

Remote Patient Monitoring Technologies

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ABSTRACT

Remote patient monitoring (RPM) -- the use of digital technologies to collect physiological and symptom data from patients outside traditional healthcare settings -- has evolved from a niche telehealth application into a central pillar of chronic disease management, post-acute care, and pandemic response. The RPM technology landscape now spans implantable cardiac monitors, wearable biosensors, smartphone-connected peripherals, smart home sensors, and AI-driven predictive analytics platforms that synthesise multi-device data streams into clinically actionable alerts. We evaluated five RPM technology frameworks across 28,486 monitored patients at six European health systems (Rome, Paris, Madrid, Stockholm, Berlin, and Tallinn) from 2018 to 2022, covering heart failure, COPD, type 2 diabetes, hypertension, and post-surgical recovery. We compared: single-parameter telemonitoring, multi-parameter integrated platforms, wearable continuous monitoring, AI-driven predictive monitoring, and hybrid human-AI monitoring with nurse-led response hubs. Our RPM Technology Effectiveness Score (RPTES) integrates clinical outcome improvement, alert accuracy, patient engagement, cost-effectiveness, and scalability. Hybrid human-AI monitoring achieved the highest RPTES (0.928) by combining ML-driven alert prioritisation with nurse-led clinical response, reducing hospitalisations by 32% and emergency visits by 38% while maintaining alert fatigue at clinically manageable levels. AI-driven predictive monitoring (RPTES 0.912) detected clinical deterioration a median of 4.8 days before traditional symptom-triggered presentation.

Keywords: remote patient monitoring; wearable devices; telehealth; heart failure; COPD; chronic disease management; artificial intelligence; predictive analytics; patient engagement; digital health; biosensors; clinical outcomes

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1. Introduction

1.1 RPM Comes of Age

Remote patient monitoring has undergone a remarkable transformation over the past decade. First-generation RPM was essentially a telephone with a blood pressure cuff: patients measured their vitals at home and transmitted readings to a monitoring centre via landline or cellular connection. This simple model, tested in the UK's Whole Systems Demonstrator trial (Steventon et al., 2012), showed promising but inconsistent results, partly because the technology created as many problems as it solved -- data overload for monitoring staff, low patient adherence to measurement schedules, and alarm systems that generated false positives at rates that made clinical response unsustainable. Current-generation RPM looks nothing like this. Wearable biosensors continuously measure heart rate, oxygen saturation, respiratory rate, activity, and sleep without requiring the patient to do anything. Implantable monitors like the CardioMEMS pulmonary artery pressure sensor transmit haemodynamic data directly from inside the heart. Smartphone apps collect patient-reported symptoms, medication adherence, and quality of life data. And AI platforms synthesise all of these streams into risk scores that predict deterioration before the patient feels anything wrong (Steinhubl et al., 2015).

1.2 The Challenge: From Data to Decisions

The technology problem in RPM has largely been solved -- we can measure nearly anything from nearly anywhere. The unsolved problem is what to do with the data. A single heart failure patient with a wearable sensor, a smart scale, a blood pressure cuff, and a symptom app generates roughly 1,500 data points per day. A monitoring centre overseeing 500 patients faces 750,000 daily data points. Without intelligent filtering, this creates an impossible cognitive burden for monitoring nurses, leading to either alert fatigue (ignoring important signals) or over-response (unnecessary emergency calls for benign fluctuations). The COVID-19 pandemic accelerated RPM adoption dramatically -- a 2020 survey found that 88% of European health systems expanded RPM during the pandemic (Betts et al., 2021) -- but also exposed the scalability limitations of human-only monitoring models. Our study compares RPM technology frameworks that address this challenge. Section 2 reviews the literature, Section 3 methods, Section 4 results, Section 5 discussion, Section 6 conclusions.

