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Edge Intelligence Empowering Primary Healthcare: A Review of Health Monitoring Systems for Resource-Limited Communities

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Abstract: Approximately billions of people worldwide live in regions with scarce medical resources, where unstable electricity supplies and inadequate high-speed internet coverage render traditional telemedicine solutions unworkable. This paper systematically reviews recent advances in edge artificial intelligence (Edge AI) for health monitoring in resource-constrained environments, with a focus on the intelligent health monitoring system as a core case study. The system employs a modified low-cost smartphone paired with a portable multi-parameter sensor, with all AI models running locally on the device—completely eliminating dependence on internet connectivity. Following simple training, community health workers can collect patient vital signs, and the system provides real-time triage recommendations. In field deployments across rural Oman, the system achieved a preliminary triage accuracy of 91% for common infectious diseases and chronic conditions, with a cost of less than \$0.50 per use. This paper further explores the theoretical implications and practical challenges of edge intelligence for health equity in Global South countries, proposing that a “plug-and-play” edge intelligence architecture represents a viable technological pathway to bridge the global health divide.

Keywords: Edge artificial intelligence; resource-limited settings; community health monitoring; health equity; triage system

1. Introduction

The central paradox of global health is that the places most in need of medical resources are often those with the least infrastructure to support modern healthcare technology. According to World Health Organization estimates, approximately half of the world's population lacks access to essential health services, with a significant proportion living in rural and remote areas of low- and middle-income countries. These regions face not only an absolute shortage of physicians and hospital beds but also structural barriers including unstable electricity, limited internet coverage, and transportation difficulties.

Traditional telemedicine, which relies on internet connectivity to enable video consultations and remote monitoring, encounters a “double failure” in infrastructure-poor settings. On one hand, the lack of high-speed networks makes real-time video transmission impossible; on the other hand, cloud-dependent applications become completely non-functional in offline environments. Research from Sultan Qaboos University in Oman has identified inadequate technical infrastructure, insufficient healthcare worker training, and the absence of unified digital systems as primary barriers to telemedicine adoption. This problem is not unique to Oman—from Tanzania to Rwanda, Nigeria to India, the “connectivity divide” has become a critical bottleneck limiting the accessibility of digital health technologies.

Against this backdrop, edge artificial intelligence (Edge AI) offers a new technological paradigm for primary healthcare. Unlike cloud-dependent AI, which requires remote computation, Edge AI deploys model inference directly on end-user devices, enabling local data processing and immediate feedback. The core advantages of this approach align remarkably well with the needs of resource-limited settings: no internet connection required, low power consumption, low cost, and enhanced data privacy.

This paper focuses on the intelligent health monitoring system using it as a representative case study of Edge AI empowering primary healthcare. The paper systematically analyzes the system's technical architecture, implementation outcomes, and scalability. It begins by examining the real-world constraints on healthcare delivery in resource-limited regions, then provides an in-depth analysis of the system's technical design and deployment experience, and finally explores the prospects and challenges of edge intelligence for global health equity from a theoretical perspective.

2. Healthcare Challenges and Technological Opportunities in Resource-Limited Settings

2.1 The Triple Divide: Distance, Workforce, and Connectivity

The healthcare challenges facing resource-limited regions can be understood through three interrelated dimensions. The first is the geographic distance divide. Across vast rural areas, travel from villages to township health centers or county hospitals often requires hours or even an entire day. For patients with chronic diseases, the transportation costs and time burdens of regular follow-up create substantial barriers to treatment adherence. Baseline research conducted by Al-Farsi's team

in rural Oman found that one elderly female hypertensive patient had not had her blood pressure measured for three years due to transportation difficulties—a finding that reflects a widespread pattern rather than an isolated case.

The second is the human resource divide. The global distribution of healthcare workers is highly uneven, with low-income countries having fewer than one-tenth the number of physicians per capita compared to high-income countries. Community health workers (CHWs) have been widely recognized as a key strategy for bridging this gap. A study from Tanzania demonstrated that while trained CHWs could correctly assess 90% of common childhood illnesses (malaria, pneumonia, diarrhea), their accuracy in identifying danger signs fell to just 39%. This finding reveals the boundaries of CHW capability: algorithmic clinical pathways can improve standardization, but complex judgments still require technical support.

The third is the digital infrastructure divide. Internet connectivity is a prerequisite for most digital health solutions, yet approximately one-third of the global population remains offline, with the vast majority concentrated in South Asia, sub-Saharan Africa, and other regions. Even in areas with network coverage, bandwidth limitations and unstable connectivity prevent cloud-based applications from functioning reliably. A study of medical imaging AI applications in Rwanda found that system integration challenges (26.2%) and high costs (27.1%) were primary barriers to AI adoption in primary care, with a 58-percentage-point gap in AI adoption rates between teaching hospitals and district hospitals.

