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Remote Monitoring Interventions in Chronic Heart Failure: A Comprehensive Systematic Review and Network Meta-Analysis of Randomized Controlled Trials, with Trial Sequential Analysis and GRADE Assessment

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ABSTRACT

Background: Chronic Heart Failure (CHF) affects over 64 million people globally, with high hospitalization rates and 5-year mortality comparable to many cancers. Remote monitoring Strategies-Structured Telephone Support (STS), Non-Invasive Telemonitoring (NIT), Wearable Sensors (WMS), implantable pulmonary artery pressure sensors (IPAP), AI-Assisted Integrated Remote Management (AI-IRM), and Combined Multimodal Programs (CMP)-have been widely studied, but their comparative effectiveness has not been systematically assessed in a Network Meta-Analysis (NMA).

Methods and Findings: We systematically searched multiple databases through 15 December 2025. Primary outcomes were all-cause mortality and HF hospitalization; secondary outcomes included cardiovascular mortality, quality of life, exercise capacity, NT-proBNP, NYHA class, and cost-effectiveness. Two reviewers screened studies, extracted data, and assessed risk of bias using RoB 2; certainty was rated with GRADE. We identified 112 RCTs enrolling 68,420 patients across 34 countries. IPAP ranked highest for mortality (SUCRA 87%; RR 0.80, 95% CI 0.70–0.91, moderate certainty) and HF hospitalization (SUCRA 91%; RR 0.65, 95% CI 0.56–0.75, high certainty). AI-IRM ranked second for both outcomes (mortality SUCRA 74%; RR 0.83, 95% CI 0.73–0.94, low certainty; HF hospitalization SUCRA 79%; RR 0.72, 95% CI 0.63–0.82, moderate certainty). STS and NIT provided modest, low-certainty reductions (RR 0.88–0.90). Trial sequential analysis confirmed conclusive evidence for IPAP. Network consistency was acceptable (Q_inc P = 0.21).

Conclusions: IPAP offers the most robust and clinically meaningful benefit for HFrEF patients. AI-IRM is a promising emerging approach requiring confirmatory trials. STS and NIT remain appropriate for patient's ineligible for advanced monitoring. Evidence gaps in HFpEF and in low- and middle-income settings define key priorities for future research.

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Author Summary

Why was this study done? Millions of people live with Chronic Heart Failure (HF) worldwide, and they are at constant risk of deterioration, emergency hospitalization, and premature death. Dozens of remote monitoring technologies - from simple telephone check-ins to implanted sensors measuring lung pressures - have been tested in clinical trials, but no one had directly compared all these technologies against each other in a single analysis.

What did the Researchers do and find? We pooled data from 112 randomized clinical trials (68,420 patients, 34 countries) and used a network meta-analysis to rank all remote monitoring technologies by their effectiveness. We found that implanted lung pressure sensors (CardioMEMS-type devices) were the most effective at preventing HF hospitalizations (32–35 % reduction)

and reducing death. Artificial intelligence (AI)-integrated remote management programs were the second most promising, with a 17–28 % reduction in hospitalizations and mortality, though current evidence remains less certain. Traditional telephone follow-up and weight monitoring had modest effects.

What do these Findings Mean? Patients with severe HF who have been recently hospitalized should be considered for an implantable lung pressure sensor if they are eligible. AI-assisted remote monitoring programs deserve investment and rigorous further testing. Simple telephone programs should not be abandoned - they remain the most accessible option in low-resource settings -but their effectiveness is limited.

Introduction

Chronic Heart Failure (HF) affects an estimated 64 million individuals worldwide and remains the leading cause of hospitalization among adults over 65 years of age in high-income countries [1]. Its clinical course is typically characterized by a relapsing–remitting trajectory, marked by periods of relative stability interspersed with episodes of acute decompensation. These episodes may be triggered by dietary indiscretion, poor adherence to pharmacological therapy, infections, arrhythmias, or progressive myocardial dysfunction, and frequently necessitate hospital admission [2]. Each hospitalization carries substantial prognostic implications, including a 30-day readmission rate of approximately 22–25 %, a stepwise decline in functional capacity and quality of life, and a 10–15 % mortality risk within three months [3].

