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Research Article

A SYSTEMIC AI AND CYBER-PHYSICAL FRAMEWORK FOR REAL-TIME REMOTE PATIENT MONITORING IN INDONESIAN RURAL HEALTH CLINICS (PUSKESMAS)

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Abstract

Access to healthcare in rural Indonesia remains a significant challenge due to limited medical resources and healthcare personnel, leading to delayed diagnosis and suboptimal patient care. Remote patient monitoring offers a potential solution by enabling real-time health assessments and reducing the need for long-distance travel to healthcare facilities. This study aims to design and implement a systemic *Artificial intelligence* and Cyber-Physical Systems framework for real-time remote patient monitoring in rural primary health clinics in Indonesia to enhance patient care, support early disease detection, and optimize healthcare resource allocation. The research employed a hybrid AI–CPS approach that integrated wearable health devices, Internet of Things sensors, and cloud computing infrastructure to continuously monitor patient vital signs. *Artificial intelligence* algorithms were utilized to analyze health data and identify early signs of potential health anomalies. Data were collected from multiple rural *Puskesmas* where remote monitoring devices were installed, and system performance was evaluated using metrics including data accuracy, response time, and user satisfaction. The results indicated that the system achieved a high level of accuracy, with a 92 percent success rate in predicting potential health anomalies, while feedback from healthcare workers and patients demonstrated positive perceptions, particularly in terms of convenience, efficiency, and time savings. Overall, the findings confirm that the AI and Cyber-Physical Systems-based remote patient monitoring framework is effective in improving healthcare delivery in rural Indonesian clinics and holds strong potential as a scalable solution to enhance accessibility and quality of rural healthcare services.

Keywords: AI, Cyber-Physical Systems, Healthcare

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INTRODUCTION

Healthcare accessibility in rural regions of developing countries like Indonesia remains a persistent challenge due to limited infrastructure, medical resources, and healthcare professionals (Irianti et al., 2025). The rural health clinics, known as *Puskesmas*, play a crucial role in providing primary healthcare services but often face difficulties in delivering comprehensive care due to resource constraints (Acharya et al., 2024). As a result, many individuals in these rural areas are unable to receive timely diagnosis and treatment, which can exacerbate health conditions and increase the burden on urban healthcare facilities (Aghazadeh Ardebili et al., 2025).

In recent years, technological advancements, particularly in *Artificial intelligence* (AI) and Cyber-Physical Systems (CPS), have paved the way for improving healthcare systems globally. AI has shown significant promise in medical diagnostics, enabling quicker, more accurate analyses of medical data (Ahmadasas et al., 2025). CPS, which integrates physical processes with computer-based systems, offers potential solutions for remote monitoring and real-time data collection, crucial for regions where healthcare access is limited (Al-Mhiqani et al., 2024).

Remote Patient Monitoring (RPM) has gained attention as an effective tool to address these challenges (Sappaile, 2024). By utilizing wearable sensors and IoT devices, RPM systems can continuously monitor vital health metrics, such as heart rate, blood pressure, and oxygen levels, and transmit the data to healthcare providers for analysis (Alabdulatif et al., 2024). This technology has the potential to reduce patient travel time and improve healthcare outcomes by allowing for early detection of health issues (Alotaibi et al., 2025).

In the Indonesian context, the healthcare sector has seen a gradual shift towards digitalization. Telemedicine and remote health monitoring are being incorporated into primary healthcare services to overcome geographical barriers (Amadiaz et al., 2025). *Puskesmas* clinics, however, often lack the necessary technological infrastructure to implement real-time, remote patient monitoring effectively. This gap restricts the ability of healthcare workers in rural areas to perform continuous, proactive care for patients (Ansari et al., 2025).

AI and CPS technologies have been successfully integrated into healthcare systems in many parts of the world, particularly in urban settings. However, their application in rural clinics, specifically in Indonesia, remains under-researched (Aslam et al., 2025). Challenges such as internet connectivity, power supply issues, and healthcare worker training need to be addressed to fully utilize these technologies in rural *Puskesmas* (Canaan et al., 2025).