2.2 Limitations of Traditional Telemedicine Approaches

The experience of telemedicine in Gulf countries such as Oman provides concrete evidence of these challenges. Sultan Qaboos University Hospital launched a virtual clinic service during the COVID-19 pandemic to provide continuity of care for outpatients via telephone and video conferencing. Patient feedback was positive, with many requesting continued use after the pandemic—suggesting a success story on the surface. However, in-depth research reveals that behind this surface-level success lie deeper structural problems.

Research on psychiatric teleconsultations found that technical barriers were only part of the story. Physicians reported that patient medical records were outdated and fragmented, requiring substantial time to verify contact information before each remote consultation. The absence of an electronic prescribing system meant that even after completing a remote consultation, patients still had to return to the tertiary hospital in person to collect medications—significantly reducing the convenience telemedicine was meant to provide. In emergency situations, the lack of clear protocols for managing high-risk patients remotely left physicians uncertain about how to handle, for example, a patient at risk of suicide. These issues reveal a fundamental limitation: traditional telemedicine treats connectivity as a “sufficient condition” while overlooking the overall fragility of the primary healthcare ecosystem.

From a broader perspective, the adoption of AI health applications in Global South countries also faces structural risks related to dataset bias. Most existing AI models are trained on data from high-income country populations, and their performance may degrade significantly when applied to populations with different racial or socioeconomic characteristics. A systematic review found that algorithmic bias can reduce diagnostic accuracy for minority ethnic groups by as much as 17%. This means that simply transplanting “Northern” technologies to “Southern” contexts may not only be ineffective but could potentially exacerbate existing health inequities.

2.3 Edge AI as an Alternative Paradigm

The core proposition of Edge AI is to challenge “connectivity-centrism”: by performing data processing and model inference entirely on the device, it eliminates dependence on both the cloud and network connectivity. This technical approach is exceptionally well-suited to the constraints of resource-limited settings.

The first advantage is autonomy. Edge AI systems do not rely on external infrastructure and can operate even when offline or during power outages (using battery power). The second is low latency. Real-time inference enables immediate feedback—for triage decisions, the difference between a system that responds in seconds versus one that requires minutes of waiting is qualitative, not merely quantitative. The third is privacy protection. Data remains on the device, eliminating ethical and legal concerns about cross-border data transmission. The fourth is cost control. With no need to purchase servers or pay for cloud computing, a single smartphone can support an entire village-level health monitoring network.

From the perspective of edge computing technology, an Edge AI system designed for primary healthcare must satisfy three key technical requirements: low power consumption (running for days on battery or solar power), lightweight models (running smoothly on low-end smartphones), and ease of use (interfaces designed to accommodate users with limited formal education). Recent advances in model compression techniques (such as quantization, pruning, and knowledge distillation) and specialized inference engines have made it feasible to deploy real-time AI models on ARM-based mobile devices. These developments provide the technical foundation for large-scale deployment of Edge AI in primary healthcare.

3. Case Study: Al-Farsi Team’s Intelligent Health Monitoring System

3.1 System Architecture and Technical Design

The intelligent health monitoring system follows three core design principles: simplicity, low cost, and offline operation. The technical architecture can be summarized as “one phone, one sensor, one model”: a modified low-cost smartphone, a portable multi-parameter sensor, and a set of locally-run Edge AI models.

The system hardware consists of two core components. The first is a modified Android smartphone pre-loaded with an offline AI inference engine and triage decision system, capable of communicating with the sensor via Bluetooth. The second is a portable multi-parameter sensor integrating photoplethysmography (PPG) and electrocardiogram (ECG) modules, capable of simultaneously measuring blood pressure, heart rate, body temperature, and blood oxygen saturation. The sensor is small, low-power, and can operate for a full day on a single battery charge.

On the software side, the system employs a lightweight neural network architecture with a model size under 5MB, enabling real-time inference on low-end smartphones. All AI models run locally: vital signs collected by the sensor are transmitted to the smartphone via Bluetooth, and the model instantly outputs a triage recommendation—whether the patient should remain at the village health post for observation, be referred to a township health center, or be urgently transported to a county-level hospital. The triage decision is based on a hybrid clinical pathway combining rule-based logic and machine learning: the model first detects abnormalities in each physiological parameter, then integrates symptom questionnaire data for comprehensive assessment, and finally outputs a graded recommendation.

3.2 Field Deployment and Implementation Outcomes

The system was validated through field deployments in rural Oman, covering multiple villages with long-term deficits in basic healthcare coverage. The study employed a “CHW-plus-system” service delivery model: after two days of training, CHWs carried the equipment for door-to-door or fixed-point data collection, with the system providing real-time triage recommendations and CHWs taking appropriate action based on those recommendations.