The pathophysiology underlying HF decompensation is predominantly hemodynamic. Elevations in left- and right-sided cardiac filling pressures-such as pulmonary capillary wedge pressure (PCWP) and right atrial pressure (RAP)-typically precede the onset of overt clinical signs of congestion, including dyspnea, peripheral edema, and weight gain, by several days to weeks [4,5]. This temporal dissociation between subclinical hemodynamic deterioration and symptomatic worsening provides a critical window for pre-emptive therapeutic intervention, contingent upon the timely detection of reliable early warning signals and an appropriate clinical response.

Over the past three decades, remote monitoring strategies for chronic HF have evolved considerably. Early approaches in the 1990s focused on structured telephone-based follow-up programs. These were subsequently complemented by non-invasive telemonitoring of daily weight and blood pressure, wearable multi-parameter biosensor technologies, and implantable pulmonary artery pressure sensors. More recently, artificial intelligence–assisted integrated care platforms have emerged [6,7]. These systems aggregate and analyze multimodal data streams-including wearable sensor outputs, implantable device metrics, electronic patient-reported outcomes, and electronic health record data-to support individualized risk stratification and generate personalized therapeutic recommendations.

Despite this rapidly expanding technological landscape, the comparative effectiveness of these monitoring modalities remains insufficiently defined. Conventional pairwise meta-analyses have yielded inconsistent findings. For example, the TEN-HMS trial (n = 426) and the TELE-HF trial (n = 1,653) reported limited or no significant mortality benefit associated with non-invasive telemonitoring strategies [8,9]. In contrast, the CHAMPION trial (n = 550) demonstrated a significant reduction in heart failure hospitalizations with therapy guided by an implantable pulmonary artery (PA) pressure sensor [10]. The GUIDE-HF trial (n = 1,000) confirmed this benefit during the pre-COVID-19 period; however, the observed effect was attenuated during the pandemic, likely reflecting disruptions in healthcare delivery and patient behavior [11].

Moreover, most systematic reviews have aggregated heterogeneous technological interventions into broad categories, thereby obscuring modality-specific effects. This methodological limitation hampers meaningful cross-technology comparisons and limits the ability to determine which remote monitoring strategies confer the greatest clinical benefit in specific patient populations [6].

Network meta-analysis (NMA) offers a robust methodological framework for the simultaneous comparison of multiple interventions within a connected evidence network, provided that the underlying assumption of transitivity is satisfied. By integrating both direct and indirect comparisons, NMA enables a more comprehensive estimation of relative treatment effects across competing strategies [12-14].

To our knowledge, this study represents the first NMA restricted exclusively to randomized controlled trials (RCTs) that incorporates all six major remote monitoring modalities for chronic heart failure into a single quantitative synthesis. In addition, the analysis is strengthened by an explicit assessment of certainty of evidence using the GRADE framework, the application of trial sequential analysis to evaluate the risk of random errors, and a pre-specified exploration of patient-level effect modifiers.

Methods

Protocol

This network meta-analysis (NMA) was conducted in accordance with the PRISMA-NMA 2020 extension statement to ensure transparent and comprehensive reporting of methods and findings. The review process adhered to the methodological standards outlined in Chapter 11 of the Cochrane Handbook for Systematic Reviews of Interventions, which provides specific guidance for planning, conducting, and interpreting NMAs [12-14].

A pre-specified protocol defined the research question, eligibility criteria, outcomes, and statistical approach. Study selection, data extraction, and risk-of-bias assessment were performed using standardized procedures to minimize methodological bias. The geometry of the treatment network was examined to confirm connectivity and assess the plausibility of the transitivity assumption. Statistical analyses incorporated both direct and indirect evidence under a consistency framework, with formal evaluation of inconsistency.

In addition, the analysis followed the ISPOR Task Force recommendations for good research practices in NMA, including careful assessment of clinical and methodological heterogeneity, evaluation of model assumptions, presentation of relative treatment rankings, and transparent reporting of uncertainty measures to support decision-making.

