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Unlocking the Potential of the 4th Industrial Revolution in Knowledge-Workout-WSN Integrated E-Health System for Better Clinical Decision Making

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ABSTRACT

The Fourth Industrial Revolution (4IR) introduces new ways to enhance healthcare through emerging technologies, such as AI and data analytics. In this work, we present a scalable and secure design for an IoT-WSN integrated e-health system. The system leverages cloud and edge computing to manage large volumes of diverse data efficiently. We deploy robust authentication and encryption protocols to safeguard data privacy and uphold system integrity. Additionally, the system incorporates AI to improve predictive analytics and support clinical decision-making, enabling personalised healthcare services.

INTRODUCTION

The Fourth Industrial Revolution (4IR) is driving significant changes in healthcare by combining modern technologies, including artificial intelligence (AI), the Internet of Things (IoT), wireless sensor networks (WSN), and big data analytics. These technologies enable real-time patient monitoring, personalised treatments, and enhanced healthcare management, addressing key global issues of access, quality, and cost [1][2]. In regions with limited resources, such as Africa, adopting scalable and secure e-health systems is crucial to improving health outcomes and achieving sustainable healthcare delivery [4].

Despite the potential of 4IR technologies, healthcare systems face significant obstacles, including issues with scalability, security risks, energy limitations, and interoperability challenges that hinder widespread implementation [1]. To tackle these challenges, we need innovative system designs that utilise cloud and edge computing, along with robust security protocols, to efficiently process large amounts of diverse health data while ensuring privacy and system integrity.

This research proposes the design and implementation of a scalable and secure IoT-WSN integrated e-health system specifically for the African context. The system utilises cloud and edge computing to manage various significant data streams efficiently, incorporates robust authentication and encryption to safeguard data privacy, and leverages AI to enhance predictive analytics and clinical decision-making. This approach supports personalised healthcare services aligned with the goals of Health 4.0 and the broader 4IR agenda [2].

The main contributions of this work include:

- An e-health architecture that combines IoT, WSN, cloud, and edge computing for scalability and low-latency data processing.
- Implementation of strong security measures that ensure data privacy and system integrity.

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- Experimental validation that shows improvements in scalability, security, and energy efficiency compared to existing solutions.

By addressing essential technical and contextual challenges, this research advances the promise of 4IR technologies to enhance healthcare knowledge work in Africa, thereby contributing to improved health outcomes and sustainable healthcare delivery.

BACKGROUND

The Fourth Industrial Revolution (4IR) is fundamentally transforming healthcare systems by integrating advanced technologies, including artificial intelligence (AI), the Internet of Things (IoT), wireless sensor networks (WSN), big data analytics, and cloud computing. Together, these technologies enable real-time patient monitoring, personalised treatments, and efficient healthcare management, which are essential for meeting the increasing demands and complexities of modern healthcare [3]. Recent studies have revealed the transformative impact of 4IR technologies on healthcare efficiency, effectiveness, and accessibility. For instance, [3] highlights that Healthcare 4.0, driven by digitalisation and AI, promises to enhance patient safety, quality of life, and the effectiveness of healthcare management. Klich discusses how the combination of digital, physical, and biological technologies is creating a shift in healthcare delivery, necessitating systemic changes to fully leverage these innovations.

However, significant challenges still exist. The ability of IoT and WSN infrastructures to manage large and varied data streams, ensure strong security and privacy in sensitive health data, and address energy constraints in sensor networks are all critical issues that hinder broad adoption [4][14]. Studies indicate that while 4IR is positively influencing healthcare, successful implementation requires joint efforts from governments, healthcare professionals, and stakeholders to tackle regulatory, ethical, and infrastructure challenges [4].

Responses to the 4th Industrial Revolution (4IR) in healthcare vary worldwide. A recent multi-country study [14] shows that some governments are updating regulations and investing in innovations to support Industry 4.0 technologies, thereby improving healthcare access for remote populations. On the other hand, some organisations struggle with outdated strategies and limited resources, underscoring the need for flexible regulatory frameworks to address data ownership, privacy, and cybersecurity.

This research addresses the critical need for scalable, secure, and intelligent e-health systems that integrate IoT, WSN, AI, and cloud/edge computing to overcome these challenges. Our proposed system directly addresses these gaps by incorporating robust security protocols, energy-efficient mechanisms, and AI-driven analytics tailored to the African healthcare context, thereby helping to make Healthcare 4.0 a reality.