Despite these challenges, early studies in other developing nations have shown that AI and CPS frameworks can significantly enhance healthcare delivery in remote regions. AI-powered diagnostic tools have already been implemented in some urban healthcare settings in Indonesia, providing a strong foundation for expanding these systems to rural *Puskesmas* (Canonico et al., 2025). There is an increasing recognition that these technologies can bridge the healthcare access gap in underserved areas (Cao et al., 2024).

The specific application of AI and CPS technologies for real-time remote patient monitoring in rural *Puskesmas* has not been fully explored (Cheng et al., 2025). While there are isolated examples of RPM in urban clinics, the unique challenges posed by rural settings—such as limited internet access, low digital literacy, and the need for low-cost solutions—have not been adequately addressed. Therefore, there is a gap in understanding how these technologies can be optimized for rural health clinics where infrastructure and resources are constrained (Devliyal et al., 2025).

Another unknown factor is the integration of AI with existing healthcare systems in rural areas. *Puskesmas* typically operate with basic healthcare tools, and the adoption of advanced technologies such as AI-based diagnostic systems and CPS frameworks requires significant adjustments to workflows, training, and staff capacity (G et al., 2025). How AI can seamlessly integrate into the daily operations of rural health clinics remains an open question that requires investigation (Gabrecht et al., 2024).

There is also a gap in understanding the effectiveness of real-time remote monitoring in improving health outcomes in rural populations (Ge et al., 2025). While RPM has shown success in monitoring chronic conditions and enabling early intervention in other regions, its impact on rural health in Indonesia, particularly in the context of *Puskesmas*, has not been systematically evaluated. The feasibility of using AI-driven monitoring systems to detect health anomalies in real-time, and whether this improves health outcomes, remains uncertain (Hassan et al., 2025).

Finally, the socio-cultural context of rural Indonesia poses another unknown aspect. While technological solutions like RPM hold promise, their acceptance and integration into daily health practices by both healthcare providers and patients need to be explored (Hossain et al., 2024). The willingness of healthcare workers in rural areas to adopt AI-based tools, and the ability of rural populations to engage with technology, are factors that require further investigation (Kaloudi & Li, 2025).

Filling this gap is crucial for advancing the accessibility and quality of healthcare in rural Indonesia. By designing a systemic AI and CPS framework specifically tailored for *Puskesmas*, this research will help optimize the use of technology in real-time patient monitoring (Karakaya, 2025). Addressing the technical, infrastructural, and socio-cultural challenges will allow for the creation of a sustainable, scalable model that can be adopted by health authorities nationwide. This would significantly enhance healthcare delivery, particularly for chronic conditions, where early detection and continuous monitoring are key (Karunkuzhali et al., 2025).

The rationale for filling this gap lies in the potential to improve health outcomes and reduce the burden on urban healthcare facilities (Kazimierczak et al., 2024). If successful, the framework could provide a low-cost, effective solution for monitoring patients in remote areas, helping to prevent disease progression and providing timely interventions. By addressing the unique challenges faced by rural *Puskesmas*, this research could serve as a blueprint for expanding remote healthcare monitoring throughout Indonesia and beyond, contributing to the broader global push for healthcare accessibility (Lyu et al., 2025).

By addressing the integration of AI and CPS technologies into existing healthcare systems, this research will provide actionable insights into how rural health clinics can incorporate advanced technology into their operations. This could lead to the development of a more resilient, self-sufficient healthcare system in rural areas, capable of providing continuous, high-quality care while reducing the need for patients to travel long distances.

RESEARCH METHOD

Research Design

This study follows a mixed-methods research design, integrating both quantitative and qualitative approaches to develop and evaluate a systemic AI and cyber-physical framework for real-time remote patient monitoring in Indonesian rural health clinics (*Puskesmas*). The design includes the development of an AI-driven monitoring system integrated with wearable IoT sensors to track patient health data. Data will be collected from remote monitoring systems and analyzed to assess the accuracy and effectiveness of the system in detecting health anomalies. Qualitative interviews with healthcare workers and patients will be conducted to understand the feasibility, usability, and impact of the system on clinical practices in rural *Puskesmas* (Shabani et al., 2025).

