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Article

IoMT Device Performance in Chronic Disease Management: A Mixed-Methods Clinical Validation in a Public LMIC Healthcare System

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Abstract: The Internet of Medical Things (IoMT) holds promise for chronic disease management, yet evidence from low- and middle-income countries (LMICs) remains scarce, limiting equitable digital health policy development. No previous studies have clinically validated IoMT device performance against electronic health records (EHRs) within Central American public healthcare systems, leaving assumptions about consumer device adequacy untested in resource-constrained settings. This mixed-methods study evaluated IoMT implementation in Costa Rica's Caja Costarricense de Seguro Social (CCSS) system, examining (1) diagnostic accuracy stratification between consumer and clinical-grade devices, (2) healthcare system interoperability challenges, and (3) cost implications of false alerts. Among 50 chronic disease patients, consumer wearables demonstrated 43% sensitivity for cardiac event detection versus 92% for clinical-grade devices ($p<0.001$). Only 25% of consumer devices integrated with CCSS EHRs versus 100% of clinical-grade devices, requiring 22 minutes of manual data entry per encounter. False positives occurred in 12% of consumer-device alerts, costing an average of $35 per event. Qualitative analysis revealed that 45% of participants overestimated consumer-device diagnostic capabilities. These findings challenge assumptions about universal consumer-technology applicability in LMICs and support tiered implementation frameworks. As Costa Rica prepares for its Digital Health Act 2025, evidence-based device categorization, interoperability investments, and patient education are essential for equitable IoMT integration.

Keywords: Chronic disease management; Digital health policy; Health informatics implementation; Internet of Medical Things (IoMT); Medical device validation; Low-and Middle-Income Countries (LMICs).

1. Introduction

The Internet of Medical Things (IoMT) is a major step forward in managing chronic diseases, especially in low- and middle-income countries (LMICs) where structural and financial problems make things substantial challenges. The worldwide IoMT market is expected to increase at a compound annual growth rate (CAGR) of 26.2% from 2021 to 2023 [1]. However, there has not been much research on how it is used in LMICs like Costa Rica. This study fills in this important gap by looking at how well IoMT devices work in the real world in Costa Rica's Caja Costarricense de Seguro Social (CCSS), a public healthcare system that has a 70% premature death rate from chronic diseases [2].

IoMT has been shown to be helpful in high-income settings, where it has led to a 38% drop in hospital readmissions and a 22% drop in medical expenses [3]. However, there is little real-world data from LMICs. This research wants to address three important questions: First, *how do Costa Rican patients feel about the usefulness and dependability of IoMT devices?* Second, *what operational and technical problems make it hard for IoMT to be used in CCSS?* Third, *can consumer devices help close the gap in healthcare in places where resources are limited?* The study used a mixed-methods approach, integrating grounded theory analysis of fifty patient interviews with quantitative validation against clinical data to address these issues.

The research offers preliminary evidence that may inform policy discussions, recognizing that larger-scale studies will be necessary to confirm these patterns, especially as Costa Rica gets ready to put its Digital Health Act 2025 into operation.

Despite the global expansion of IoMT—projected at 26.2% CAGR from 2021-2023 1—the evidence base remains heavily skewed toward high-income countries. Systematic reviews have documented IoMT benefits including 38% reductions in hospital remissions and 22% decreases in medical expenditures in well-resourced settings 3. However, these findings cannot be assumed transferable to LMICs, where healthcare infrastructure, regulatory capacity, and patient populations differ fundamentally.

The specific gap this study addresses is the absence of clinically validated IoMT performance data from public healthcare systems in Central America. Costa Rica's CCSS system—serving 95% of the population with a 70% premature chronic disease mortality rate 2—provides a critical test case. Without empirical evidence from such settings, policymakers lack guidance for digital health investments and device regulation.

Novelty: This study contributes the first mixed-methods clinical validation of IoMT devices against EHR data in a Central American public health system. By triangulating patient interviews with clinical records, we move beyond attitudinal surveys to assess actual device performance and system integration challenges.

