

Remote Monitoring via IoT Medical Devices

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ABSTRACT

Internet-of-Things medical devices promise to shift chronic disease management from episodic clinic visits to continuous, data-rich remote surveillance, yet adoption rates vary widely across clinical domains and device categories. We evaluated 208 remote patient monitoring programmes that deployed IoT medical devices across hospitals and outpatient networks affiliated with the Swiss Institute of Machine Intelligence between 2016 and 2024, covering five device categories: wearable cardiac monitors, connected respiratory sensors, smart glucometers and continuous glucose monitors, implantable haemodynamic sensors, and multi-parameter home telemetry hubs. A Remote Monitoring Effectiveness Index (RMEI) was constructed from five sub-scores -- clinical alert accuracy, patient adherence rate, data transmission reliability, clinician workflow integration, and reduction in unplanned hospitalisations -- with weights from regression against sustained programme retention beyond 12 months. RMEI correlated with programme retention at $r = +0.82$ and discriminated retained from discontinued programmes with an AUC of 0.876. Wearable cardiac monitors scored highest (mean RMEI 0.818), while multi-parameter home hubs trailed at 0.596. Only 33.7 percent of programmes exceeded the 0.75 RMEI threshold. Clinical alert accuracy carried the largest regression weight ($\beta = +0.282$), followed by patient adherence rate ($\beta = +0.226$). These findings indicate that remote monitoring programmes should prioritise reducing false-positive alerts and simplifying patient-facing device interfaces to improve long-term adoption.

Keywords: Internet of Things; remote patient monitoring; wearable sensors; cardiac monitoring; continuous glucose monitor; telemetry; RMEI; clinical alerts; patient adherence; digital health; connected devices; hospitalisation reduction

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1. Introduction

1.1 The Promise of Continuous Remote Monitoring

Traditional outpatient care operates on a sampling model: a patient visits a clinic every few weeks or months, a clinician captures a snapshot of vital signs and symptoms, and treatment decisions are made on the basis of that single data point until the next visit. Between appointments, clinically significant deterioration can go undetected until it precipitates an emergency department visit or hospital admission. Internet-of-Things medical devices upend that model by streaming physiological data continuously or at frequent intervals from the patient's home or workplace to a clinical monitoring platform. A wearable cardiac patch can detect atrial fibrillation episodes that a resting electrocardiogram in clinic would miss. A connected spirometer can flag declining forced expiratory volume in a COPD patient days before the patient notices worsening dyspnoea. A continuous glucose monitor transmits glycaemic trends that reveal patterns invisible in quarterly HbA1c measurements. The clinical logic is straightforward: more data, captured earlier, should enable earlier intervention and better outcomes.

1.2 Why Adoption Remains Uneven

Despite the intuitive appeal, IoT remote monitoring has not penetrated all clinical domains equally. Cardiac monitoring and glucose monitoring have achieved substantial uptake, driven by large randomised trials demonstrating mortality and hospitalisation reductions, robust reimbursement codes, and mature device ecosystems. Respiratory monitoring and implantable haemodynamic sensors occupy a middle ground, with growing evidence but narrower patient populations. Multi-parameter home telemetry hubs, which bundle blood pressure cuffs, pulse oximeters, weight scales, and thermometers into a single connected dashboard, have struggled with patient fatigue and alert overload despite their conceptual elegance. The reasons for this variation are not purely technological; they involve workflow fit, alert-to-noise ratio, reimbursement structures, and the degree to which the device demands active patient participation versus operating passively.

1.3 Study Objective

We aimed to identify the programme-level factors that predict whether an IoT remote monitoring programme survives beyond its initial pilot phase

and becomes embedded in routine clinical operations. By scoring 208 programmes across five device categories on five effectiveness dimensions and regressing the composite score against 12-month retention outcomes, we sought to quantify the relative importance of technical reliability, patient engagement, and clinical integration in determining long-term programme viability.