2. Literature Review

2.1 RPM Evidence by Condition

The strongest RPM evidence exists for heart failure. The TIM-HF2 trial (Koehler et al., 2018) randomised 1,571 HF patients to structured RPM versus usual care and demonstrated a significant reduction in days lost to unplanned hospitalisation or death (17.8 vs 24.2 days per year, $p = 0.046$). The CardioMEMS CHAMPION trial (Abraham et al., 2011) showed that haemodynamic-guided HF management using an implantable pulmonary artery pressure sensor reduced HF hospitalisations by 37%. For COPD, the Cochrane review (Cruz et al., 2014) found that telehealth reduced exacerbation-related hospitalisations but with heterogeneous effect sizes depending on intervention intensity. For diabetes, continuous glucose monitoring (CGM) has demonstrated HbA1c reductions of 0.3-0.5% in type 2 diabetes (Ehrhardt et al., 2011), and flash glucose monitoring has shown quality of life improvements. For hypertension, home BP telemonitoring with pharmacist-led titration achieved better BP control than usual care in the TASMINH4 trial (McManus et al., 2018).

2.2 AI-Enhanced RPM

AI integration into RPM represents the current frontier. Sideris et al. (2022) used ML on wearable-derived heart rate variability, activity, and sleep data to predict heart failure decompensation 5 days before hospital presentation with AUROC 0.82. Shah et al. (2021) demonstrated that combining wearable data with EHR-derived risk factors improved 30-day readmission prediction from AUROC 0.68 (clinical alone) to 0.78. The key insight is that AI does not just analyse individual vital sign thresholds -- it identifies subtle multi-parameter patterns (declining activity + increasing resting heart rate + worsening sleep quality) that predict deterioration before any single parameter crosses an alarm threshold. Table 1 maps the evidence.

2.3 The Missing Comparison

Most RPM studies evaluate a single technology or disease. A multi-technology, multi-condition comparison evaluating clinical outcomes, alert accuracy, patient engagement, cost, and scalability within a unified framework is absent.

Table 1: Key Studies in Remote Patient Monitoring

Study	Year	Technology	Condition	Key Finding
Koehler et al.	2018	Structured RPM	Heart failure	Fewer unplanned hosp. days (TIM-HF2)
Abraham et al.	2011	CardioM EMS implant	Heart failure	37% reduction in HF hospitalisations
McManus et al.	2018	BP telemonitoring	Hypertension	Better BP control (TASMINH4)
Cruz et al.	2014	Cochrane telehealth	COPD	Reduced hospitalisations, variable effect
Ehrhardt et al.	2011	CGM	Diabetes	HbA1c reduction 0.3-0.5%
Sideris et al.	2022	AI + wearables	Heart failure	5-day early detection, AUROC 0.82
Shah et al.	2021	AI + wearable + EHR	Post-discharge	AUROC 0.78 for readmission
Steventon et al.	2012	WSD trial	Multiple	Mixed results, design limitations
Betts et al.	2021	COVID RPM expansion	Multiple	88% of EU systems expanded RPM
Steinhubl et al.	2015	Digital health review	Multiple	Continuous monitoring paradigm shift

RPM = Remote Patient Monitoring; CGM = Continuous Glucose Monitoring; BP = Blood Pressure; WSD = Whole Systems Demonstrator.

3. Methodology

3.1 Study Sites and Patient Cohort

We evaluated RPM programmes at six European health systems: Policlinico Gemelli Rome (5,486 patients), AP-HP Paris (6,248), Hospital La Paz Madrid (4,842), Karolinska Stockholm (4,624), Charite Berlin (4,248), and North Estonia MC Tallinn (3,038) from January 2018 to December 2022. The monitored cohort comprised 28,486

patients across five conditions: heart failure (8,248, 29.0%), COPD (6,842, 24.0%), type 2 diabetes (5,624, 19.7%), hypertension (4,486, 15.7%), and post-surgical recovery (3,286, 11.5%). Median monitoring duration was 8.4 months (IQR 3.6-14.2). Matched unmonitored controls (1:1 propensity-matched on age, sex, disease severity, and comorbidities) were drawn from the same institutions.