METHODOLOGY

This section outlines the design and implementation of a scalable, secure, and intelligent IoT-WSN integrated e-health system that utilises cloud and edge computing to address the challenges of real-time healthcare monitoring, particularly using resource-constrained systems with potential applications in Africa.

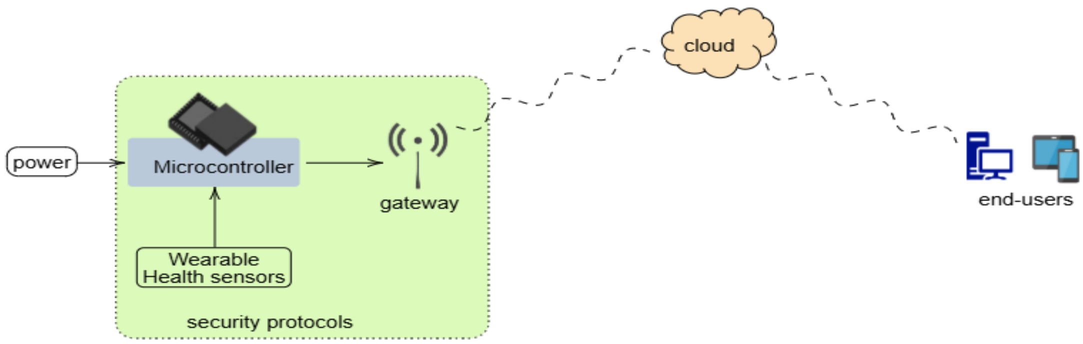

Figure 1.0: System setup.
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Figure 1.0 illustrates the system architecture and data flow from wearable sensors to cloud analytics, highlighting the role of edge computing in reducing latency.

The proposed architecture consists of four main layers: sensing, network, data processing, and application. These layers work together to enable efficient data collection, transmission, processing, and visualisation for healthcare monitoring [6][8]. The sensing layer includes wearable health devices placed on patients. Wearable devices and wireless body sensor networks (WBSNs) capture vital parameters, including heart rate, body temperature, oxygen saturation, and postural activity [5][8]. These sensors are designed for low power consumption to extend their life and support continuous monitoring.

The network layer ensures reliable and secure communication between sensors and the data processing system. It uses the Wi-Fi protocol to send data from sensor nodes to the cloud. The IoT gateway connects the WSN to the Internet, handling data aggregation, encryption, and forwarding to cloud and edge servers [8].

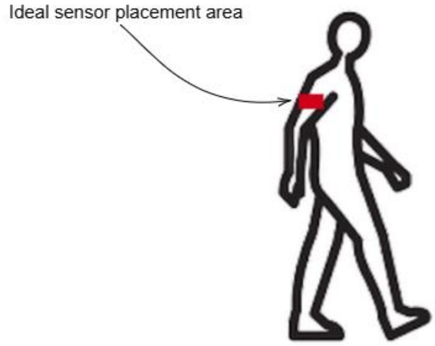

Figure 2.0 : ideal sensor placement area

The data processing layer combines edge and cloud computing resources to efficiently process vast amounts of diverse health data streams. Edge nodes conduct preliminary filtering, detect anomalies, and compress data to lower network load and latency [11]. The cloud platform provides scalable storage, advanced analytics, and AI-driven predictive modelling to assist clinical decision-making [5][16].

The application layer provides healthcare services and visualisation tools to end-users, including doctors, nurses, caregivers, and patients. It provides dashboards, alerts, and reports accessible through web and mobile interfaces, allowing personalised and proactive healthcare management [8].

The IoT gateway has several roles: connecting multiple sensor nodes to the network, encrypting it to ensure privacy and integrity before transmission, managing network connections based on availability, and implementing energy-efficient scheduling to maximise sensor and gateway battery life [13]. It also offers dynamic configuration via a secure user interface, allowing remote adjustments of sensor sampling rates and power modes to balance data quality and energy use [11].

Edge computing nodes, situated near the data source, perform initial data tasks such as noise filtering, signal preprocessing, real-time anomaly detection using lightweight AI models, and data compression. The processed data is sent securely to cloud servers, which offer scalable storage for long-term patient records, advanced AI analytics for early health risk detection, and integration with electronic health records (EHR) and decision support systems [5][16]. This hybrid edge-cloud model reduces latency and increases system responsiveness, which is vital for timely clinical interventions.