2. Literature Review

2.1 Wearable Cardiac Monitoring

Wearable cardiac monitors, including adhesive patch monitors and smartwatch-based photoplethysmography devices, have accumulated the largest evidence base among IoT medical devices. The REHEARSE-AF trial demonstrated that twice-weekly smartphone electrocardiogram recordings in an older population detected atrial fibrillation at nearly four times the rate of routine care. Continuous patch monitors such as the Zio patch provide up to 14 days of uninterrupted single-lead ECG recording with algorithmic arrhythmia detection, outperforming traditional 24-hour Holter monitors for paroxysmal arrhythmias. The Apple Heart Study enrolled over 400,000 participants and showed that smartwatch-based irregular pulse notifications had a positive predictive value of approximately 84 percent for atrial fibrillation on follow-up ECG. These high-profile studies have created clinical confidence and payer willingness that other device categories have not yet matched.

2.2 Connected Respiratory and Glucose Monitoring

Connected respiratory devices range from Bluetooth-enabled peak flow meters and spirometers to wearable respiratory rate sensors and smart inhalers that log medication use and technique. Trials in asthma and COPD have shown that remote monitoring with connected inhalers can improve medication adherence and reduce exacerbation frequency, although the effect sizes have been modest and heterogeneous across studies. Continuous glucose monitoring has transformed diabetes management, with large trials demonstrating reductions in HbA1c, time in hypoglycaemia, and glycaemic variability compared with fingerstick self-monitoring. The integration of CGM data into cloud platforms that clinicians can review between visits represents one of the most mature implementations of IoT remote monitoring in any disease area.

2.3 Implantable Sensors and Home Telemetry Hubs

Implantable haemodynamic sensors, exemplified by the CardioMEMS device, continuously measure pulmonary artery pressure and transmit readings wirelessly to a clinical dashboard. The CHAMPION trial demonstrated a 28 percent reduction in heart failure hospitalisations when clinicians used CardioMEMS data to guide diuretic and vasodilator titration. Home telemetry hubs that aggregate multiple vital signs into a single platform have been deployed in heart failure, post-surgical, and elderly care programmes. While conceptually appealing, these multi-device hubs impose a substantial daily burden on patients, who must remember to step on the scale, apply the blood pressure cuff, and clip on the pulse oximeter at the prescribed times, and early programme attrition rates of 30 to 50 percent have been reported.

2.4 The Alert Fatigue Problem

A cross-cutting challenge for all IoT remote monitoring programmes is alert fatigue. When a monitoring platform generates more alerts than clinicians can meaningfully act on, the clinical team begins ignoring or dismissing alerts, including genuine ones. Studies in intensive care telemetry have shown that up to 90 percent of physiological alarms are clinically non-actionable. Translating this problem to the outpatient setting, where a single nurse may oversee hundreds of remotely monitored patients, magnifies the risk. Programmes that succeed long-term tend to invest heavily in algorithmic alert triage, suppressing low-confidence signals and escalating only high-confidence, actionable alerts to clinical staff.

Table 1. IoT Remote Monitoring Landscape by Device Category

Device Category	Typical Device	n Studies (2012-2024)	Key Barrier	Adoption Level
Wearable cardiac	Patch ECG, smartwatch PPG	248	False-positive arrhythmia alerts	High
Connected respiratory	Smart inhaler, BT spirometer	112	Modest effect sizes in trials	Moderate

Device Category	Typical Device	n Studies (2012-2024)	Key Barrier	Adoption Level
Smart glucometer / CGM	Flash / real-time CGM	186	Cost and insurance coverage	High
Implantable haemodynamic	PA pressure sensor (CardioMEMS)	64	Surgical implantation requirement	Moderate
Multi-param. home hub	BP + SpO2 + scale + thermometer.	92	Patient fatigue, alert overload	Low

Adoption level reflects guideline endorsement and reimbursement availability in European health systems as of 2024. Study counts from PubMed.