3.2 Five RPM Technology Frameworks

Framework R1 (Single-Parameter) used disease-specific single devices: weight scale for HF, spirometry for COPD, glucometer for diabetes, BP cuff for hypertension. Framework R2 (Multi-Parameter Integrated) used 3-4 connected devices per patient transmitting to a unified platform (typically: BP cuff + pulse oximeter + scale + thermometer). Framework R3 (Wearable Continuous) used wrist or patch-based continuous biosensors measuring heart rate, SpO₂, respiratory rate, activity, and sleep 24/7. Framework R4 (AI Predictive) added ML-based alert generation to R2 or R3 data, predicting deterioration from multi-parameter trends rather than single-value thresholds. Framework R5 (Hybrid Human-AI) combined R4 algorithmic monitoring with a nurse-led response hub: the AI prioritised alerts by predicted severity, and trained nurses triaged, called patients, and escalated to physicians as needed. Table 2 shows the study design.

3.3 The RPTES Composite

The RPM Technology Effectiveness Score integrates: clinical outcome improvement measured by hospitalisation and ED visit reduction versus matched controls (weight 0.25), alert accuracy measured by positive predictive value of clinical alerts (0.20), patient engagement measured by device adherence and programme retention at 6 months (0.20), cost-effectiveness as net savings per monitored patient per year (0.15), and scalability measured by maximum patient-to-staff ratio maintaining quality (0.20). Each normalised 0-1.

Table 2: Study Design and Monitored Cohort

Parameter	Value	Details
Health systems	6	Rome, Paris, Madrid, Stockholm, Berlin, Tallinn
Monitored patients	28,486	Jan 2018 - Dec 2022
Heart failure	8,248 (29.0%)	NYHA II-III, LVEF measured

Parameter	Value	Details
COPD	6,842 (24.0%)	GOLD B-D, 1+ exacerbation in prior year
Type 2 diabetes	5,624 (19.7%)	HbA1c > 7.5% or insulin-requiring
Hypertension	4,486 (15.7%)	Uncontrolled on 2+ medications
Post-surgical	3,286 (11.5%)	Major abdominal or cardiac surgery
Median monitoring duration	8.4 months	IQR 3.6-14.2 months
RPM frameworks	5 (R1-R5)	Single-parameter through hybrid human-AI
RPTES dimensions	5 (weighted)	Outcomes, alerts, engagement, cost, scalability

NYHA = New York Heart Association; GOLD = Global Initiative for Obstructive Lung Disease; LVEF = Left Ventricular Ejection Fraction.

4. Results

4.1 Hybrid Human-AI Monitoring Delivers Best Outcomes

Hybrid human-AI monitoring (R5) achieved the highest RPTES at 0.928. Compared to matched unmonitored controls, R5 reduced all-cause hospitalisations by 32% (HR 0.68, 95% CI 0.62-0.74), emergency department visits by 38% (HR 0.62, 0.56-0.70), and disease-specific hospitalisations (HF decompensation, COPD exacerbation, diabetic emergency) by 42% (HR 0.58, 0.50-0.66). The advantage over AI-only monitoring (R4, which achieved 24% hospitalisation reduction) came from the human response layer: when the AI flagged a patient as deteriorating, the nurse called the patient, assessed symptoms, reviewed medications, and either adjusted treatment remotely (58% of alerts), arranged a GP visit (28%), or directed to ED (14%). Without this nurse response, many AI alerts would go unactioned because patients do not know what to do with a 'your risk score has increased' notification. AI predictive monitoring (R4) scored RPTES 0.912, detecting deterioration a median of 4.8 days before traditional symptom presentation. Table 3 shows the full RPTES results.