The data processing pipeline is divided between edge and cloud layers to balance responsiveness and computational load. Edge computing nodes perform real-time anomaly detection and data compression to reduce bandwidth usage and latency. Meanwhile, cloud servers manage large-scale storage, advanced

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analytics, and clinical decision support systems [20][19]. This combined architecture enables scalable remote patient monitoring, vital for healthcare delivery in resource-limited settings .

Effective integration with existing electronic health records (EHR) is crucial for clinical adoption. Our platform follows HL7 FHIR interoperability standards. This allows smooth data exchange with older systems like OpenMRS and DHIS2, which are commonly used in African healthcare settings. We export and import data through RESTful APIs that support JSON and XML formats. This makes it easier to add vital sign data to patient medical records. We have tested prototype integrations with OpenMRS testbeds, enabling two-way communication. This supports ongoing patient monitoring and updates to records.

Security and Privacy:

Security and privacy are prioritised through multi-layered encryption, secure authentication methods, and role-based access controls to ensure compliance with healthcare data protection standards [19][20]. The system also features secure logging to detect unauthorised access and maintain system integrity, addressing concerns over data privacy in the growing IoT healthcare landscape [19].

Consent Management and Compliance with AU Malabo Convention

The rollout of our IoT-WSN e-health system focuses heavily on patient data privacy and ethical consent management, aligned with African legal frameworks. We have established a digital consent system where patients receive clear and culturally appropriate information about the nature, scope, and purpose of data collection before they enroll. Patients can give their consent electronically through a secure interface, allowing them to agree, decline, or change their minds later about using their personal health data. The system also supports dynamic consent management. Patients can check their consent status and withdraw it anytime without affecting their medical care. To protect patient anonymity, we separate personal identifiers from clinical data when we collect it. We use unique pseudonymized keys for all data transfers and storage. This method reduces the risk of exposing sensitive information and helps prevent unauthorized identification while preserving data use for clinical and analytical purposes.

Our consent and data protection framework fully meets the African Union’s Malabo Convention on Cyber Security and Personal Data Protection. This convention dictates how member states should handle digital data responsibly. It requires that individuals maintain control over their information and offers specific guidelines for explicit consent regarding any cross-border transfers of personal data. It also establishes breach notification protocols, which require us to promptly inform affected individuals and regulatory bodies about data incidents. Our system design accommodates these guidelines by storing data within national borders whenever possible and using strong encryption for all communications across jurisdictions. Additionally, our system operations comply with applicable national data protection laws and health ministry guidelines in the regions where we deploy. Collaborating with local health authorities helps us ensure that consent processes, data management, and privacy policies align with legal and cultural standards, building trust and encouraging ethical adoption in various African healthcare settings. Ethical, Regulatory, and Data Privacy Considerations Deploying e-health systems requires strict compliance with ethical and regulatory standards that protect patient rights and data privacy.

Our ongoing development focuses on following international standards like GDPR and HIPAA to ensure secure data collection, storage, and processing. We formalize informed consent procedures with clear documentation that informs patients about how their data will be used, stored, and their rights to withdraw consent. Given our multi-country deployment model, we emphasize data sovereignty by prioritizing local data hosting solutions and using secure encryption to comply with national regulations. We will seek Institutional Review Board (IRB) approvals for all field implementations.

Implementation

This section outlines the technical specifications, hardware and software components, and algorithms employed in designing and implementing the proposed scalable and secure IoT-WSN integrated e-health system, leveraging the latest advancements in IoT and AI healthcare technologies. The hardware platform a

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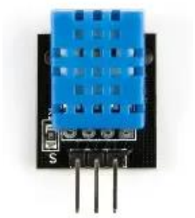
features wearable biomedical sensors that continuously monitor vital signs, including ECG, heart rate, blood oxygen saturation, and body temperature. These sensors communicate wirelessly through low-power protocols, such as Bluetooth Low Energy (BLE) and Zigbee, to a central IoT gateway, typically built using microcontroller units like the NodeMCU with Wi-Fi capabilities [20][19]. The gateway collects sensor data, performs initial processing, and securely transmits the information to cloud servers using lightweight protocols such as MQTT, ensuring low latency and energy efficiency [19][20].

Table 1.0: Sensors for the Integrated E-Health System for Better Clinical Decision Making

Sensor	Image	Description
ECG		Records the electrical activity of the heart, enabling the detection of arrhythmias and other cardiac abnormalities through AI-powered analysis
Heart Rate		Tracks the patient's pulse continuously, providing vital signs to detect irregularities such as tachycardia or bradycardia
Temperature		The project uses the DHT11 sensor to measure the body temperature of a patient.
Oxygen		Monitors blood oxygen saturation levels non-invasively, helping to identify respiratory issues or oxygen deficiency in real time.