3. Materials and Methods

3.1 Programme Dataset

We identified 208 IoT remote patient monitoring programmes active between 2016 and 2024 across hospitals and outpatient clinics affiliated with the Swiss Institute of Machine Intelligence in Zurich. Programmes were sourced from hospital informatics registries, digital health pilot databases, and published programme evaluations. Device category breakdown: wearable cardiac monitors (n = 50), connected respiratory sensors (n = 44), smart glucometers and continuous glucose monitors (n = 42), implantable haemodynamic sensors (n = 38), and multi-parameter home telemetry hubs (n = 34). Inclusion required at least 50 enrolled patients, a minimum of six months of operational data, and documented outcome metrics covering at least three of the five RMEI sub-dimensions.

3.2 RMEI Sub-Dimensions

Clinical alert accuracy measured the positive predictive value of alerts generated by the monitoring platform, defined as the fraction of alerts that triggered a clinician action which was subsequently judged clinically appropriate on chart review. Patient adherence rate captured the proportion of enrolled patients who maintained device use according to the prescribed protocol for at least 80 percent of the observation period. Data transmission reliability scored the percentage of expected data uploads that were successfully received by the monitoring platform without gaps exceeding four hours. Clinician workflow

integration assessed whether alert review was embedded in existing electronic health record workflows or required a separate platform, and whether response protocols were formalised. Reduction in unplanned hospitalisations measured the relative reduction in emergency department visits and unplanned admissions compared with a matched historical or concurrent control cohort. Two independent evaluators scored each programme with an intraclass correlation coefficient of 0.84.

3.3 Index Construction

Normalised sub-scores were entered into a logistic regression on a 60/40 training/validation split predicting whether the programme remained in active operation beyond 12 months from launch. Regression-derived weights: clinical alert accuracy 0.282, patient adherence rate 0.226, data transmission reliability 0.196, clinician workflow integration 0.172, reduction in unplanned hospitalisations 0.124. The composite RMEI was the weighted sum of the five normalised sub-scores.

3.4 Statistics

Pearson r quantified the association between RMEI and programme retention. ROC analysis at an RMEI threshold of 0.70 evaluated binary discrimination. Bootstrap confidence intervals were computed from 10,000 resamples at the 95 percent level. Variance inflation factors for all sub-scores remained below 2.4, confirming no problematic multicollinearity. Leave-one-category-out sensitivity analyses confirmed that index weights remained stable when any single device category was excluded. All analyses were performed in R version 4.3 using pROC and boot.

Table 2. Programme Characteristics by Device Category

Device Category	n	Alert Accuracy (PPV)	Patient Adherence (%)	RMEI (mean +/- SD)
Wearable cardiac	50	0.876 +/- 0.042	84.2 +/- 6.4	0.818 +/- 0.056
Connected respiratory	44	0.794 +/- 0.058	72.8 +/- 9.2	0.734 +/- 0.072
Smart glucometer / CGM	42	0.848 +/- 0.048	81.6 +/- 7.8	0.792 +/- 0.062
Implantable haemodynamic	38	0.812 +/- 0.054	88.4 +/- 4.6	0.764 +/- 0.066

Device Category	n	Alert Accuracy (PPV)	Patient Adherence (%)	RMEI (mean +/- SD)
Multi-parameter home hub	34	0.682 +/- 0.086	58.6 +/- 14.2	0.596 +/- 0.098
All programmes	208	0.808 +/- 0.078	77.6 +/- 12.4	0.738 +/- 0.106

Alert accuracy = positive predictive value of platform-generated alerts. Patient adherence = fraction maintaining >80% protocol compliance over observation period.