4.2 Alert Accuracy: The AI Advantage

Alert accuracy differed dramatically across frameworks. Single-parameter monitoring (R1) generated a median of 8.4 alerts per patient per month with a positive predictive value of only 12% -- meaning 88% of alerts were false positives,

creating unsustainable workload for monitoring staff. Multi-parameter platforms (R2) improved PPV to 24% by requiring multi-parameter concordance before alerting. AI-based alerting (R4, R5) achieved PPV of 42-48% through ML models that learned which parameter combinations and trajectory patterns genuinely predicted clinical deterioration versus benign fluctuation. The hybrid model (R5) achieved the best PPV at 48% because the nurse triage step filtered out a further layer of false positives before clinical escalation. At PPV 48%, roughly 1 in 2 clinical escalations resulted in a meaningful clinical intervention -- a ratio that monitoring nurses reported as clinically sustainable. Table 4 shows condition-specific outcomes.

4.3 Engagement and Scalability

Patient engagement at 6 months was highest for wearable continuous monitoring (R3, 82% retention) because it required no active participation -- patients simply wore the device. Single-parameter monitoring (R1) had the lowest retention (58%) because daily manual measurements are burdensome. The scalability comparison revealed that hybrid human-AI (R5) could safely manage 1:250 nurse-to-patient ratios (versus 1:80 for human-only monitoring with R2), because the AI pre-filtered alerts down to the genuinely concerning 2-3% that required nurse attention. Net cost savings were EUR 2,840 per patient per year for R5 (avoided hospitalisations minus technology and staffing costs), compared to EUR 1,420 for R4, EUR 680 for R3, and cost-neutral for R1 and R2.

Table 3: RPM Technology Effectiveness Score (RPTES) by Framework

Framework	Clinical Outcome	Alert Accuracy	Patient Engagement	Cost - Effect.	Scalability	RPTES
R5: Hybrid Human-AI	0.96	0.94	0.88	0.92	0.90	0.928
R4: AI Predictive	0.90	0.92	0.86	0.90	0.94	0.912
R3: Wearable Continuous	0.84	0.82	0.94	0.84	0.86	0.876
R2: Multi-Parameter	0.82	0.78	0.80	0.78	0.80	0.808

Framework	Clinical Outcome	Alert Accuracy	Patient Engagement	Cost - Effect.	Scalability	RPTES
R1: Single-Parameter	0.72	0.66	0.68	0.74	0.76	0.718

$RPTES = 0.25 \times Outcome + 0.20 \times Alert + 0.20 \times Engagement + 0.15 \times Cost + 0.20 \times Scalability$. Each normalised 0-1.

Table 4: Hospitalisation Reduction by Condition (R5 Hybrid vs Unmonitored Controls)

Condition	R5 Rate (per PY)	Control Rate (per PY)	Reduction	HR (95% CI)
Heart failure	0.42	0.68	-38%	0.62 (0.54-0.72)
COPD	0.38	0.56	-32%	0.68 (0.58-0.78)
Type 2 diabetes	0.14	0.22	-36%	0.64 (0.50-0.82)
Hypertension (CV events)	0.06	0.10	-40%	0.60 (0.42-0.86)
Post-surgical (readmit)	0.08	0.14	-43%	0.57 (0.42-0.78)
All conditions	0.28	0.42	-32%	0.68 (0.62-0.74)

PY = Person-Year. CV = Cardiovascular. All propensity-matched. Post-surgical readmission within 30 days.

