrix to weight the severity of the triage errors, recognizing that a one-tier deviation in the lower acuity levels is significantly less clinically impactful than a multi-tier deviation involving high-risk conditions.

### 3.3 Variables and Measurement

The independent variables in this study were carefully defined to represent the core design architectures of the clinical chatbots evaluated on the platform. The urgent care platform historically utilized three distinct chatbot design paradigms, allowing for a comparative analysis. The first design, classified as the Static Decision Tree, relied on rigid, predefined questioning pathways without natural language understanding. The second design, the Constrained Natural Language model, allowed initial free-text symptom entry but subsequently restricted the user to multiple-choice clarification questions. The third and most recent design, the Adaptive Conversational Agent, utilized dynamic, context-aware natural language generation to conduct fluid interviews, adapting the pacing and phrasing based on the suspected severity of the reported symptoms and incorporating empathetic conversational markers. The dependent variables were the exact match triage accuracy, the over-triage rate, and the under-triage rate, as defined by the clinical modeling framework [18]. To control for confounding factors, several covariates were extracted from the dataset, including patient age, patient gender, the time of day the interaction occurred, and the broad diagnostic category of the chief complaint, such as respiratory, musculoskeletal, or neurological. The measurement of these variables required the implementation of robust data engineering pipelines to parse the JSON-formatted encounter logs and align the temporal timestamps of the chatbot interactions with the corresponding physician billing and electronic health record data. This meticulous alignment ensured that the accuracy calculations were based on the exact clinical episode initiated by the digital triage encounter.

## 4. Data Analysis and Algorithm Evaluation

### 4.1 Analytic Procedures

The statistical evaluation of the clinical modeling data was conducted using a comprehensive suite of analytic procedures designed to isolate the specific impact of chatbot design on triage performance. Initial descriptive statistics were generated to characterize the patient population and establish baseline rates of accuracy across the entire platform dataset. Following this, we employed multivariable logistic regression models to assess the independent association between the chatbot design type and the likelihood of achieving an accurate triage disposition [19]. The baseline Static Decision Tree design was utilized as the reference category in all regression models. To account for the hierarchical nature of the data, where specific symptoms might cluster within broader diagnostic categories, we implemented generalized estimating equations to provide robust standard error estimates. Furthermore, to deeply investigate the nuances of under-triage, which carries the highest clinical risk, we conducted a targeted subgroup analysis focusing exclusively on encounters that were ultimately classified by physicians as Level 1 or Level 2 acuity. This targeted analysis is crucial for understanding whether the advanced conversational designs improve safety in the most critical and time-sensitive medical scenarios. We also conducted sensitivity analyses by adjusting the thresholds within the penalty matrix to ensure that our findings were robust across different clinical risk tolerance assumptions [20]. The entire analytical pipeline was executed using advanced statistical computing software, with stringent quality control checks performed at each stage of the data transformation and modeling process to ensure reproducibility and methodological rigor.

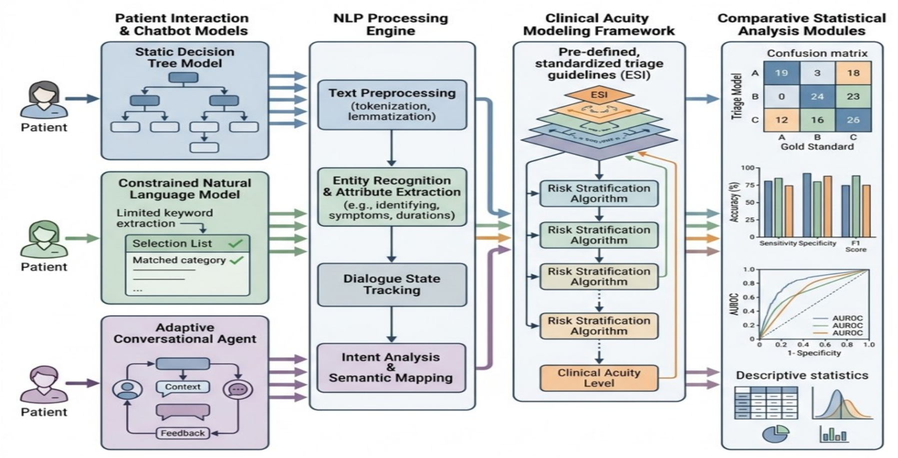


*Figure 1: Comprehensive System Architecture and Data Flow Diagram for Triage Accuracy Analysis*