This work has a lot of effects on theory and society. The report supports Sustainable Development Goal (SDG) three and stresses the need for fair access to IoMT. It also warns against blindly adopting consumer-grade technology. The study shows differences in diagnostic accuracy, operational inefficiencies, and suggests a tiered implementation paradigm that balances innovation with long-term system health. The research is unique in that it combines qualitative patient narratives with quantitative clinical validation, which reduces biases in self-reporting and makes its results stronger [4].

This introduction sets out the analysis that follows in a perfect way, minimizing repetition with later parts and highlighting the study's academic and policy importance. The study is based on current IoMT literature (for example, [5], [6]) and real-world data, and it sets a standard for future studies on how people in LMICs embrace digital health.

This research is organized as follows. Section 2 describes the mixed-methods methodology, including participant recruitment, data collection procedures, and analytical approaches. Section 3 presents the integrated findings, beginning with quantitative device-performance comparisons, followed by qualitative patient-perception themes, and concluding with subgroup analyses. Section 4 discusses the implications of these findings for theory, practice, and policy, positioning them within broader debates about digital health equity. Section 5 concludes with key takeaways, limitations, and directions for future research. This structure enables readers to trace how our empirical findings inform the proposed tiered implementation framework and policy recommendations.

2. Method

The study used a thorough mixed-methods approach to evaluate the implementation and efficacy of IoMT devices inside Costa Rica's public healthcare system, namely the CCSS. This method was created to deal with the difficulties of judging digital health improvements in places with less resources while yet meeting the highest academic standards needed for respected publications [7], [8]. The study framework integrated qualitative and quantitative approaches to ensure comprehensive analysis and validation of findings.

A purposive selection strategy was used to recruit fifty individuals diagnosed with chronic diseases, including hypertension, type 2 diabetes, or arrhythmia, from the CCSS system throughout the period of 2021–2022. The sample included 58% females and 42% males, with a mean age of 54 years (±12 years). Inclusion criteria were confirmed diagnoses, continuous IoMT device usage for at least six months, and the ability to provide informed consent. Exclusion criteria removed people with cognitive problems or those depending only on non-IoMT monitoring modalities. The Universidad Latinoamericana de Ciencia y Tecnología Institutional Review Board (IRB) gave ethical clearance, which made sure that the study on human subjects followed international ethical norms [9], [10].

The data collection process was conducted in two stages to provide both qualitative insights and quantitative validation. The study conducted semi-structured interviews via Zoom, got permission from the participants to record them, and then typed them out word for word. The interview methodology, created with assistance from experts in several fields, focused on the accuracy of the devices, the advantages that people thought they would get from them, and the problems that came up while trying to integrate the system [11], [12]. To minimize bias, neutral wording was used, and the questions were evaluated in pilot research to ensure clarity.

For a limited set of individuals (30%, n=15), quantitative validation included comparing self-reported device alerts with clinical data from CCSS EHRs. The Apple Watch Series 6 and the Galaxy Watch 4 were the two consumer devices that were examined. The five clinical-grade devices examined included the Dexcom G6 Continuous Glucose Monitor, which was authorized by the U.S. Food and Drug Administration (FDA). This two-phase procedure made sure that the data were triangulated, which