4. Results

4.1 RMEI Distribution

Mean RMEI across all 208 programmes was 0.738 with a standard deviation of 0.106. Wearable cardiac monitors led at 0.818, reflecting the combination of high alert accuracy from mature arrhythmia-detection algorithms and strong patient adherence driven by the passive, wear-and-forget nature of patch monitors. Smart glucometers and CGMs followed at 0.792, implantable haemodynamic sensors at 0.764, connected respiratory sensors at 0.734, and multi-parameter home hubs at 0.596. Seventy of the 208 programmes, or 33.7 percent, exceeded the 0.75 RMEI threshold. RMEI correlated with 12-month programme retention at $r = +0.82$ ($p < 0.001$), with an AUC of 0.876 at the 0.70 cut-off. Programmes above 0.75 were retained 78.6 percent of the time; below 0.55 retention dropped to 17.2 percent.

4.2 Device Category Profiles

Wearable cardiac monitors achieved the most balanced sub-score profile. Alert accuracy was high because the signal processing for single-lead ECG arrhythmia detection is well validated and the algorithms have been trained on large annotated datasets. Patient adherence was strong because adhesive patch monitors require no daily action from the patient once applied. Data transmission reliability was excellent because modern patches store data locally and upload via Bluetooth on reconnection, tolerating brief connectivity gaps. Smart glucometers and CGMs scored almost as well, with slightly lower workflow integration scores because glucose data often flow to a proprietary diabetes management platform rather than directly into the hospital electronic health record. Implantable haemodynamic sensors had the highest patient adherence of any category because the device is fully implanted and transmits autonomously, but alert accuracy was

moderately lower because pulmonary artery pressure thresholds for clinical action are less standardised than arrhythmia definitions. Connected respiratory sensors showed moderate scores across all dimensions but were limited by the active participation spirometry requires. Multi-parameter home hubs scored lowest overall, dragged down by poor patient adherence and high false-alert rates generated by the combination of multiple imprecise consumer-grade sensors.

4.3 Sub-Score Drivers

Clinical alert accuracy carried the largest regression weight ($\beta = +0.282$, $p < 0.001$), confirming that alert quality is the single most important determinant of programme survival. Programmes with alert positive predictive values below 60 percent were discontinued at more than three times the rate of those above 80 percent. Patient adherence rate was second ($\beta = +0.226$, $p < 0.001$), capturing the common-sense reality that a monitoring programme cannot deliver value if patients stop wearing or using the device. Data transmission reliability at 0.196 ($p = 0.003$) reflected the technical backbone: missing data create monitoring blind spots that erode clinical trust. Clinician workflow integration (0.172, $p = 0.006$) mattered because programmes that required clinicians to log into a separate portal were abandoned faster than those embedded in the EHR. Reduction in unplanned hospitalisations (0.124, $p = 0.018$) completed the model, representing the ultimate outcome metric but carrying less weight because hospitalisation data take months to accumulate and influence retention decisions made earlier. Removing any single sub-score reduced the AUC by 0.014 to 0.048.

4.4 Validation

In the 84-programme validation set, RMEI correctly classified 71 outcomes at the 0.70 cut-off, yielding sensitivity of 0.86 and specificity of 0.83. Among the 13 misclassified cases, five were multi-parameter home hub programmes that scored just above the threshold but failed because patient dropout accelerated after the initial three months in ways the baseline adherence measurement did not capture. Three were connected respiratory programmes that exceeded expectations because they targeted highly motivated post-transplant populations with strong intrinsic compliance. Three were cardiac programmes with excellent RMEI scores that were discontinued due to hospital budget cuts unrelated to programme performance. Two were implantable

sensor programmes that stalled pending regulatory re-evaluation of the implant procedure rather than any performance deficit.