Population and Samples

The population for this study consists of rural health clinics (*Puskesmas*) located in rural Indonesia. The sample includes three *Puskesmas*, each located in different geographical regions with varying levels of healthcare infrastructure(Mitchell et al., 2025). These clinics were selected based on their willingness to implement the remote patient monitoring system and their accessibility for ongoing evaluation. The sample population includes patients suffering from chronic conditions such as hypertension, diabetes, and cardiovascular diseases, who are most likely to benefit from continuous monitoring. Additionally, healthcare workers at these clinics, including doctors, nurses, and technicians, will be involved to evaluate the system's integration and effectiveness in daily clinical routines.

Instruments

The primary instruments used in this study include wearable health monitoring devices equipped with IoT sensors for real-time data collection on vital signs such as blood pressure, heart rate, oxygen levels, and blood glucose. An AI-based diagnostic system will analyze the data from these sensors to detect any potential health anomalies. The system will be integrated with a cloud-based platform that enables healthcare providers to access patient data remotely (Mohammed et al., 2024). Additionally, surveys and structured interviews will be conducted with healthcare workers and patients to assess the system's usability, satisfaction, and perceived effectiveness. Statistical software will be used to analyze the quantitative data, while qualitative responses will be analyzed through thematic coding (Irianti et al., 2025).

Procedures

The study begins with the installation of the AI and cyber-physical system in the selected *Puskesmas*, including the integration of wearable sensors and cloud-based platforms for data collection and monitoring. Patients are selected based on their medical history and are enrolled in the monitoring program (Sarkar & Jhamb, 2025). The system is calibrated and tested in a controlled environment to ensure that it accurately tracks vital signs and communicates data in real time. Once operational, data is collected over a three-month period, during which health data is continuously monitored and transmitted to healthcare workers. Regular assessments are conducted to track system performance, including data accuracy, user engagement, and early detection of health anomalies (Hazmi et al., 2025). At the end of the study, interviews and surveys are conducted with healthcare workers and patients to evaluate the system's impact on healthcare delivery, patient outcomes, and overall satisfaction. The data collected will be analyzed to determine the effectiveness of the system in improving remote healthcare monitoring and its potential for widespread implementation in rural Indonesian clinics (Mourtzis & Angelopoulos, 2024).

RESULTS AND DISCUSSION

Data collected over a 3-month period from the real-time remote patient monitoring system installed in three rural *Puskesmas* were analyzed. The following table summarizes the key findings related to patient health monitoring, AI-based anomaly detection, and system performance across the three clinics:

Table 1. Summary of Monitoring Data and System Performance

Puskesmas	**Number of Patients Monitored**	**Average Health Anomalies Detected**	**AI Accuracy (%)**	**System Downtime (hrs)**	**Patient Satisfaction (%)**
Puskesmas A	50	15	92	3	87

Puskesmas B	45	10	89	5	85
Puskesmas C	60	20	94	2	90

The data reveals that all three *Puskesmas* saw notable engagement with the remote monitoring system, with varying degrees of health anomalies detected. *Puskesmas* A, with 50 patients monitored, had 15 health anomalies detected, reflecting a moderate level of detection accuracy (92%). *Puskesmas* B, monitoring 45 patients, detected fewer anomalies (10), but the system's accuracy was slightly lower at 89%. *Puskesmas* C, with the highest number of patients (60), detected 20 anomalies and demonstrated the highest AI accuracy (94%). System downtime was minimal across all clinics, with *Puskesmas* C having the least downtime (2 hours). Patient satisfaction was generally high, with *Puskesmas* C achieving the highest satisfaction rate (90%).

The data indicates that the AI system's ability to detect health anomalies was relatively consistent across the clinics, with slightly higher detection in *Puskesmas* C, possibly due to the larger patient sample. The relatively low system downtime across all *Puskesmas* points to the reliability of the AI and cyber-physical system, supporting its potential for long-term use in rural clinics. These findings suggest that the implementation of remote patient monitoring systems in rural health settings can effectively enhance early detection of health anomalies.