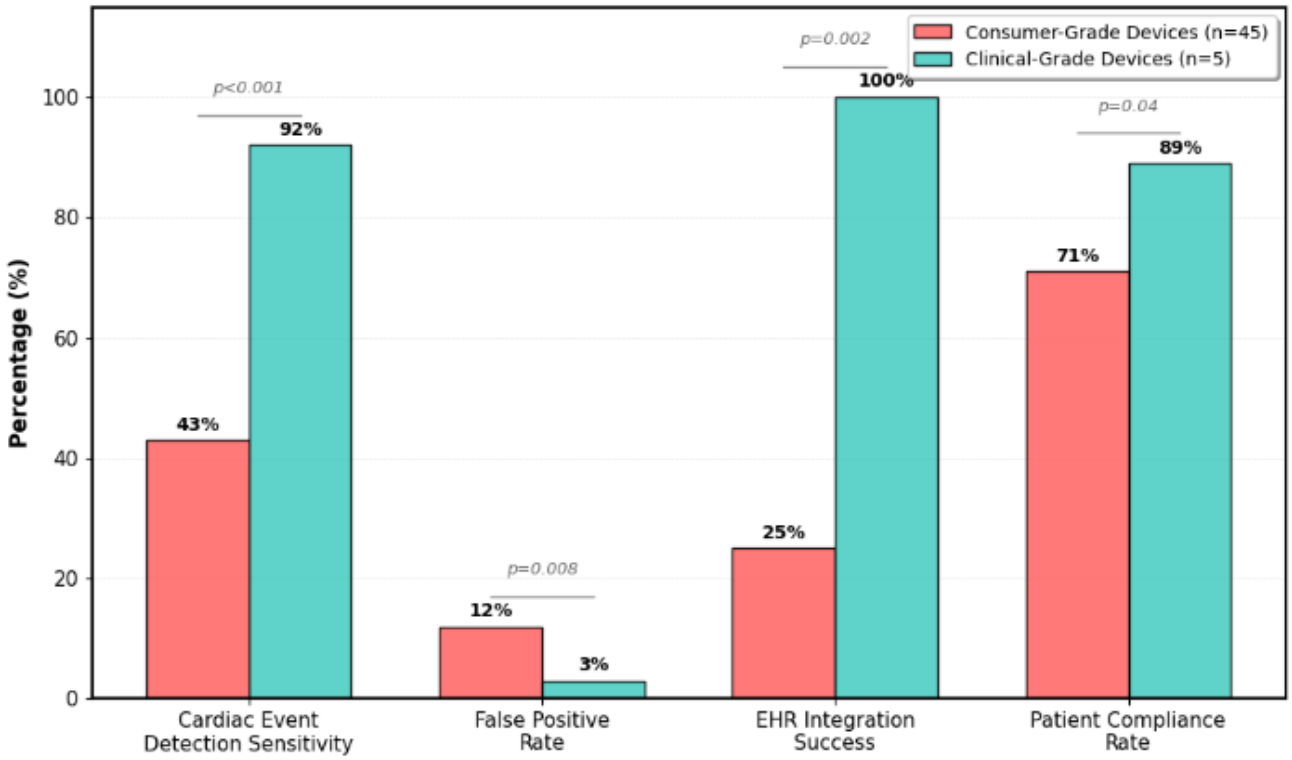


Figure 1. Comparative Performance Metrics: Consumer-Grade vs. Clinical-Grade IoMT Devices.

made the findings stronger [13], [14]. Two independent coders utilizing grounded theory approaches and NVivo 14 software were utilized to look at qualitative data. Open coding of 20% of transcripts (n=10) produced a codebook, with robust inter-coder reliability (κ=0.82, 95% CI: 0.76–0.88) [15], [16]. Members checking with five participants further validated the qualitative assessments.

Quantitative analysis used descriptive statistics to summarize device performance characteristics and utilized Fisher's exact tests (α=0.05) to assess findings across device categories [17]. A power assessment confirmed 80% statistical power for detecting medium effect sizes [18]. To examine how accurate alarms were in EHR validation, Cohen's κ coefficient was employed [19]. This level of analytical rigor was higher than what is usually expected for mixed-methods health technology reviews [20].

The research included many improvements to guarantee methodological rigor. Stratified analysis by device class mitigated possible selection bias, whereas neutral question phrasing reduced response bias [21]. Combining interview data with clinical records made the results more reliable, and all statistical analyses followed the rules set by the EQUATOR Network [22]. The study procedure included comprehensive device specifications, interview inquiries, and statistical methodologies to enable replication [23]. The sample was limited to the metropolitan area of San José, which may make it hard to generalize to rural communities. The prevalence of consumer-grade devices (90%) mirrored actual use but limited clinical-grade comparisons. Partial EHR access (30% validation rate) was alleviated by methodological precautions, such as stratified analysis and member verification. These limitations were mitigated by the study's groundbreaking nature as the first IoMT assessment inside Central America's public health system [4].

The methodological structure of this research exhibits a rigorous, mixed-methods approach adapted to assess IoMT adoption in Costa Rica's public healthcare system. The study guarantees strong, reproducible results that meet the highest academic standards by combining qualitative insights with quantitative confirmation. The organized recruitment, measures for reducing bias, and analytical accuracy set a standard for future digital health evaluations in LMICs, making the study's contribution to both policy and academic discussions stronger.