The results showed that the system achieved a preliminary triage accuracy of 91% for common infectious diseases (e.g., respiratory infections) and chronic conditions (hypertension, diabetes). This figure should be understood in context: without system support, CHWs’ accuracy in complex cases is substantially lower. The system’s performance approaches that of a junior physician. Importantly, the system demonstrated high sensitivity in identifying high-risk cases requiring emergency transport—meaning it can effectively capture danger signs that might otherwise be missed by CHWs.

One case study provides a compelling illustration. An elderly woman who had not had her blood pressure measured for three years due to transportation difficulties was found by the system to have a dangerously high reading of 190 mmHg. The system issued an immediate urgent referral recommendation, and follow-up confirmed that the patient likely avoided a stroke. This case vividly demonstrates the value of “technological silence”—the system, requiring no external network connection, “spoke” at a critical moment.

The cost of less than \$0.50 per use is equally noteworthy. This calculation includes equipment depreciation, consumables, and CHW time costs. By comparison, a patient’s travel to a county

hospital typically costs \$5-10 or more in transportation alone, plus a full day of time. From a health economics perspective, the cost-effectiveness advantages of this system are significant.

3.3 Key Contributions of the Innovation

The distinctive contribution of Al-Farsi's team lies not in simply transplanting existing Edge AI technologies to healthcare, but in reverse-engineering a "constraint-driven" technological system based on the actual constraints of resource-limited communities.

First, the system achieves the decentralization of triage decisions. Traditional triage depends on physician judgment, or at minimum on a communication link to a physician. This system encodes "triage wisdom" into locally-run AI models, endowing front-line CHWs with decision support capabilities previously unavailable to them. This approach can be understood as the "materialization of expert knowledge": rather than making every CHW an expert, it embeds experts' decision-making logic into the tools they hold.

Second, it solves the "last mile" connectivity problem. By adopting an edge computing architecture, the system entirely circumvents dependence on internet connectivity, extending the reach of digital health interventions to truly include the "offline population" previously excluded. This represents not only a technical breakthrough but also a meaningful advance in equity.

Third, it establishes a low-cost, scalable model for primary health monitoring. The system's hardware cost is controllable, CHW training duration is short, and maintenance requirements are minimal—features that give it strong potential for replication in similar settings. Importantly, the 91% triage accuracy was achieved under real-world conditions rather than ideal laboratory conditions, further strengthening the case for scalability.

4. Discussion: Edge Intelligence and the Theoretical Implications for Global Health Equity

4.1 From "Icing on the Cake" to "Timely Assistance in Times of Need"

In articulating her team's guiding philosophy, Al-Farsi stated: "The greatest application of artificial intelligence lies not in merely adding 'icing to the cake' in top-tier hospitals, but rather in providing critical assistance where it is needed most." This statement touches on a fundamental choice in the trajectory of AI development: who benefits from technological progress?

To date, the flow of global investment in AI healthcare has been highly uneven. Fields such as medical imaging AI, surgical robotics, and genomic analysis have attracted the vast majority of capital and academic attention, serving primarily the elite medical institutions of high-income countries. This "top-benefiting" pattern is not driven by technical capability but by market logic—purchasing power determines the direction of R&D. However, from the perspective of health equity, the settings with the greatest marginal health returns on AI investment lie at the other end of the spectrum: among the very populations who still lack even basic medical services.

Al-Farsi's work represents a directional shift from "top-end optimization" to "bottom-end empowerment." The core of this shift is not increased technical difficulty but a reversal of problem orientation—asking not "what more can existing technology do?" but rather "what do those people most need?" This needs-driven design philosophy is a prerequisite for Edge AI to realize its social value.

4.2 Feasibility Boundaries and Scaling Challenges

While the preliminary results of Al-Farsi's system are encouraging, multiple challenges remain between "laboratory validation" and "scaled deployment," requiring careful consideration.

The first is technical appropriateness. A 91% triage accuracy is impressive, but the distribution of the remaining 9% of errors is critical—false negatives (misclassifying a high-risk patient as low-risk) carry far greater costs than false positives. How to balance sensitivity and specificity in the current system design, and how to design safety net mechanisms to capture cases the model may miss, require further research.

The second is sustainability. System deployment heavily depends on CHW motivation and capacity. Experience from Tanzania and Nigeria shows that CHW performance is closely linked to the strength of the health system's support—without supervision, logistics, and incentives, service quality declines. Technology cannot substitute for organizational support; Edge AI systems can achieve their full potential only within a functional primary health governance framework.

The third is the economics of scale. While the per-use cost is extremely low, upfront investments in equipment, maintenance, and training still create barriers. Designing sustainable financing mechanisms (government subsidies, social enterprise models, pay-per-use, etc.) is a key variable determining whether the system can be deployed in even poorer settings.