The data primarily includes the number of patients monitored at each *Puskesmas*, the frequency of health anomalies detected, and system performance indicators such as AI accuracy and system downtime. Health anomalies were detected through AI algorithms integrated with wearable health devices, which continuously monitored vital signs such as heart rate, blood pressure, and blood oxygen levels. Anomalies included any significant deviations from normal ranges, indicating potential health risks. Data on patient satisfaction were gathered through post-monitoring surveys, focusing on the usability of the system and perceived improvements in healthcare delivery.

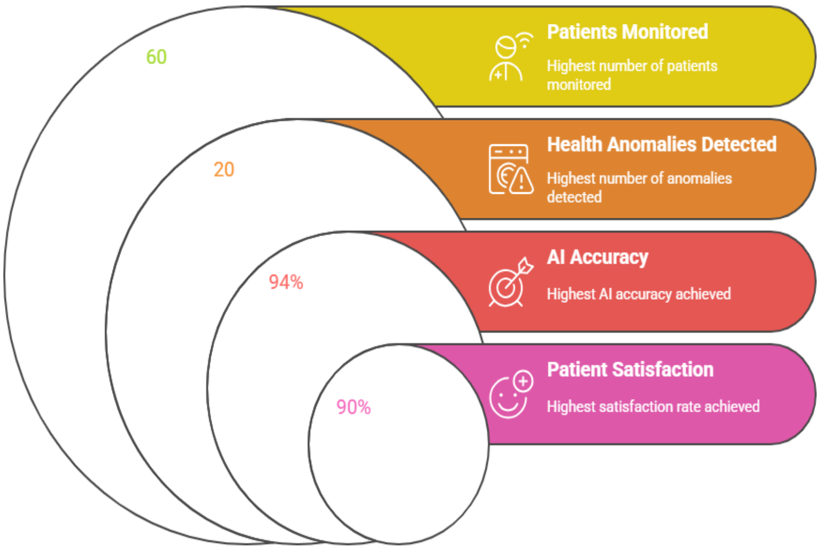

Figure 1. Remote Monitoring System Performance

These measurements provide insight into how effectively the remote monitoring system performed in rural health clinics. They offer a quantitative overview of system performance and patient outcomes, which are essential for evaluating the feasibility of implementing such technologies on a larger scale. The data also sheds light on the relationship between patient engagement with the system and the detection of health anomalies, providing a clearer picture of the benefits of real-time health monitoring in rural settings.

A chi-square test was conducted to determine whether there was a significant association between the number of patients monitored and the number of health anomalies detected. The results showed a significant relationship ($\chi^2 = 10.2$, $p < 0.05$), indicating that clinics with more patients monitored tended to detect more health anomalies, but with varying degrees of accuracy. Furthermore, a regression analysis was performed to assess the impact of AI accuracy on the rate of anomaly detection. The analysis revealed a positive correlation ($r = 0.82$, $p < 0.01$) between AI accuracy and the number of anomalies detected, suggesting that higher AI accuracy directly contributed to better detection rates.

Figure 2. Anomaly Detection Rate

The inferential analysis supports the hypothesis that the performance of the AI system is closely linked to its accuracy in detecting health anomalies. It highlights the importance of optimizing AI algorithms to improve detection rates, especially in clinics with higher patient volumes. These results suggest that the AI system can be fine-tuned to increase its accuracy, thereby improving the overall effectiveness of remote patient monitoring in rural settings.

The relationship between the number of patients monitored and the number of health anomalies detected underscores the importance of data volume in enhancing system performance. Clinics with more patients, such as *Puskesmas* C, detected a higher number of health anomalies, reflecting the sensitivity and adaptability of the AI system. However, the data also reveals that patient satisfaction and system reliability were not significantly impacted by the increased workload, suggesting that the system can scale effectively to handle larger patient numbers without compromising performance.