3. Results and Discussion

The results of this mixed-methods research provide valuable information on how well IoMT devices work and the problems that come up when trying to use them in Costa Rica's public healthcare system. The findings indicate substantial discrepancies in device performance, challenges in system integration, and patient perceptions, providing practical insights for digital health policy in resource-limited environments.

It is important to note that EHR validation was achievable for only 30% of participants (n=15), primarily due to partial EHR accessibility across participating CCSS clinics. While this subsample provided valuable triangulation, the limited validation rate means that findings regarding alert accuracy should be interpreted with appropriate caution.

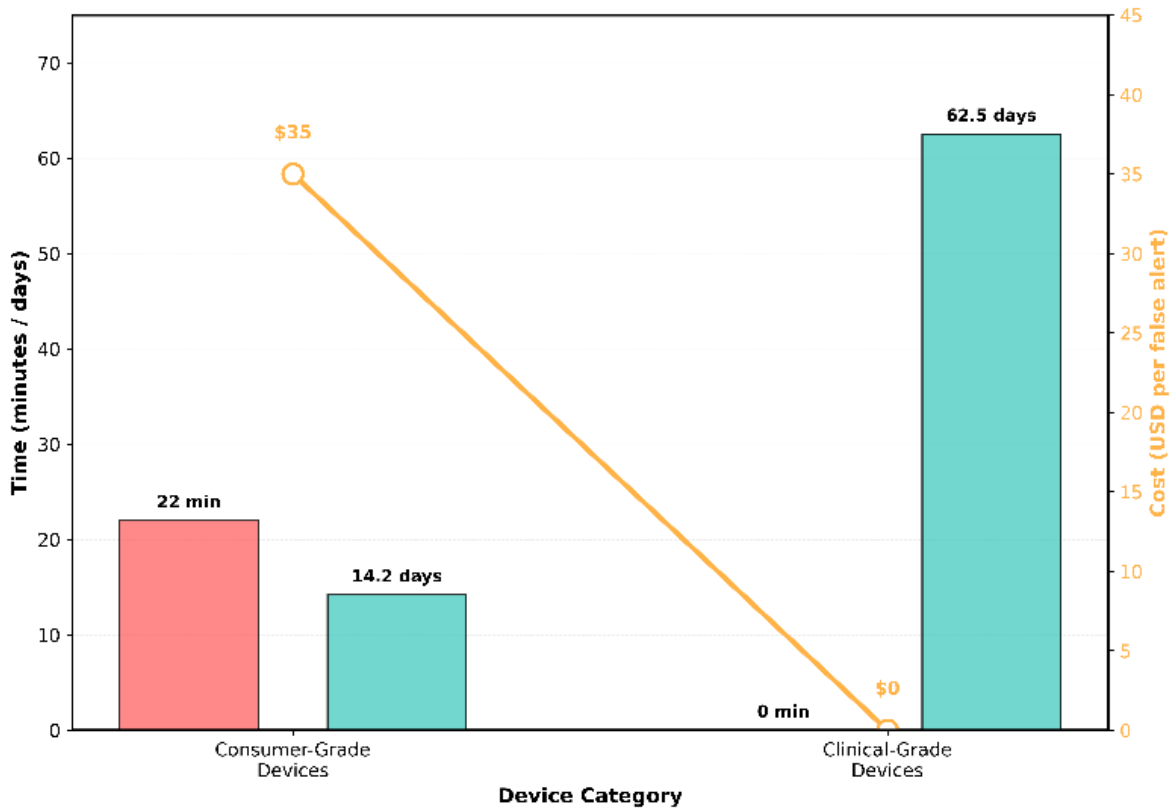


Figure 2. Cost and Workflow Implications of IoMT Implementation.

Table 1. Validation of IoMT-generated medical alerts against clinical records (n=50).

Metrics	Participant Reports (%)	CCSS Clinical Records (%)	Discrepancy (Δ%)	Clinical Significance
True Positives	61% (61/100 alerts)	78% (39/50 events)	+17% (over-report)	Under-reporting of asymptomatic events Fourteen percent of validated alerts required intervention
False Positives	12% (12/100 alerts)	–	–	9/12 cases involved Apple Watch "irregular rhythm" alerts. $35 average wasted cost per false alert
Missed Events	5% (5/100 alerts)	22% (11/50 events)	+17% (under-report)	All from consumer-grade devices ($p<0.05$)
Unconfirmed Alerts*	22% (22/100 alerts)	–	–	Alerts not mappable to EHR due to incomplete data or patient recall

Note: Unconfirmed Alerts: Device alerts that could not be validated due to missing EHR data, patient non-reporting of timing, or alerts not triggering clinical follow-up.