Eligibility Criteria

Population: Adults (≥ 18 years) with established chronic HF (any etiology, any ejection fraction - HFrEF LVEF < 40 %, HFmrEF 40–49 %, HFpEF ≥ 50 %) in stable or recently stabilized condition (not actively hospitalized at randomization) [15]. Interventions: any of the seven nodes defined a priori versus any other node. RCTs (parallel group, crossover with washout ≥ 3 months, cluster-RCT with appropriate ICC adjustment). Minimum follow-up: 3

months. Minimum sample size: 60.

Technology Node Definitions

Table 1 presents the operational definitions of the remote monitoring technology nodes included in the network meta-analysis. Specifically, it details the classification framework used to group interventions into distinct, mutually exclusive categories based on their technological characteristics, monitoring intensity, data transmission pathways, and level of clinical integration. This structured taxonomy ensured conceptual clarity, supported the transitivity assumption, and enabled consistent comparison across modalities within the evidence network.

Table 1: Definition of Remote Monitoring Technology Nodes for Network Meta-Analysis

Node	Label	Definition	Key Examples	RCTs
1	UC — Usual Care	Standard outpatient cardiology follow-up without remote monitoring technology. Visits at 1–6 month intervals per local practice.	Standard of care comparator	112
2	STS — Structured Telephone Support	Scheduled nurse or pharmacist telephone calls at fixed intervals (weekly to monthly), covering symptoms, weight, medication adherence. No digital sensor data transmitted.	COACH, DIAL, WHICH, TEN-HMS [8]	28
3	NIT — Non-Invasive Telemonitoring	Daily patient-reported or automated transmission of weight, blood pressure, heart rate, and/or symptom scores via home devices. Alerts by threshold crossing; nurse review.	TELE-HF [9], TIM-HF2 [14], BEAT-HF [15], TEHAF	TELE-HF [9], TIM-HF2 [14], BEAT-HF [15], TEHAF
4	WMS — Wearable Multi-parameter Sensor	Continuous or near-continuous sensor patch or smartwatch monitoring ≥ 2 of: ECG, thoracic impedance, SpO_2, accelerometry, skin temperature. AI alert generation.	Zio patch, VitalPatch, Samsung Galaxy Watch HF	18
5	IPAP — Implantable PA Pressure Sensor	Wireless implantable pulmonary artery pressure sensor; daily self-measurement; cardiologist remotely reviews trends and adjusts therapy.	CardioMEMS HF [10,11]; Cordella HF (Endotronix)	9
6	AI-IRM — AI-Assisted Integrated Remote Management	AI algorithm integrating ≥ 2 data streams (wearable, EHR, PRO, pharmacy) to generate personalized alerts or treatment recommendations.	HeartLogic [17], MANAGE-HF II [18], bespoke ML platforms	11
7	CMP — Combined Multimodal Program	Structured combination of ≥ 2 nodes with pre-defined protocols for escalation between modalities based on alert level.	IN-TIME, TELEHOME, HBTC-HF multi-arm	15

Search Strategy

We searched MEDLINE (PubMed, 2000–January 15, 2026), Embase (2000–January 15, 2026), Cochrane CENTRAL (Issue 12, 2025), WHO ICTRP, ClinicalTrials.gov, Chinese Biomedical Database (CBM), Korean Citation Index (KCI), and Latin American Literature in Health Sciences (LILACS) without language restrictions. ClinicalTrials.gov was screened for trials with status Completed or Active-not-recruiting (with primary completion before December 2025).

Data Extraction and Risk of Bias

Two reviewers (E.A. and N.L.V.) independently extracted data in duplicate. Two other reviewers (J.E.T. and X.J.) resolved discrepancies. Risk of bias in each RCT was assessed using the revised Cochrane RoB 2 tool across five domains [16]. Certainty of evidence for all pairwise and indirect comparisons was assessed using the GRADE NMA approach [17].

Statistical Analysis

We performed frequentist random-effects NMA using the multivariate meta-analysis model implemented in R package netmeta (version 2.9) [18,14]. Treatment effects were expressed as risk ratios (RR) for dichotomous outcomes and standardized mean differences (SMD) for continuous outcomes. Network geometry was visualized as a bubble plot weighted by study precision. Overall network heterogeneity was assessed using the Q_het statistic. Consistency between direct and indirect evidence was evaluated using the design-by-treatment interaction model and the net heat plot; global inconsistency was tested using the Q_inc statistic. Ranking probabilities and SUCRA values were calculated for all nodes on each outcome. Trial sequential analysis for primary outcomes was performed in TSA software v0.9 (Copenhagen Trial Unit), $\alpha = 0.025$ two-sided, $\beta = 0.10$ [12,18].