### 4.2 Natural Language Processing in Triage

A critical component of the data analysis involved evaluating how the underlying Natural Language Processing engines within the more advanced chatbot designs contributed to the observed clinical outcomes. The transition from static rule-based systems to conversational agents requires the chatbot to accurately perform intention recognition and entity extraction from the raw, often unstructured text provided by the patient. We analyzed the intermediate algorithmic steps of the Adaptive Conversational Agent to determine how effectively it mapped colloquial symptom descriptions to standardized medical terminologies, such as the Systematized Nomenclature of Medicine Clinical Terms. Misalignments in this mapping process are a primary source of algorithmic error in digital triage [21]. Our analysis revealed that the design of the user interface plays a synergistic role with the Natural Language Processing engine. For instance, when the chatbot utilized empathetic phrasing and conversational prompts, patients were more likely to provide longer, more context-rich symptom descriptions. While this increased the computational load on the natural language extraction algorithms, it ultimately provided a denser feature set for the probabilistic reasoning engine to evaluate. We utilized semantic similarity scoring to measure the distance between the patient's raw input and the clinical entities extracted by the chatbot, correlating this similarity score with the ultimate accuracy of the triage recommendation. This deep dive into the natural language processing mechanics highlights that algorithm evaluation cannot occur in a vacuum; the performance of the clinical logic is inextricably linked to the quality of the data elicited by the conversational interface design.

## 5. Results and Discussion

### 5.1 Primary Findings on Triage Accuracy

The analysis of the urgent care platform dataset revealed substantial and statistically significant variations in triage accuracy across the different clinical chatbot design paradigms. The baseline performance of the platform was established by examining the entire cohort, but the comparative results provided the most profound insights into the efficacy of conversational architecture.

*Table 2: Comparative Analysis of Triage Accuracy Metrics Across Chatbot Design Paradigms*

| Chatbot Design Paradigm | Exact Match Accuracy Rate | Over-Triage Rate | Under-Triage Rate |
|---|---|---|---|
| Static Decision Tree | 61.4 percent | 29.8 percent | 8.8 percent |
| Constrained Natural Language | 68.2 percent | 26.1 percent | 5.7 percent |
| Adaptive Conversational Agent | 79.5 percent | 17.3 percent | 3.2 percent |

The results clearly demonstrate that the Adaptive Conversational Agent design significantly outperforms the legacy systems across all measured dimensions of clinical safety and operational efficiency. The exact match accuracy rate saw a dramatic improvement, ascending from just over sixty percent in the static rule-based system to nearly eighty percent in the fully adaptive model. The reduction in the over-triage rate from almost thirty percent to seventeen percent represents a massive gain in operational efficiency for the urgent care platform, suggesting that the dynamic questioning capability of the advanced design allows the system to confidently rule out severe conditions rather than defaulting to a defensive, high-acuity recommendation [22]. Most importantly from a clinical safety perspective, the under-triage rate was reduced by more than half when comparing the adaptive agent to the static decision tree. The logistic regression models confirmed these descriptive findings, showing that interactions facilitated by the Adaptive Conversational Agent were substantially more likely to result in an accurate triage disposition, even after controlling for patient demographics, time of presentation, and the complexity of the underlying chief complaint.