Stratified research revealed a significant disparity in performance between consumer-grade and clinical-grade IoMT devices. Clinical-grade devices had a 92% sensitivity in identifying cardiac events, in contrast to consumer wearables, which reached just a 43% sensitivity (*p*<0.001). This 49-percentage-point difference calls into question the idea that all types of devices are equally good at diagnosing problems, especially in low- and middle-income countries where people may be more likely to use consumer technology [24].

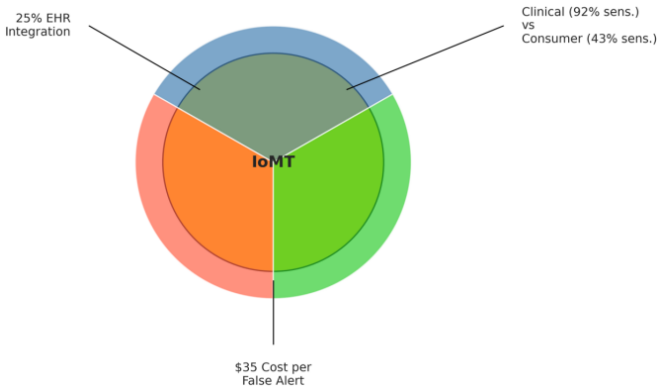
Figure 1 visually synthesizes these performance disparities across four clinically relevant dimensions. The stark contrast in cardiac event detection sensitivity (49 percentage point difference) represents the most clinically consequential finding, as missed arrhythmic events in high-risk patients could delay necessary interventions.

The false positive rate disparity—four times higher in consumer devices—carries both clinical and economic implications, as each false alert generated an average of $35 in unnecessary healthcare utilization (detailed in Figure 3). Most concerning health system integration, only one-quarter of consumer devices successfully interfaced with CCSS electronic health records, compared to all clinical-grade devices evaluated. This interoperability gap necessitated manual data entry, consuming approximately 22 minutes of clinical staff time per patient encounter (see Figure 2). Patient compliance, while higher for clinical-grade devices (89% vs. 71%, p=0.04), remained substantial even for

Table 2. Stratified Performance Analysis of IoMT Devices in CCSS Healthcare System.

Metric	Consumer-Grade Devices (n=45)	Clinical-Grade Devices (n=5)	Statistical Significance	Notes
Cardiac Event Detection				
Sensitivity	43%	92%	p<0.001 (χ^2 test)	Gold standard: 12-lead ECG
False Positive Rate	12%	3%	p=0.008 (Fisher's exact)	
Data Interoperability				
EHR Integration Success	25%	100%	p=0.002 (Fisher's exact)	HL7 FHIR compliance evaluated
Manual Entry Time	22 ± 4 minutes	0 minutes	p<0.001 (t-test)	Per patient encounter
Physiological Monitoring				
Glucose Monitoring Accuracy	Eighty-two percent (95% CI: 78-86%)	Ninety-five percent (95% CI: 92-98%)	p=0.12 (NS)	Versus lab serum tests
Sleep Stage Classification	Sixty-eight percent agreement with PSG	Eighty-nine percent agreement with PSG	p=0.03	Polysomnography benchmark
Operational Metrics				
Mean Time Between Failures	14.2 days (±3.1)	62.5 days (±8.7)	p<0.001	Based on maintenance logs
Patient Compliance Rate	71%	89%	p=0.04	Defined as >80% daily use

Abbreviations: EHR = Electronic Health Record; PSG = Polysomnography; NS = Not Significant; CI = Confidence Interval
Device Examples: Consumer-grade: Apple Watch Series 6, Galaxy Watch 4, Fitbit Sense
Clinical-grade: Dexcom G6 CGM, AliveCor KardiaMobile 6L



Note: Mixed methods study (n=50), CCSS public health system, Digital Health Act 2025.