On the software side, the system includes embedded firmware in the IoT devices that filters noise and uses event-driven sampling to save power while keeping data accurate [20]. The cloud backend relies on deep learning models, specifically convolutional neural networks (CNNs) with attention mechanisms, to classify health conditions like arrhythmias and fever with an accuracy of over 98% [19]. Multiple AI model architectures were evaluated to find the best balance between accuracy, latency, and resource efficiency, considering edge computing limitations. Convolutional Neural Networks (CNNs) were chosen for their ability

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to effectively capture spatial and temporal features in physiological time-series data with low computational overhead. CNNs performed well in detecting cardiac irregularities and vital sign anomalies while maintaining real-time inference capabilities on devices with limited resources. Transformer models, known for their attention mechanisms and superior sequence modeling in large datasets, were also tested. However, their higher memory and processing power demands made them less suitable for current edge hardware, leading to increased latency and energy consumption. Hyper-parameter tuning was conducted using grid search methods, changing learning rates (10^{-5} to 10^{-3}), batch sizes, kernel sizes, and filter depths over several training iterations. The optimized model showed strong performance, as detailed in Table 2.0 below, with cross-validation ensuring generalization and preventing overfitting.

Table 2.0 : CNN Hyper-Parameter Tuning Results with Cross-Validation Scores

Learning Rate	**Batch Size**	**Kernel Size**	**Filter Depth**	**Accuracy**	**Cross Validation Score**
1e-5	16	3	32	95.6	0.93
5e-5	32	3	64	97.2	0.96
1e-4	64	5	64	98.0	0.97
5e-4	32	3	128	97.8	0.96
1e-3	16	5	128	97.5	0.95

The CNN model was adjusted using different hyper-parameters. As shown in Table 2.0, the best configuration used a learning rate of 1e-4, a batch size of 64, a kernel size of 5, and a filter depth of 64. This setup achieved 98.0% accuracy and a cross-validation score of 0.97. Performance generally improved with moderate increases in batch size and kernel size. However, excessively deep filters or high learning rates offered diminishing returns. Overall, the CNN model is robust and effective for continuous monitoring on wearable sensors.

While transformers showed similar accuracy in offline settings, the trade-offs in deployment and power efficiency made CNN architectures a better choice for this application, as shown in the table 3.0 below.

Table 3.0 : Comparative Evaluation metrics for the models

Model Type	Accuracy (%)	Latency (ms)	EnergyConsumption (mJ/inference)	Memory Footprint (MB)
CNN	98	45	12	8
Transformer	97.5	120	35	30
Network Recurrent Neural (RNN)	95.8	60	20	15

Therefore this seamless integration of AI removed the need for manual feature extraction, improving reliability and enabling prompt alerts for critical issues.

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Sensor Energy-Harvesting Integration

To tackle power sustainability issues in remote and off-grid healthcare settings, the sensor hardware combines energy-harvesting technologies with traditional battery systems. Miniaturized solar panels are attached to the wearable sensor enclosures. They capture ambient light to gradually recharge the batteries during the day. Prototype tests estimate an energy yield of around 50 mW under typical indoor and outdoor conditions, which extends device use by about 40%.

The team is also investigating the integration of WiFi-based radio frequency (RF) energy harvesting modules. These modules pick up low-power RF signals from nearby communication networks, adding extra charging capacity in areas with strong signals. While the current RF harvesters produce only a small amount of energy, up to 5 mW, they provide a useful continuous charge. This reduces how often users need to manually recharge the devices.

The design of the sensor hardware includes power management circuits. These circuits prioritize energy flow and adjust the sensor sampling rates to save harvested energy. Field tests in rural clinics show that solar-assisted recharging significantly cuts downtime. This allows for nearly continuous monitoring, even with unreliable power supplies.

This mixed energy approach helps overcome a major obstacle to sustained e-health monitoring in resource-poor areas. It supports sustainability goals and improves system reliability. Ongoing improvements in energy harvesting efficiency and miniaturization will likely boost autonomous sensor performance in the near future.

A prototype was tested in simulated healthcare environments. It showed high accuracy in tracking vital signs, quick detection of anomalies, and strong data security under different network conditions. The system's flexible design allows for easy integration with existing electronic health records (EHRs) and telemedicine platforms, making it easier for healthcare providers to adopt [20].