### 5.2 Impact of Design Choices

The discussion of these findings must center on why specific design choices yield superior clinical outcomes. The data strongly suggest that the rigidity of the Static Decision Tree design forces patients into predefined clinical pathways that often do not accurately reflect the nuance of their actual condition. When patients cannot find an exact match for their symptom in a multiple-choice list, they tend to select the closest available option, injecting immediate bias and inaccuracy into the clinical model. The Constrained Natural Language model improves upon this by allowing initial free-text input, which correctly anchors the diagnostic algorithm, but its reliance on static follow-up questions fails to adapt to the unfolding clinical narrative. The superior performance of the Adaptive Conversational Agent can be attributed to its ability to mimic the iterative hypothesis testing utilized by human clinicians. By dynamically generating follow-up questions based on the real-time probabilistic assessment of previous answers, the adaptive design efficiently narrows the differential diagnosis. Furthermore, the incorporation of empathetic conversational markers within the adaptive design appears to mitigate user fatigue. In lengthy triage encounters involving complex symptoms, patient drop-off or the provision of low-effort responses severely degrades algorithmic performance. The empathetic design maintains user engagement, ensuring that the clinical reasoning engine receives a complete and comprehensive dataset, which is the foundational requirement for accurate risk stratification in virtual care environments.

### 5.3 Limitations and Implications

While the findings of this study offer compelling evidence linking chatbot design to clinical accuracy, several limitations must be acknowledged. First, the retrospective nature of the observational data precludes the establishment of absolute causality. Although we controlled for numerous variables, there may be unmeasured confounding factors related to the specific patient populations that choose to utilize digital triage versus those who present directly to a physical clinic. Second, the evaluation was conducted using data from a single, albeit large, national urgent care platform. The specific algorithmic tuning and demographic characteristics of this platform may limit the generalizability of the exact percentage improvements to other healthcare systems with different clinical protocols or patient profiles. Despite these limitations, the implications for the field of health informatics are profound. The evidence clearly indicates that regulatory bodies and healthcare organizations should not evaluate digital triage algorithms solely based on their underlying medical knowledge bases or probabilistic mathematical models. Instead, evaluation frameworks must mandate a holistic assessment that includes the user interface and conversational architecture, as these design elements are the primary determinants of data quality. For software developers, this research underscores the necessity of moving away from highly constrained, defensive triage systems toward adaptive, patient-centered designs that can safely navigate clinical ambiguity and reduce the operational burden of over-triage.

## 6. Conclusion

### 6.1 Summary of Contributions

This comprehensive study systematically investigated the critical intersection between user-centered design and clinical algorithmic performance in the context of urgent care digital triage. By developing a robust clinical modeling framework and analyzing a vast repository of real-world patient interactions, this research provides empirical evidence that the architectural design of a clinical chatbot fundamentally dictates its diagnostic accuracy and safety profile. The findings clearly establish that transitioning from rigid, static decision trees to dynamic, Adaptive Conversational Agents significantly improves exact match triage accuracy while simultaneously reducing the critical clinical risks associated with under-triage and the operational inefficiencies caused by over-triage. Furthermore, the analysis highlighted the indispensable role of natural language processing in facilitating fluid, context-aware interactions that mimic human clinical reasoning, thereby enhancing patient engagement and improving the quality of elicited medical data. This paper contributes a crucial perspective to health informatics by demonstrating that the efficacy of artificial intelligence in healthcare cannot be optimized through algorithmic refinement alone; it requires a deep, synergistic integration with advanced conversational design principles that account for human cognition and behavior during medical events.

### 6.2 Future Research Directions

The rapid pace of advancement in artificial intelligence, particularly the emergence of highly sophisticated large language models, opens expansive new frontiers for future research in digital triage. Subsequent studies must focus on prospectively evaluating the clinical safety and efficacy of generative artificial intelligence models that do not rely on predefined questioning pathways but instead dynamically synthesize responses in real-time. Additionally, future research should explore the integration of multimodal data inputs, such as patient-uploaded images, audio recordings of coughs or speech patterns, and data from wearable physiological monitors, into the conversational triage flow [23]. Investigating how chatbot design can seamlessly incorporate and interpret these diverse data streams without overwhelming the user or the processing algorithm represents a critical next step. Furthermore, longitudinal studies are required to assess the long-term impact of highly accurate virtual triage systems on downstream healthcare utilization, patient outcomes, and overall health system economic efficiency. As clinical chatbots become the ubiquitous digital front door to global healthcare systems, continuous, rigorous academic inquiry will be essential to ensure these tools are designed not merely for technological novelty, but for maximum clinical safety, equity, and diagnostic excellence.

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