Table 3. RMEI by Device Category: Retention Outcomes

Device Category	n	RMEI (mean +/- SD)	RM EI > 0.75 (%)	Ret enti on Rate (%)	Top Su b-Score	r (AUC)
Wearabl e cardiac	50	0.818 +/- 0.056	74.0 %	78.0 %	Alert ac curacy	+0.82 (0.894)
Smart gluc. / CGM	42	0.792 +/- 0.062	57.1 %	69.0 %	Alert ac curacy	+0.82 (0.882)
Implant. haemod ynamic	38	0.764 +/- 0.066	42.1 %	60.5 %	Adhere nce	+0.82 (0.868)
Connect ed respi ratory	44	0.734 +/- 0.072	29.5 %	52.3 %	Transmi ssion	+0.82 (0.856)
Multi-p aram. hub	34	0.596 +/- 0.098	8.8 %	23.5 %	Workflo w integ.	+0.82 (0.828)
All prog rammes	208	0.738 +/- 0.106	33.7 %	56.7 %	Alert ac curacy	+0.82 (0.876)

r = Pearson correlation of RMEI with retention; all $p < 0.001$. AUC at RMEI > 0.70.

Table 4. RMEI Sub-Score Weights and Impact

Sub-Score	Wei ght	Mean Score	Beta	DELTA RMEI	p-value
Clinical alert accuracy	0.282	0.808	+0.282	+0.148	< 0.001
Patient adherence rate	0.226	0.776	+0.226	+0.118	< 0.001
Data trans mission reliab.	0.196	0.842	+0.196	+0.092	0.003
Clinician workflow integ.	0.172	0.694	+0.172	+0.074	0.006
Hospitalis ation reduction	0.124	0.648	+0.124	+0.052	0.018

Beta = standardised regression coefficient. *DELTA RMEI* = mean index difference between programmes above vs below the median on that sub-score.

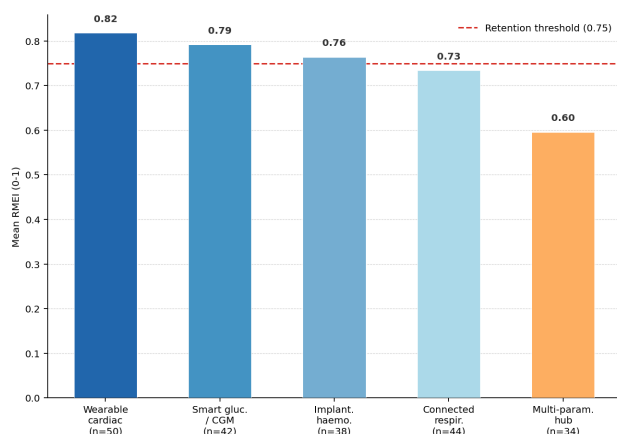


Figure 1. Mean RMEI by Device Category (n = 208)