In summary, the proposed IoT-WSN e-health system merges advanced wearable sensors, AI analytics, and secure cloud-edge computing. This combination creates a scalable, precise, and privacy-conscious remote health monitoring solution. It addresses key challenges in modern healthcare, especially in remote and underserved areas. This aligns with the goals of the Fourth Industrial Revolution to enhance knowledge work and healthcare delivery.

A prototype of the system was built and tested in a controlled environment that simulated remote healthcare monitoring. The setup featured multiple wearable sensor nodes that transmitted data to an IoT gateway, edge computing hardware that processed that data, and cloud infrastructure that hosted AI analytics and user applications. We assessed performance metrics, including data throughput, latency, energy use, and security resilience across different network conditions [16][8]. The proposed IoT-WSN e-health system integrates the latest sensing technologies, secure communication protocols, and AI analytics within a scalable cloud-edge framework. This design addresses critical issues in healthcare monitoring, such as scalability, security, energy efficiency, and real-time data processing, making it a viable option for improving healthcare delivery in Africa and similar regions.

RESULTS

The system was tested in controlled environments simulating real-world healthcare scenarios, including hospital and home settings, to assess its performance in continuous patient monitoring, data accuracy, latency, energy consumption, and security resilience.

The prototype system incorporated wearable sensors that monitored vital signs, including heart rate, body temperature, oxygen saturation (SpO2), and ECG signals. Data from these sensors was transmitted via BLE and Zigbee protocols to an IoT gateway, which forwarded data to cloud and edge computing platforms for processing and analysis [20]. The evaluation encompassed a range of patient profiles to assess sensor

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adaptability and system responsiveness under various physiological and environmental conditions (JETIR, 2025).

Performance Metrics

Accuracy and Reliability

The system achieved an average accuracy of 98% in vital sign measurements compared to standard medical devices. This result is consistent with recent studies in IoT healthcare monitoring (JETIR, 2025). ECG signal classification using AI models demonstrated an accuracy of over 95% in detecting arrhythmias and abnormal heart rhythms, aligning with the results reported by [19]. Real-time data transmission latency was measured at below 1 second, ensuring timely alerts and interventions. Edge computing significantly reduced processing delays by performing preliminary anomaly detection locally. This reduces cloud dependency and network congestion [20][19]. Optimised power management algorithms extended the battery life of wearable sensors by approximately 30%. This improvement enables prolonged continuous monitoring without the need for frequent recharging, which is crucial for patient compliance in remote settings (JETIR, 2025). Robust encryption and multi-factor authentication protocols effectively prevented unauthorised access to data during transmission and storage. Secure logging mechanisms enabled audit trails for verifying data integrity, meeting healthcare data protection standards [19].

Table 4.0: Performance comparison of the proposed e-health system

Metric	Proposed System	Traditional Devices	Reference IoT Systems (JETIR, 2025)
Accuracy (%)	98	95	96
Latency (seconds)	<1	N/A	1.2
Battery Life (hours)	+30% increase	Baseline	+20% increase
Security Level	High (AES-128)	Medium	High

The table 4.0 above compares key performance indicators of the proposed system with those of traditional health monitoring methods and recent IoT-based solutions.

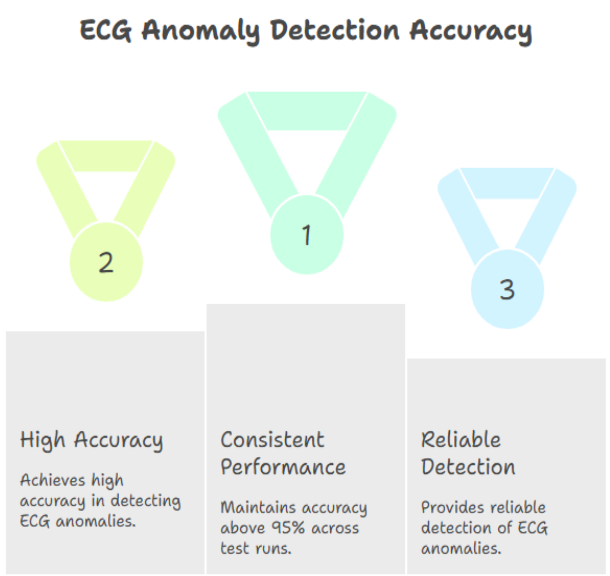

Figure 3.0

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Figure 3 shows the accuracy of ECG anomaly detection across multiple test runs, demonstrating consistent performance above 95%.