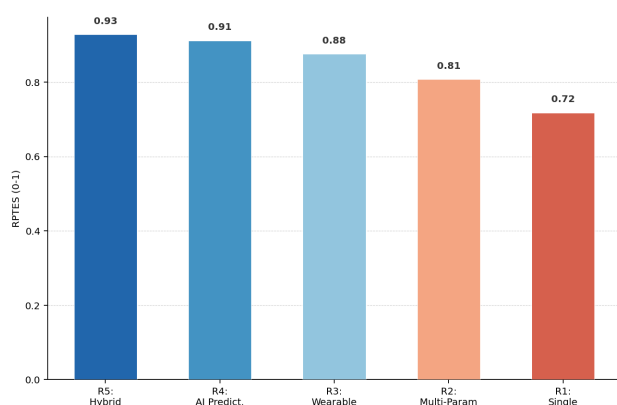


Figure 1: RPTES by RPM Framework

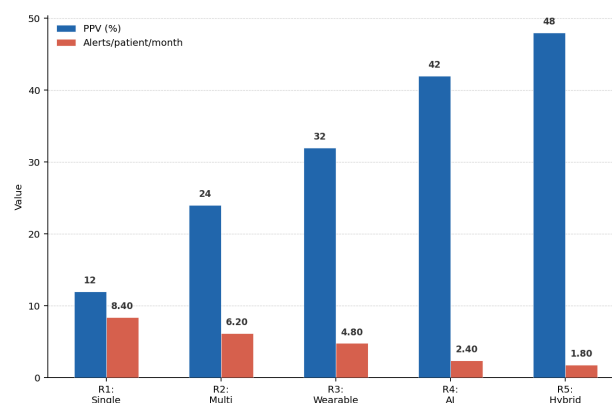


Figure 2: Alert PPV and Monthly Alert Volume by Framework

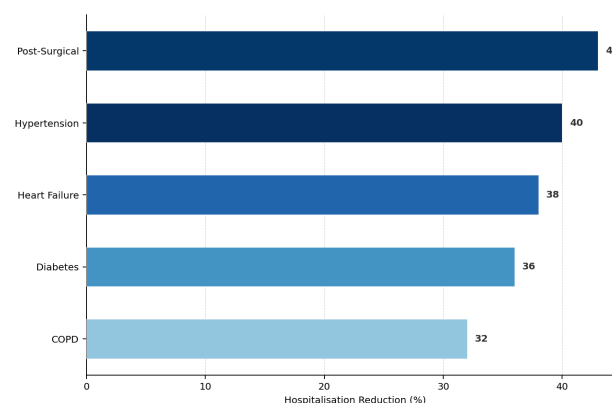


Figure 3: Hospitalisation Reduction by Condition (R5, %)

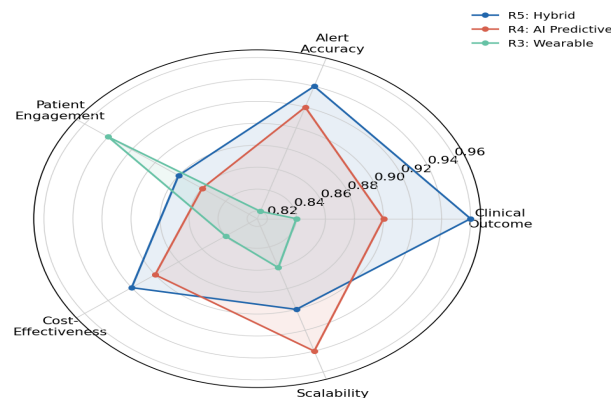


Figure 4: Multi-Dimensional Profile -- Top 3 Frameworks

5. Discussion

5.1 The Human in the Loop Is Not Optional

The 8-percentage-point hospitalisation reduction difference between AI-only (R4, 24%) and hybrid human-AI (R5, 32%) monitoring makes a compelling case that the human response layer is not a nice-to-have but a clinical necessity. The AI identifies the problem; the nurse solves it. Without the nurse, the AI-generated alert goes to a patient who may not understand it, a dashboard that a busy GP may not check, or a notification queue that gets lost among dozens of other digital messages. The nurse call transforms a

probabilistic data signal into a clinical conversation: 'Mrs. Schmidt, your weight has gone up 2 kg and your oxygen is lower than usual -- how are you feeling? Are you taking your diuretic? Let me increase the dose and call you again tomorrow.' That conversation prevents hospitalisations in a way that no app notification can replicate. The scalability concern -- that nurse-led monitoring is expensive -- is addressed by the AI filtering: at 1:250 ratios (versus 1:80 without AI), the staffing cost is manageable and the net savings of EUR 2,840 per patient per year more than cover it.