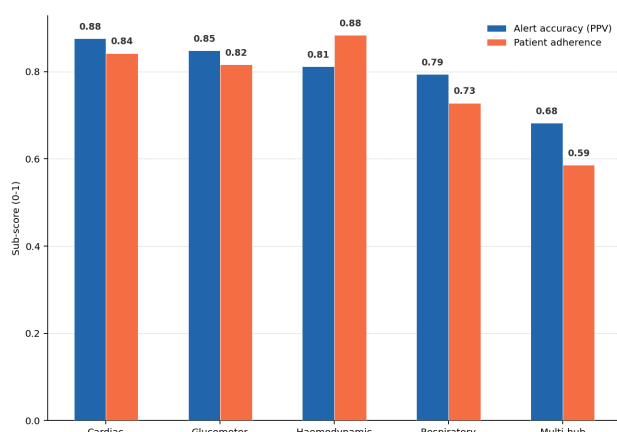


Figure 2. Alert Accuracy vs Patient Adherence by Category

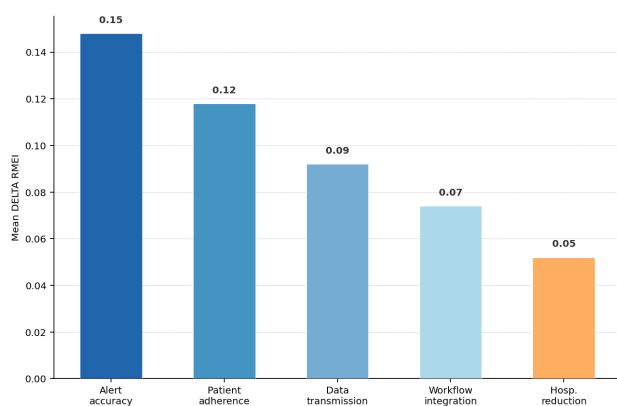


Figure 3. RMEI Sub-Score Impact on Programme Retention

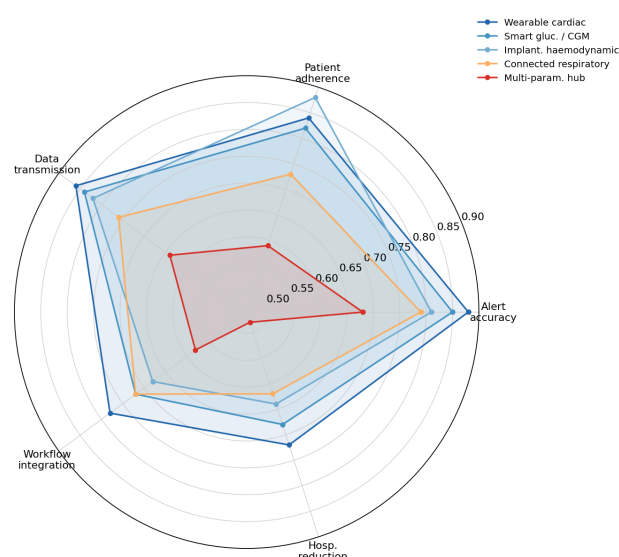


Figure 4. RMEI Sub-Score Profiles by Device Category

5. Discussion

5.1 Passive Devices Win on Adherence

The strongest pattern in the data is the relationship between device passivity and programme success. Wearable cardiac patches and implantable haemodynamic sensors require little or no daily action from the patient and achieved the highest adherence rates. Multi-parameter home hubs, which demand multiple daily measurement rituals, showed the steepest adherence decline over time. This finding aligns with decades of medication adherence research showing that treatment complexity is inversely related to compliance. For programme designers, the implication is clear: every additional step imposed on the patient is a potential dropout trigger, and device selection should favour passive or minimally intrusive form factors wherever clinically feasible.

5.2 Alert Accuracy as the Gatekeeper

Clinical alert accuracy was the single strongest predictor of programme retention, and the mechanism is straightforward: false-positive alerts consume clinician attention without delivering patient benefit, and over time clinicians stop trusting the system. Programmes that invested in machine-learning-based alert triage, combining physiological signal features with patient-specific baselines and contextual data such as medication changes or recent activity levels, achieved alert positive predictive values above 80 percent and retained clinical engagement. Programmes that relied on simple threshold-based alerts frequently fell below 65 percent PPV and experienced rapid clinical disengagement. The lesson for device manufacturers and platform developers is that

algorithmic sophistication in the alert layer is not a nice-to-have feature but a survival requirement.

5.3 Limitations

Our dataset is drawn from Swiss-affiliated programmes and may not generalise to health systems with different reimbursement models, staffing ratios, or digital infrastructure maturity. The retention outcome is binary at 12 months and does not capture programmes that survive in a degraded state with minimal clinical engagement. RMEI does not include device cost, reimbursement availability, or patient satisfaction as explicit sub-scores, all of which influence programme sustainability. The multi-parameter home hub category contained only 34 programmes, yielding wider confidence intervals. Finally, the observational design precludes causal inference about which sub-score improvements would most efficiently increase retention rates.