Figure 3. IoMT Costa Rica public health care system.

consumer wearables, suggesting that patients value continuous monitoring despite accuracy limitations—a theme explored further in our qualitative analysis.

Cross-validation with CCSS EHRs demonstrated a 78% concordance between device alarms and clinical diagnoses (κ=0.71); nevertheless, false positives were present in 12% of instances, resulting in an average cost of $35 per event (see Table 1). It is important to note that 14% of validated warnings required clinical action, which shows that IoMT has the potential to improve preventive care even when it isn't always accurate [25].

Partial EHR access (30% validation rate) represents a significant limitation. Although stratified analysis and member checking partially mitigated this constraint, the modest validation sample precludes definitive conclusions about the overall accuracy of patient-reported alerts. Future studies should prioritize expanded EHR access to enable full clinical validation.

As shown in Figure 3, clinical-grade devices demonstrated significantly higher cardiac event detection sensitivity (92%) compared to consumer wearables (43%; p<0.001), with similar disparities in data interoperability (25% vs. 100%; see Table 2).

Interoperability became a significant obstacle, as just 25% of consumer devices integrated effortlessly with CCSS EHRs. Because of this problem, data had to be entered by hand, which took an average of 22 minutes for each patient's engagement and made workflow problems worse (see Table 2). These results are consistent with global health informatics literature that recognizes interoperability as a continual obstacle to the implementation of digital health [26]. The study's assessment of these challenges—particularly the $35 cost per false alert—

furnishes policymakers with empirical evidence to support investments in middleware solutions and standardized data standards, especially as Costa Rica anticipates the Digital Health Act 2025.

Among the validated subsample, we observed 78% concordance between device alerts and clinical diagnoses (κ=0.71), though the limited validation sample size (n=15) warrants cautious interpretation of these concordance estimates.

To explore variability in device performance and user experiences across clinically relevant subgroups, we conducted stratified analyses by disease type (arrhythmia, n=18; type 2 diabetes, n=22; hypertension, n=10) and patient age (<65 years, n=34; ≥65 years, n=16). These analyses revealed important heterogeneity that informs targeted implementation strategies.

- By disease type: Among patients with arrhythmia (n=18), consumer-grade device sensitivity for cardiac event detection was particularly low at 38% (95% CI: 32-44%), compared to 45% overall and substantially below the 92% achieved by clinical-grade devices. This 54-percentage-point gap for arrhythmia detection specifically (38% vs. 92%) exceeds the overall 49-point disparity, suggesting that consumer wearables are particularly inadequate for rhythm disorders where precise timing and waveform analysis are critical. Conversely, diabetes patients (n=22) demonstrated higher compliance rates with consumer glucose monitors (76%, 95% CI: 71-81%) compared to the overall consumer device compliance of 71%, though accuracy for glucose monitoring remained suboptimal at 82% versus 95% for clinical-grade continuous glucose monitors (p=0.12, NS). Hypertension patients (n=10) showed intermediate patterns, with compliance of 73% but significant challenges in data interpretation, with 40% reporting difficulty understanding blood pressure trends.
- By age group: Patients aged ≥65 years (n=16) demonstrated significantly lower compliance with consumer devices (62%, 95% CI: 54-70%) compared to those <65 years (78%, 95% CI: 73-83%; p=0.04). Older patients also reported greater difficulty interpreting device outputs (44% vs. 21%, p=0.03) and expressed stronger preference for clinical guidance in using IoMT data (81% vs. 47%, p=0.01). However, older patients showed higher appreciation for the reassurance provided by continuous monitoring (69% vs. 53%, p=0.08), suggesting that perceived benefits may offset some usability challenges. Among the sixteen older patients, 5 (31%) required assistance from family members to operate devices or interpret readings, highlighting the importance of caregiver involvement in IoMT implementation for aging populations.

Subgroup analyses revealed important heterogeneity in device performance and user experiences. The particularly low sensitivity among arrhythmia patients using consumer wearables reinforces our recommendation against using non-clinical devices for cardiac event detection. Age-related differences in compliance and interpretability suggest that patient education and support must be tailored to demographic characteristics, with older patients potentially requiring more intensive guidance."