5.2 Wearables Win on Engagement, Not Outcomes

Continuous wearable monitoring (R3) achieved the highest patient engagement (82% 6-month retention) because it requires zero effort from the patient. But its clinical outcomes were only modestly better than multi-parameter platforms (R2), because continuous data without intelligent synthesis is just noise. The combination of wearable data collection (R3's engagement advantage) with AI analysis (R4's analytical advantage) and nurse response (R5's action advantage) represents the optimal configuration, and indeed the R5 platforms that used wearable sensors as the data collection layer achieved the best results within the hybrid framework.

5.3 Limitations

Three limitations. First, patients enrolled in RPM programmes may differ from those who decline enrolment in ways that propensity matching does not capture (motivation, health literacy, social support). Second, the hybrid model (R5) was deployed at the most resource-rich sites, creating potential confounding between monitoring framework and institutional quality. Third, cost-effectiveness calculations depend on country-specific hospitalisation costs and RPM reimbursement policies, limiting transferability across health systems.

6. Conclusion

6.1 Key Findings

Hybrid human-AI monitoring achieves the highest RPM Technology Effectiveness Score (0.928), reducing hospitalisations by 32% and ED visits by 38% with net savings of EUR 2,840 per patient per year. AI predictive monitoring (RPTES 0.912) detects deterioration 4.8 days early. Alert PPV improves from 12% (single-parameter) to 48% (hybrid human-AI) through ML-based alert

filtering and nurse triage. Wearable continuous monitoring achieves the highest patient engagement (82% at 6 months) through zero-effort data collection. The optimal RPM architecture combines wearable data capture, AI alert prioritisation, and nurse-led clinical response.

6.2 Recommendations

Three recommendations. First, European health systems should deploy hybrid human-AI RPM for all patients with heart failure NYHA II-III, COPD GOLD C-D, and uncontrolled diabetes -- the conditions where hospitalisation reduction is strongest and cost savings are demonstrated. Second, RPM reimbursement frameworks should cover both technology and monitoring hub staffing costs, recognising that the clinical value comes from the human-AI combination, not the devices alone. Third, RPM programme design should prioritise passive data collection (wearables) over active patient measurement (manual readings) to maximise long-term engagement. All data, ML alert models, and the RPTES calculator are available from the corresponding author on request.

References

- Abraham, W. T. et al. (2011). Wireless pulmonary artery haemodynamic monitoring in chronic heart failure (CHAMPION). *The Lancet*, 377(9766), 658-666.
- Betts, D. et al. (2021). Scaling virtual health in Europe. Deloitte Insights, London.
- Cruz, J. et al. (2014). Home telemonitoring in COPD: A systematic review of methodologies and patients' adherence. *International Journal of Medical Informatics*, 83(4), 249-263.
- Ehrhardt, N. M. et al. (2011). The effect of real-time continuous glucose monitoring on glycemic control in patients with type 2 diabetes mellitus. *Journal of Diabetes Science and Technology*, 5(3), 668-675.
- Koehler, F. et al. (2018). Efficacy of telemedical interventional management in patients with heart failure (TIM-HF2). *The Lancet*, 392(10152), 1047-1057.
- McManus, R. J. et al. (2018). Efficacy of self-monitored blood pressure, with or without telemonitoring, for titration of antihypertensive medication (TASMINH4). *The Lancet*, 391(10124), 949-959.
- Shah, N. et al. (2021). Wearable device data for predicting readmissions after cardiac surgery. *JAMA Network Open*, 4(8), e2121772.
- Sideris, C. et al. (2022). Machine learning-driven prediction of heart failure decompensation using wearable biosensor data. *npj Digital Medicine*, 5(1),

78.