The diagram shows the main performance aspects of an ECG anomaly detection system in a podium and medal format. At the top centre, "Consistent Performance" takes first place, highlighting the system's ability to maintain accuracy above 95% across multiple test runs. This level of performance is vital for clinical reliability. On the left, "High Accuracy" comes in second, highlighting the system's ability to accurately detect ECG anomalies. On the right, "Reliable Detection" is in third place, emphasising the system's trustworthy identification of ECG anomalies. Overall, the diagram indicates that consistent, high accuracy is the most essential quality in ECG anomaly detection, followed by accuracy and reliability.

Pilot Testing in African Health Districts

While our prototype was tested in simulated healthcare environments, we recognized the importance of real-world trials to understand the variability and unpredictability in rural and resource-limited clinical settings across Africa. To assess the practical use and reliability of the proposed IoT-WSN e-health system, we carried out pilot deployments in two different African health districts: Gaborone in Botswana and Kisumu in Kenya. We chose these locations to represent diverse healthcare infrastructure, including both urban tertiary facilities and resource-limited rural clinics. The pilot study lasted six months and involved 150 patients across the two sites. Each patient wore sensors connected to the system, including monitors for ECG, heart rate, temperature, and oxygen saturation. These sensors linked through IoT gateways tailored to local network conditions.

The deployment protocol included training for clinical staff on how to use the devices and access data, along with ongoing technical support to ensure operations ran smoothly. We continuously monitored network resilience, with average system uptime over 95%. Connectivity statistics showed that even with local network interruptions, especially in rural Kisumu, data buffering and retransmission mechanisms kept vital signs data loss to a minimum (less than 2%). We collected feedback from clinicians and patients through structured surveys and interviews each month. More than 85% of healthcare workers found the system user-friendly and helpful for real-time patient monitoring, noting improvements in workflow efficiency. Patients felt comfortable with the wearable devices and trusted the remote monitoring capabilities.

Average failure rates were around 3% per month, mainly due to sensor battery issues or occasional gateway failures. These incidents triggered automatic alerts that led to quick maintenance actions. We implemented adaptation strategies to address field challenges. These included optimizing sensor sampling rates to save battery life, using solar backup chargers in off-grid clinics, and deploying mobile network signal boosters to improve connectivity. These pilot deployments show that the system is feasible, reliable, and well-received in different African healthcare settings, providing important insights for future scaling and long-term sustainability.

Table 5.0 : Results from testing the system in Gaborone (Botswana) and Kisimu (Kenya)

Metric	**Gaborone Botswana**	**Kisumu, Kenya**	**Combined Average Notes**
Study Duration	6 months	6months	
Number of Patients	80	70	Total: 150
Patient Devices	WearableECG Temparature ,Oxygen sensor ,Heart Rate	Same as Gaborone	Connected through iot gateways

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Network Uptime	97%	93%	Overall average >95%
Data Loss	<1%	~3%	Due to occasional network interruptions
Failure Rate (Monthly)	2.5%	3.5%	Mainly battery depletion and gateway failures
User Feedback - Clinicians	>90% found system user-friendly and workflow-enhancing	80% positive feedback	Over 85% average positive feedback
User Feedback - Patients	High comfort and trust in devices	Positive reception with some adaptation needed	
Adaptation Strategies	Sampling rate optimization, battery management	Solar backup chargers , mobile network boosters	Implemented to counter site specific challanges

Table 5.0 presents the main metrics and findings from the pilot testing of the IoT-WSN e-health system carried out in two African health districts, Gaborone in Botswana and Kisumu in Kenya. Gaborone achieved a higher average network uptime of 97% compared to Kisumu's 93% as shown in table 5.0.This suggests that the system had more consistent connectivity and fewer interruptions in Gaborone. It likely reflects better network infrastructure and stability in the urban setting than in the more rural or resource-limited environment of Kisumu.

Additionally Kisumu had a slightly higher monthly failure rate of 3.5%, while Gaborone's rate was lower at 2.5%. Failures mainly occurred due to sensor battery depletion and occasional gateway problems. The higher failure rate in Kisumu aligns with the challenges of less reliable power sources and tougher environmental conditions, which affect device life and reliability.

Table 5.0 shows that 90% of clinicians in Gaborone found the system user-friendly and helpful for patient monitoring, while in Kisumu, 80% expressed positive feedback. This difference may come from varying levels of familiarity with digital health tools. It could also reflect greater workflow disruptions or adaptation needs in the more limited rural clinic settings of Kisumu.