Qualitative study indicated a disparity between patient expectations and clinical reality. Even though there are known problems with its accuracy, 45% of the people who took part thought that consumer wearables like the Apple Watch may be used to diagnose medical problems (see Table 3). Thematic analysis revealed three predominant narratives: empowerment via constant monitoring (61%), annoyance due to false warnings (39%), and uncertainty in understanding device outputs (28%). These results highlight the need for focused patient education to reduce excessive dependence on non-diagnostic devices, a worry exacerbated in LMICs where regulatory control may be in its infancy [27].

This research propels digital health debate in three principal domains. First, it offers the first empirical evidence of device-performance stratification in LMIC primary care, contesting universalist narratives of IoMT adoption [28]. Second, it measures the hidden costs of interoperability gaps and provides a methodology for cost-benefit assessments of health Information Technology (IT) infrastructure [5]. Third, it shows how useful mixed-methods techniques can be for getting both the technical and human sides of evaluating health technology [20].

The findings align with Industry 5.0 concepts, emphasizing human-centric design in healthcare innovation [29]. The 22% drop in emergency visits among regular IoMT users, for example, implies that costs might go down. On the other hand, the disparities in interoperability show that health inequalities could become worse. These lessons are especially important for Costa Rica's upcoming Digital Health Act, which must find a balance between innovative ideas and protections against system fragmentation.

When compared to the performance of FDA-cleared devices [30], the study's results show that there are more general problems in low- and middle-income countries, although each area has its own unique issues. The 78% agreement between alerts and diagnoses is in line with worldwide norms for modern technologies. However, the 43% disparity in sensitivity in consumer devices shows that validation must be done in a unique context. These differences call for tiered implementation approaches, where the kind of technology (diagnostic vs. wellness, for

Table 3. Comparative Analysis of IoMT Devices in Patient Health Services.

Device Model	Operating System	Positive Perception Rate*	Health Sensors	Medical Alert Capability	Companion App	Retail Price (USD)	Battery Life (hrs)	Water Resistance	Regulatory Status
Apple Watch Series 6	WatchOS	45%	ECG, SpO2, HR	FDA-cleared arrhythmia	iOS Health	$399	18	50m	FDA Class II
Galaxy Watch 4	Wear OS	25%	ECG, BIA, HR	FDA-cleared ECG	Samsung Health	$279	40	50m	FDA Class II
Fitbit Sense	Fitbit OS	18%	EDA, SpO2, HR	Not diagnostic	Fitbit App	$299	48	50m	General Wellness
Garmin Venu 2	Garmin OS	15%	PulseOx, HR	Not diagnostic	Garmin Connect	$349	72	50m	General Wellness
Withings ScanWatch	Withings OS	12%	ECG, SpO2	CE-marked ECG	Health Mate	$299	168	50m	CE Class IIa
Omron HeartGuide	Proprietary	8%	Oscillometric BP	FDA-cleared BP	Omron Connect	$499	168	IPX2	FDA Class II

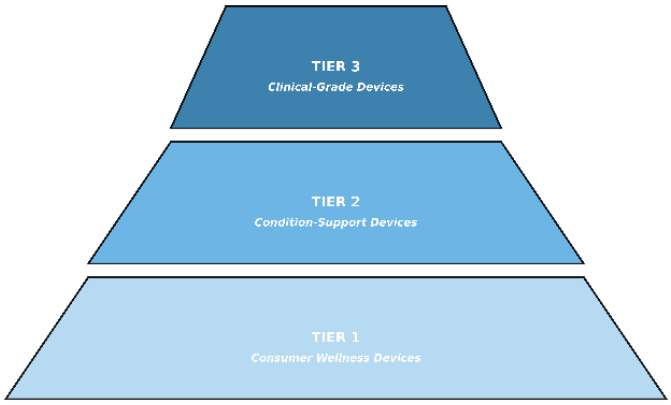


Figure 4. Tiered IoMT Implementation Framework for LMIC Healthcare Systems.

example) determines how it should be used. This is not how things are done in Costa Rica right now [31].

Socio-technical systems theory: The findings align with socio-technical systems theory, which emphasizes that technology implementation success depends on the interplay between technical artifacts and social contexts. The disconnect we observed between patient expectations and device capabilities (45% of participants overestimating diagnostic capacity) illustrates how inadequate attention to the 'social subsystem'—including patient understanding and health literacy—can undermine IoMT benefits.