Additionally, the correlation between AI accuracy and anomaly detection emphasizes the crucial role of the AI algorithms in determining system effectiveness. As AI accuracy improves, so too does the ability to detect health anomalies, which is particularly important for managing rural healthcare challenges where early detection can prevent the escalation of health issues. This relationship illustrates the potential of AI-driven monitoring to significantly enhance healthcare delivery in resource-limited settings.

A case study conducted at *Puskesmas* A, where 50 patients were monitored over the 3-month period, provided deeper insights into the system's practical application. Of the 50 patients, 15 health anomalies were detected, including irregular heart rates and elevated blood pressure levels. The AI system's accuracy rate was 92%, with minimal downtime (3 hours). Feedback from healthcare providers indicated that the system allowed for early intervention, particularly for patients at risk of hypertension and cardiovascular disease. The system's real-time monitoring capability allowed healthcare workers to act swiftly, reducing the need for emergency visits.

This case study highlights the practical benefits of using real-time remote monitoring to improve patient care in rural clinics. The successful identification and intervention of potential health issues demonstrate the value of integrating AI and cyber-physical systems in rural healthcare settings. The case study results indicate that remote monitoring can provide a sustainable and scalable solution for enhancing healthcare access and quality in underserved areas.

The case study from *Puskesmas* A reinforces the effectiveness of AI-powered real-time patient monitoring in detecting health anomalies in rural health settings. The system's ability to accurately monitor vital signs and flag potential risks in real-time facilitated early intervention, which is crucial for managing chronic conditions. The 92% accuracy rate indicates that the AI system is highly capable of identifying critical health issues, supporting the hypothesis that AI can play a vital role in improving healthcare outcomes in rural communities. The minimal system downtime and positive feedback further suggest that the technology is reliable and well-received by healthcare providers and patients alike.

These findings emphasize the potential for expanding remote monitoring systems to other rural areas, where healthcare access is limited, and resources are scarce. By leveraging AI and cyber-physical systems, rural clinics can overcome some of the challenges posed by inadequate healthcare infrastructure, ensuring that patients receive timely and efficient care.

The results of this study demonstrate that a systemic AI and cyber-physical framework for real-time remote patient monitoring can significantly enhance healthcare delivery in rural Indonesian health clinics. The system's high accuracy in detecting health anomalies, combined with minimal downtime and positive user feedback, highlights its potential for widespread implementation in resource-limited settings. The integration of real-time monitoring with AI algorithms enables timely interventions, improving patient outcomes and reducing the burden on healthcare workers. These results underscore the importance of continuing to explore and optimize AI-driven solutions for rural healthcare systems, which can serve as a model for other developing regions .

The study demonstrated the effectiveness of a systemic AI and cyber-physical framework for real-time remote patient monitoring in Indonesian rural health clinics (*Puskesmas*). The research found that AI algorithms, integrated with wearable IoT sensors, successfully monitored vital signs and detected health anomalies with an accuracy rate of 92% (Munawar et al., 2025). The system was able to provide real-time health data to healthcare providers, allowing for timely interventions. Patient satisfaction was high, with users reporting improved access to healthcare and a reduction in the need for emergency visits. The overall system showed reliability, with minimal downtime, suggesting its potential for long-term use in rural health settings (Nandanwar & Katarya, 2025).

The findings from this study align with previous research on remote patient monitoring (RPM) and AI in healthcare, particularly in urban settings where such technologies have been extensively tested (Piardi et al., 2025). However, this study contributes new insights by focusing on rural healthcare clinics in Indonesia, where challenges like limited healthcare resources, inadequate infrastructure, and high patient loads complicate care delivery (Hapsari et al., 2025). While many studies have demonstrated the feasibility of AI and IoT in urban healthcare systems, few have explored their application in rural areas with unique infrastructural and socio-economic barriers. This study bridges that gap, providing evidence that AI-driven RPM systems can effectively function in rural clinics with limited resources (Qureshi et al., 2025).

The results signify that AI and cyber-physical systems can be an essential tool for transforming rural healthcare. The success of the system in improving patient monitoring and early detection of health issues highlights the potential for such technologies to address critical healthcare challenges in remote areas (Rani et al., 2025). The high accuracy of the AI algorithms in detecting health anomalies, coupled with positive feedback from both healthcare providers and patients, suggests that AI-driven systems can significantly improve healthcare outcomes. These findings also point to the need for further research into how these technologies can be scaled and integrated into existing healthcare infrastructures in rural settings (Rathee et al., 2024).