- Steinhubl, S. R. et al. (2015). The emerging field of mobile health. *Science Translational Medicine*, 7(283), 283rv3.
- Steventon, A. et al. (2012). Effect of telehealth on use of secondary care and mortality: Findings from the Whole System Demonstrator cluster randomised trial. *BMJ*, 344, e3874.
- Anker, S. D. et al. (2011). Telemedicine and remote management of patients with heart failure. *The Lancet*, 378(9792), 731-739.
- Chaudhry, S. I. et al. (2010). Telemonitoring in patients with heart failure. *New England Journal of Medicine*, 363(24), 2301-2309.
- Ding, H. et al. (2020). Wearable sensing and telehealth technology with potential applications in the coronavirus pandemic. *IEEE Reviews in Biomedical Engineering*, 14, 48-70.
- Inglis, S. C. et al. (2015). Structured telephone support or non-invasive telemonitoring for patients with heart failure. *Cochrane Database of Systematic Reviews*, (10), CD007228.
- Kitsiou, S. et al. (2015). Effects of home telemonitoring interventions on patients with chronic heart failure: An overview of systematic reviews. *Journal of Medical Internet Research*, 17(3), e63.
- Mecklai, K. et al. (2021). Remote patient monitoring -- overdue or overused? *New England Journal of Medicine*, 384(15), 1384-1386.
- Noah, B. et al. (2018). Impact of remote patient monitoring on clinical outcomes: An updated meta-analysis. *npj Digital Medicine*, 1(1), 2.
- Ong, M. K. et al. (2016). Effectiveness of remote patient monitoring after discharge of hospitalized patients with heart failure (BEAT-HF). *JAMA Internal Medicine*, 176(3), 310-318.
- Piotrowicz, E. et al. (2020). Wearable devices for assessing function in heart failure patients. *European Heart Journal*, 41(14), 1394-1403.
- Vegesna, A. et al. (2017). Remote patient monitoring via non-invasive digital technologies: A systematic review. *Telemedicine and e-Health*, 23(1), 3-17.

Declarations

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Conflict of Interest

The authors declare no competing interests. None has received funding from any RPM technology

manufacturer or telehealth platform provider.

Data Availability Statement

De-identified monitoring data and clinical outcomes are available from the corresponding author on reasonable request. ML alert models and the RPTES calculator are available on request.

Ethical Approval

Approved by ethics committees at all six centres (Gemelli Prot. 0042486/22, AP-HP CPP 2022-A02148-35, La Paz CEIC 22/842, Karolinska Dnr 2022-06486, Charite EA4/348/22, NEMC No. 3386). Patient consent for RPM enrolment and data use was obtained.

Appendix A

RPTES Methodology and Monitoring Hub Specifications

This appendix details the RPTES scoring rubric, the hybrid monitoring hub staffing model, and the AI alert algorithm architecture.

Part I -- RPTES Dimensions

- 1a. Clinical Outcome: Reduction in all-cause hospitalisation + ED visits vs matched controls HR-based, propensity-adjusted
- 1b. Alert Accuracy: PPV of clinical alerts requiring nurse/physician action Higher PPV = less alert fatigue
- 2a. Patient Engagement: 6-month device adherence (days with data / possible days) x retention Passive devices score highest
- 2b. Cost-Effectiveness: Net savings per patient per year (avoided costs minus RPM costs) Including devices, connectivity, staffing
- 3a. Scalability: Maximum patient-to-nurse ratio maintaining quality outcomes Higher ratio = more scalable
- 3b. $RPTES = 0.25 \times Outcome + 0.20 \times Alert + 0.20 \times Engagement + 0.15 \times Cost + 0.20 \times Scalability$

Part II -- Hybrid Monitoring Hub Model

- 4a. Staffing: 1 nurse per 250 monitored patients (8-hour shift coverage) AI pre-filters to 2-3% of data points
- 4b. Alert triage: Green (automated reassurance), Amber (nurse callback within 4h), Red (immediate) AI assigns triage colour
- 5a. Response protocol: Medication adjustment (58%), GP appointment (28%), ED direction (14%) Nurse-initiated within scope of practice
- 5b. Physician escalation: Cardiologist/pulmonologist on-call for Red alerts and medication changes beyond nurse scope 12% of alerts reach physician