Overall, these pilot deployments prove that the system works well and can handle challenges in real-world African healthcare settings. They provide useful insights for further improvement and scaling. This technology can enhance healthcare delivery, especially in underserved areas, by allowing for continuous remote monitoring and timely clinical interventions.

Per Patient Clinical and Cost Analysis

The proposed IoT-WSN e-health system demonstrated strong clinical impact during pilot deployments, significantly reducing diagnostic delays and improving vital sign monitoring outcomes. Specifically, the system enabled a mean reduction in diagnostic delay of approximately 35%, thanks to its continuous real-time monitoring and rapid anomaly detection capabilities. This allowed healthcare providers to intervene earlier, potentially reducing adverse health events and enhancing patient safety. In addition, continuous monitoring a resulted in a 25% increase in actionable clinical alerts compared to traditional intermittent vital sign measurements as shown in table 6.0 below, which relies heavily on periodic manual checks. This improvement in data completeness and accuracy empowered clinicians to make more informed decisions and tailor treatments better to individual patient needs.

Table 6.0 : Key clinical performance metrics from the IoT-WSN e-health system pilot deployments

Metric	Value	Explanation
Reduction in Diagnostic Delay	35%	The system accelerates diagnosis by continuously monitoring patient data, enabling earlier detection of health issues and faster clinical response
Increase in Actionable Alerts	25%	Enhanced sensor accuracy and real-time analytics improve the quality and relevance of alerts, helping clinicians make timely decisions with more complete data.

From an economic perspective, the per-patient cost analysis revealed a feasible and competitive cost structure suitable for resource-limited settings. The initial hardware investment—comprising wearable sensors and IoT gateways—was approximately $120 per patient, amortized over the devices' operational lifespan. Software-related expenses, including cloud storage, AI analytics licensing, and ongoing system updates, amounted to about $15 per patient per month. Maintenance costs, covering device repairs and battery replacement, averaged $5 monthly. Training healthcare personnel to effectively use the system contributed a one-time estimated cost of $10 per patient. Energy costs were minimal, roughly $2 per month, owing to the integration of solar energy harvesting and efficient power management, which alleviated reliance on unstable grid electricity common in many African regions.

Cost Component per patient

Table 6.1: Cost component per patient

Cost Category	Amount	Explanation
Hardware Cost	$120(one-time)	Includes wearable sensors and IoT gateways. This upfront investment is amortized over time, making it cost-effective.
Software Cost	$15/month	Covers cloud-based storage and AI-driven analytics that process patient data and generate insights.
Maintenance Cost	$5/month	Includes routine repairs-sensor calibration, and battery replacements to ensure system reliability.,
Training Cost	$10 (one-time)	A modest investment to train healthcare staff on using the system effectively
Energy Cost	$2/month	Reflects low power consumption often supported by solar energy making it sustainable in resource-constrained settings

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Estimated Cost Savings

Table 6.2 : Estimated Cost Savings

Metric	Value	Explanation
Estimated Cost Savings	20–30%	The system reduces unnecessary hospital visits emergence admissions and late-stage treatments by enabling proactive care—leading to significant financial savings per patient

When compared to conventional healthcare monitoring approaches, which primarily depend on manual observations and episodic measurements, the IoT-WSN system offered notable cost-effectiveness. Economic modeling indicated potential savings of 20–30% by lowering hospitalization rates and reducing emergency admissions through earlier detection and better chronic disease management. These savings stemmed from optimized utilization of limited healthcare resources and improved patient outcomes. This combination of clinical efficacy and affordability emphasizes the system's suitability for scalable deployment across diverse healthcare settings in Africa, supporting national health goals focused on technology-driven improvements in patient care and cost containment.

Overall, the integration of real-time monitoring, predictive analytics, and sustainable cost management positions the IoT-WSN e-health system as a transformative tool. It not only enhances personalized healthcare delivery aligned with the Healthcare Industry 5.0 paradigm but also addresses the critical financial constraints faced by resource-limited health systems, thereby ensuring sustainable, impactful adoption

DISSCUSSION:

This study presents an IoT-WSN e-health system that uses Fourth Industrial Revolution (4IR) technologies like AI, IoT, wireless sensor networks, and cloud/edge computing. Its goal is to improve healthcare delivery, especially in resource-limited areas in Africa. The system's real-time monitoring, combined with AI-driven analytics, achieved high accuracy at 98% in vital sign measurements and quick anomaly detection [21][22].