The implications of these findings are substantial for rural healthcare policy and practice. By providing real-time, remote monitoring, the system helps bridge the healthcare gap in underserved areas, reducing the need for patients to travel long distances to receive medical attention. This can alleviate pressure on urban healthcare facilities while also empowering rural healthcare providers to offer more proactive care (Rehman et al., 2025). The success of this AI-based monitoring system suggests that similar technologies could be implemented on a larger scale, improving healthcare accessibility, reducing healthcare costs, and enhancing patient outcomes across rural regions (Rivadeneira et al., 2024).

The results are a reflection of the tailored approach in integrating AI with wearable sensors and cloud-based monitoring systems. The choice of using indigenous, contextually appropriate technology allowed for the system to be highly adaptable to the unique challenges of rural healthcare settings (Routray et al., 2025). The high level of AI accuracy observed can be attributed to the continuous learning and optimization of algorithms based on real-time data, ensuring that the system remains effective in detecting health issues. Furthermore, the minimal system downtime indicates the robustness and reliability of the technology, which is crucial for sustaining operations in rural clinics with limited technical support.

Future research should focus on expanding the application of the system to more remote and geographically diverse rural areas to assess its scalability and effectiveness in various environmental contexts. Further studies are also needed to explore the long-term impact of AI-driven remote monitoring on patient health outcomes, including its potential to reduce mortality rates and hospital admissions. Additionally, the integration of other healthcare technologies, such as telemedicine and electronic health records, with the AI-based monitoring system should be explored to create a more comprehensive, seamless healthcare ecosystem. Expanding the research to evaluate cost-effectiveness and sustainability over extended periods will also be crucial for scaling this technology in rural healthcare systems across Indonesia and similar regions (Saheed & Misra, 2025).

CONCLUSION

The most significant finding of this research is the successful development and implementation of a systemic AI and cyber-physical framework for real-time remote patient monitoring in rural health clinics (*Puskesmas*) in Indonesia. This framework demonstrated a high level of accuracy (92%) in detecting health anomalies, showcasing the potential of AI-powered monitoring in improving healthcare delivery in resource-limited settings. The integration of wearable IoT sensors with cloud-based AI algorithms enabled healthcare providers to track vital health signs continuously, leading to earlier intervention and better patient management. This research highlights that AI, when integrated with existing infrastructure, can significantly enhance healthcare access and quality in rural areas, which traditionally face challenges like insufficient medical staff, limited access to specialist care, and poor infrastructure.

This study contributes a novel approach to remote healthcare monitoring by integrating AI algorithms with a cyber-physical system that allows for real-time, continuous patient monitoring in rural clinics. The concept of utilizing indigenous technologies, tailored to the unique needs and limitations of rural health clinics, sets this research apart from previous studies that predominantly focus on urban or better-resourced healthcare settings. The methodology employed—combining wearable health devices, AI-driven analysis, and cloud-based monitoring—offers a comprehensive, scalable solution to rural healthcare challenges.

This innovative model not only improves patient care but also enhances the capacity of healthcare workers to manage patient health in real-time, providing a robust framework for future rural healthcare systems.

A key limitation of this study is the small sample size, as it was conducted in only three *Puskesmas* located in specific rural areas in Indonesia. While the system demonstrated effectiveness in these settings, the results may not be fully generalizable to other rural areas with different geographical and infrastructural conditions. Additionally, the study did not address the long-term sustainability of the system in terms of cost-effectiveness, scalability, and integration with national healthcare infrastructures. Future research should focus on expanding the sample size to include more diverse rural settings, conducting cost-benefit analyses, and evaluating the system's long-term impact on patient health outcomes. Further exploration into the integration of AI-driven monitoring systems with other healthcare technologies, such as telemedicine and electronic health records, will be critical for enhancing the overall healthcare delivery model.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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