4.3 Theoretical Implications for Global South Contexts

From a broader academic perspective, Al-Farsi's work offers several theoretical implications for research on "AI healthcare in the Global South."

The first implication concerns the theorization of "technology appropriateness." Existing technology diffusion theories often assume a linear "advanced-backward" trajectory, suggesting that developing countries will naturally benefit as technology costs decline. However, the constraints of resource-limited settings (offline, no electricity, low education) are not transitional "backwardness" but genuine "design parameters" that technology systems must respect. The practice of Edge AI suggests that solutions designed for extreme environments may foster reverse innovation—solutions validated in the "South" may also prove valuable for marginalized communities in the "North."

The second implication concerns the measurement of equity. Traditional health equity research focuses on the equality of resource distribution. However, in the age of AI healthcare, equity must also encompass “accessible technological capability”—even if a service is physically available, if the infrastructure it depends on (such as internet connectivity) is absent, equity remains hollow. Edge AI enables offline populations to access intelligent health services for the first time, representing an expansion of “connectivity equity.”

The third implication concerns a rebalancing of academic research priorities. The current mainstream agenda in AI healthcare research focuses overwhelmingly on continuous model performance optimization, with insufficient attention to the heterogeneity of deployment environments. Future research should place greater emphasis on an “implementation science” perspective: how do models perform under real-world conditions? What are their failure modes? How do users interact with technical systems? The answers to these questions may guide practice more effectively than accuracy metrics alone.

5. Conclusion and Future Directions

The intelligent health monitoring system represents a systematic exploration of Edge AI technology for primary healthcare. The key contributions of this research are threefold. First, it demonstrates that under extreme resource constraints (offline, no power, CHWs with limited education), it is possible to build a low-cost, highly usable intelligent triage system. Second, it establishes a complete research framework from technical design to field deployment to outcome evaluation. Third, and perhaps most importantly, it provides an actionable pathway to health equity through technology—enabling the most marginalized populations to benefit from AI healthcare for the first time.

The limitations of the system must also be acknowledged. The current scope of covered disease conditions is limited, focusing primarily on common infectious diseases and a subset of chronic conditions. Long-term follow-up data are not yet available. Cross-cultural and cross-regional generalizability remain to be validated. Future research should extend from “model optimization” to “system optimization”: exploring mechanisms for deep integration with primary health governance systems; conducting larger-scale, longer-duration follow-up studies to assess long-term health outcomes; and investigating optimal models of human-AI collaboration so that AI systems truly enhance—rather than replace—CHW capabilities.

The core principle of “Big Health” is “leaving no one behind.” Given the structural constraints that are unlikely to change fundamentally in the near term, Edge AI offers a complementary technological pathway. It cannot substitute for long-term investments in health system strengthening, but it can provide critical support at the time and place of greatest need. As Al-Farsi suggests, the greatest value of artificial intelligence may lie not in helping those who already have much to gain more, but in providing those who have nothing with the most basic means of survival.

References

- [1] Al-Mahrouqi T, Al Harrasi A, Al Rajhi F, et al. Telepsychiatry in Oman within the broader framework of telehealth. *BJPsych International*, 2025.
- [2] Baynes C, et al. Quality of Sick Child-Care Delivered by Community Health Workers in Tanzania. *International Journal of Health Policy and Management*, 2018.
- [3] Gajarawala SN, Pelkowski JN. Telehealth benefits and barriers. *Journal for Nurse Practitioners*, 2021.
- [4] Gopal B, et al. Artificial intelligence in medical imaging: Utilization, challenges, and practitioner perceptions in Rwanda. *Journal of Medical Imaging and Radiation Sciences*, 2025.
- [5] HealAI Project. The future of first-aid response, on device. *Devpost*, 2025.
- [6] Hussain S, et al. Can artificial intelligence revolutionize healthcare in the Global South? A scoping review of opportunities and challenges. *Digital Health*, 2025, 11: 20552076251348024.
- [7] Morley J, et al. The ethics of AI in health care: A mapping review. *Social Science & Medicine*, 2020, 260: 113172.
- [8] SPEC-AI Nigeria Investigators. Contextual challenges in implementing artificial intelligence for healthcare in low-resource environments: insights from the SPEC-AI Nigeria trial. *Frontiers in Cardiovascular Medicine*, 2025, 12: 1516088.
- [9] BioGAP-Ultra Project Team. BioGAP-Ultra: A Modular Edge-AI Platform for Wearable Multimodal Biosignal Acquisition and Processing. *arXiv:2508.13728*, 2025.
- [10] Bridging the digital divide: artificial intelligence as a catalyst for health equity in primary care settings. *International Journal of Medical Informatics*, 2025.