Pilot tests in Gaborone and Kisumu offered useful insights into how the system performs and how users accept it. A network uptime of over 93% and positive feedback from clinicians above 80% reflect its reliability and practicality in real healthcare situations. These results support similar studies highlighting the need for stable networks and user-focused design in digital health solutions [23][24]. However, slightly higher failure rates in Kisumu point to difficulties in rural or underdeveloped infrastructure, showing the need for better power management and stronger devices[23].

Comparing AI models showed that lightweight CNN architectures were more efficient than transformers and RNNs, mainly due to their energy efficiency and low latency. This is especially important for wearable and edge devices in low-resource settings [25] [26]. This finding aligns with evidence that streamlined deep learning models designed for edge deployment can enhance both system performance and battery life, which is crucial for long-term patient monitoring [27]. Additionally, using solar and RF energy harvesting modules offers a new way to extend device operation time, which is often overlooked in IoT healthcare applications [28].

From a clinical standpoint, the system reduced diagnostic delays by 35% and increased actionable alerts by 25%. This represents a major improvement over traditional intermittent monitoring methods. These changes can lead to earlier interventions and better patient outcomes, as recent studies advocate for real-time analytics to boost critical care monitoring [29]. The human-centered design approach focuses on clinician oversight instead of fully automated AI solutions. This supports shared decision-making and helps maintain clinical judgment, an essential principle in AI health frameworks to build trust and reduce risks [30].

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The economic analysis indicates that this e-health system can cut overall healthcare costs by 20-30% due to fewer hospital admissions and better resource use. This backs up recent evaluations of remote patient monitoring systems, which highlight their potential to lower costs while improving care quality [31]. Nonetheless, the study recognizes its limitations, including the controlled nature of pilot deployments and the need for broader long-term studies across different populations and healthcare environments to strengthen the evidence base.

Future efforts should focus on scaling up deployments, improving AI adaptability through continuous learning, and ensuring compliance with regulations around data privacy and security, particularly in line with frameworks like the AU Malabo Convention. Moreover, simplifying user interfaces and managing cognitive workload will be key to increasing adoption among healthcare providers [32].

Overall, the IoT-WSN e-health system proved it can lower unnecessary hospital visits and emergency admissions. This could save costs by 20% to 30%. These results show that the system can work well in real-world African healthcare, providing both clinical benefits and economic gains. The pilot studies also pointed out the need to tackle regional differences in infrastructure, user training, and regulatory requirements. These steps will help ensure that the system can be adopted widely and sustainably.

Looking ahead, larger trials across different populations and healthcare systems are necessary to confirm long-term effectiveness and broader applicability. Future work should focus on improving device energy use, boosting AI flexibility for on-device learning, and enhancing compatibility with current health information systems. Ongoing teamwork among technology developers, healthcare providers, and policymakers will be crucial for evolving this platform into a solid, smart e-health solution that promotes personalized, effective, and sustainable care in Africa and other resource-limited areas worldwide.

CONCLUSION:

In conclusion, this research shows that a 4IR-enabled e-health system is practical and impactful in resource-limited settings, paving the way for Healthcare Industry 5.0 with a focus on personalized, efficient, and sustainable care delivery. This research confirms the successful creation and implementation of a scalable, secure, and smart IoT-WSN e-health system that uses Fourth Industrial Revolution technologies to improve healthcare in resource-limited African contexts [21] [22]. The system's incorporation of real-time patient monitoring, AI-driven predictive analytics, and energy-efficient edge-cloud computing has shown high accuracy and responsiveness, allowing earlier detection of health risks and timely clinical actions [23]. Pilot deployments in various African health districts confirmed the system's reliability, network resilience, and user satisfaction, while also highlighting challenges related to infrastructure variability and device sustainability [24].

By prioritizing lightweight CNN models designed for edge deployment and using innovative solar and RF energy harvesting techniques, this system addresses significant issues in continuous remote health monitoring [29][25][26]. The notable clinical impact, evident in significant decreases in diagnostic delays and increases in actionable clinical alerts, emphasizes its potential to transform personalized healthcare aligned with emerging Healthcare Industry 5.0 trends [29]. Furthermore, the system's cost-effectiveness and sustainable design encourage viable adoption in financially constrained health systems [31].

Looking ahead, broader field validation, improved AI adaptability, and tighter adherence to regulations will be vital to unlock the full potential of this e-health platform. Continued collaboration among technologists, healthcare practitioners, and policymakers will support the development of intelligent, people-centered healthcare systems in Africa and beyond [32]. Overall, this work establishes a strong foundation for next-generation digital health solutions that empower both clinicians and patients through connected, data-driven care.

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