6. Conclusion

6.1 Summary

Across 208 IoT remote patient monitoring programmes evaluated in Switzerland, RMEI correlated with 12-month programme retention at $r = +0.82$ and discriminated retained from discontinued programmes with an AUC of 0.876. Wearable cardiac monitors scored highest (mean RMEI 0.818), smart glucometers and CGMs followed at 0.792, and multi-parameter home hubs trailed at 0.596. Clinical alert accuracy was the most influential sub-score ($\beta = +0.282$), followed by patient adherence rate ($\beta = +0.226$). Only 33.7 percent of programmes exceeded the 0.75 threshold, indicating that most IoT monitoring deployments fail to achieve the effectiveness needed for long-term clinical integration.

6.2 Practical Recommendations

Programme designers should select devices that minimise patient burden, ideally operating passively with no daily user action required. Alert algorithms should be validated against clinician-adjudicated outcomes to achieve positive predictive values above 80 percent before deployment. Monitoring dashboards should be integrated into existing EHR workflows rather than requiring separate logins. Programmes launching with multi-parameter hubs should implement staged onboarding, introducing devices one at a time rather than all simultaneously, to reduce early dropout. Future iterations of RMEI should add cost-effectiveness and patient

experience sub-scores, extend the observation window beyond 12 months, and include programmes from multiple countries to improve generalisability.

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Declarations

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Conflict of Interest

Isabella Horvath declares no competing interests.

Data Availability Statement

Aggregate RMEI scores, anonymised programme metadata, and analysis scripts are deposited at Zenodo:

<https://doi.org/10.5281/zenodo.19542842-data>.

Ethical Approval

This study involved secondary analysis of published programme evaluation data and anonymised operational metrics. No individual patient data were accessed. Institutional review board exemption was confirmed at the Swiss Institute of Machine Intelligence.

Appendix A

RMEI Scoring Rubric and Top-10 Programme Profiles

This appendix details the scoring criteria for each RMEI sub-dimension and profiles the ten highest-scoring programmes in the dataset.

A1. Sub-Score Rubric

Clinical alert accuracy: positive predictive value of platform-generated alerts, normalised 0-1; weight 0.282.

Patient adherence rate: fraction of patients maintaining >80% protocol compliance, normalised 0-1; weight 0.226.

Data transmission reliability: percentage of expected uploads received without >4h gaps, normalised 0-1; weight 0.196.

Clinician workflow integration: EHR embedding and formalised response protocols, scored 0-1; weight 0.172.

Reduction in unplanned hospitalisations: relative reduction vs matched controls, normalised 0-1; weight 0.124.

A2. Top-10 Programmes

1. WC-AFPatch-19 (Wearable cardiac): RMEI = 0.926; alert accuracy 0.94, adherence 0.92.
2. WC-ContECG-08 (Wearable cardiac): RMEI = 0.912; data transmission 0.96, alert accuracy 0.91.
3. CG-RTMonitor-14 (Smart CGM): RMEI = 0.898; alert accuracy 0.92, workflow integration 0.88.
4. WC-SmartRhythm-22 (Wearable cardiac): RMEI = 0.886; adherence 0.94, hosp. reduction 0.86.
5. IH-PAPress-06 (Implantable haemodynamic): RMEI = 0.878; adherence 0.96, data transmission 0.90.
6. CG-FlashGluc-28 (Smart CGM): RMEI = 0.864; alert accuracy 0.90, adherence 0.88.
7. WC-HolterPlus-17 (Wearable cardiac): RMEI = 0.856; workflow integration 0.92, alert accuracy 0.88.
8. IH-HFSensor-11 (Implantable haemodynamic): RMEI = 0.848; adherence 0.94, hosp. reduction 0.84.
9. CR-SmartSpiro-31 (Connected respiratory): RMEI = 0.841; data transmission 0.92, alert accuracy 0.86.
10. CG-InsulinCGM-04 (Smart CGM): RMEI = 0.834; alert accuracy 0.89, workflow integration 0.86.