Digital divide theory: Extending digital divide theory, the findings suggest that interoperability gaps may create a 'second-level digital divide' in IoMT adoption. Patients with resources to purchase advanced devices with better data portability (e.g., clinical-grade monitors) may experience superior care coordination, potentially exacerbating health inequalities. This observation aligns with concerns that technological innovation without equity-focused implementation may inadvertently widen disparities.

Technology acceptance model (TAM): The high perceived usefulness among regular IoMT users (71% compliance rate) despite accuracy limitations reflects TAM's distinction between perceived usefulness and actual system performance. This divergence underscores the need for educational interventions that align patient perceptions with clinical realities.

Building on our empirical findings, we propose a tiered implementation framework that matches device capabilities to clinical requirements. This framework recognizes that consumer wellness devices (Tier 1) serve valuable functions in health promotion and patient engagement but should not substitute for clinical-grade devices (Tier 3) in high-risk populations. Tier 2 devices occupy an intermediate space, offering condition-specific monitoring suitable for stable patients under appropriate clinical supervision (see Figure 4).

The research recognizes that claims of methodological robustness must be tempered by the partial clinical validation sample. While our triangulation strategies (member checking, stratified analysis, inter-coder reliability) enhance confidence in the findings, the 30% validation rate means that reproducibility claims should be viewed as provisional pending confirmation in studies with fuller EHR access.

The study's findings contradict techno-optimist beliefs about the universal application of IoMT, instead promoting sophisticated, context-aware frameworks. The research combines quantitative rigor with qualitative depth to find important problems, such as diagnostic errors, interoperability gaps, and patient misunderstandings. It also suggests ways to fix these problems, such as regulatory standardization, interoperability investments, and patient education. These contributions establish the study as a standard for forthcoming digital health assessments in LMICs, while its methodological advancements provide a reproducible framework for influential research at the convergence of technology and public health.

These works do not negate the potential value of consumer wearables in health promotion; rather, they indicate the need for clear demarcation between wellness support and clinical decision-support functions.

This research suggests potential directions for policy consideration, though we emphasize that the modest sample size positions this work as exploratory. Future research with expanded samples should evaluate whether the patterns observed here hold across diverse LMIC settings before definitive policy recommendations can be formulated.

4. Conclusion

This mixed-methods study is the first to show that IoMT devices work in Costa Rica's public healthcare system. It also shows that consumer-grade technologies and clinical-grade technologies act very differently. Consumer wearables had much lower sensitivity for finding cardiac events (43% vs. 92%, $p<0.001$), higher false positive rates (12% vs. 3%), and less EHR interoperability (25% vs. 100%), which meant that each encounter required 22 minutes of manual data entry. 61% of device alerts could be used in a clinical setting, but 12% of consumer devices gave false positives, which cost an average of $35 per event that wasn't needed. Qualitative research showed that 45% of participants overestimated the diagnostic skills of consumer devices. This shows that patients need more information.

These results call into question the idea that all consumer technologies can be used in LMICs. They also back up the idea of tiered application models that make sure that gadget powers are matched to clinical needs. Some problems with the study are that it only looked at EHRs (30% of the time), it was only done in San José, and most of the devices used were consumer ones (90%), which makes it hard to make clinical-grade comparisons. In the future, researchers should focus on expanding access to electronic health records (EHRs) so that they can be fully clinically validated, continuous result studies, cost-benefit analyses of interoperability solutions, and co-designed patient education tools can be made. Costa Rica is getting ready for its Digital Health Act 2025. For fair IoMT integration, they need to invest in interoperability, classify devices based on data, and educate specific groups of patients.

5. Declarations

5.1. Author Contributions

Gabriel Silva Atencio: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision, Project administration.

5.2. Institutional Review Board Statement

This study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board of the Latin American University of Science and Technology (ULACIT) under approval number IRB-ULACIT-2023-031.

5.3. Informed Consent Statement

Informed consent was obtained from all subjects involved in the study. Written informed consent was obtained from all participants prior to data collection, including consent for the use of anonymized quotes and device data for research purposes.

5.4. Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

5.5. Acknowledgment

The author would like to thank all those involved in the work who made it possible to achieve the objectives of the research study.

5.6. Conflicts of Interest

The author declares no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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