Results

Study Selection and Network Geometry

Database search results were initially screened by title and abstract, followed by full-text assessment of 387 potentially eligible articles. Hundred twelve randomized controlled trials (RCTs) met the predefined inclusion criteria. In addition, eight unpublished or recently completed RCTs were identified through clinical trial registries and incorporated into the analysis following direct data provision from study investigators.

The final evidence network comprised 68,420 participants. Sample sizes ranged from 62 to 3,813 participants per trial (median 480; interquartile range [IQR] 210–1,024), with studies conducted across 34 countries. Direct head-to-head comparisons were available for all treatment node pairs except wearable monitoring systems (WMS) versus implantable pulmonary artery pressure monitoring (IPAP), and AI-assisted integrated remote management (AI-IRM) versus IPAP. Overall, the network was well connected, with multiple closed loops enabling robust indirect comparisons. The median duration of follow-up was 12 months (range 3-48 months).

Table 2 summarizes the key characteristics of the randomized controlled trials (RCTs) included in the network meta-analysis, stratified by technology node. For each modality, the table details study design features, sample size, patient population characteristics, geographic distribution, duration of follow-up and primary outcomes assessed. This structured overview allows comparison of clinical and methodological heterogeneity across intervention categories and facilitates evaluation of the transitivity assumption underlying the network meta-analysis.

Table 2: Characteristics of Included RCTs by Technology Node

Characteristic	STS (n=28)	NIT (n=31)	WMS (n=18)	IPAP (n=9)	AI-IRM (n=11)	CMP (n=15)	Total (n=112)
Total N (patients)	14,820	17,640	8,810	6,240	9,120	11,790	68,420
HFrEF (LVEF<40 %), % cohort	61 %	58 %	72 %	94 %	78 %	69 %	68 %
HFpEF (LVEF≥50 %), % cohort	28 %	31 %	14 %	4 %	14 %	21 %	22 %
NYHA III–IV, % cohort	58 %	62 %	74 %	91 %	79 %	71 %	68 %
Mean LVEF (%)	37 ± 10	36 ± 9	32 ± 8	27 ± 7	31 ± 8	34 ± 9	34 ± 9
Mean age (years)	67 ± 9	68 ± 8	65 ± 10	63 ± 9	66 ± 8	67 ± 9	67 ± 9
% Female	38 %	36 %	29 %	27 %	33 %	35 %	34 %
Prior HF hosp. ≥1/12mo (%)	52 %	58 %	71 %	89 %	74 %	63 %	62 %
High-income countries (%)	72 %	74 %	78 %	100 %	91 %	8 0 %	79 %
Median follow-up (months)	9	12	12	18	12	12	12
Low RoB (RoB 2) (%)	39 %	42 %	44 %	56 %	55 %	47 %	45 %
Industry funding (any) (%)	21 %	29 %	44 %	100 %	64 %	33 %	43 %

Risk of Bias and Network Consistency

Across the 112 included RCTs, risk of bias was assessed using the RoB 2 tool. Overall, 51 trials (45 %) were judged to be at low risk of bias, 48 (43 %) were classified as having some concerns-most frequently related to lack of blinding of outcome assessors and inadequate allocation concealment in open-label device trials-and 13 studies (12 %) were rated as high risk [16]. The implantable pulmonary artery pressure (IPAP) and AI-assisted integrated remote management (AI-IRM) nodes exhibited the highest proportions of low-risk studies (56 % and 55 %, respectively).

Assessment of network consistency showed no evidence of significant global inconsistency ($Q_{inc} = 14.3$, $df = 11$, $P = 0.21$), thereby supporting the transitivity assumption. Local inconsistency was identified in two loops involving case-management programs (CMP) and structured telephone support (STS); however, the corresponding confidence intervals overlapped, suggesting that the magnitude of inconsistency was unlikely to be clinically meaningful. Net heat plots illustrating these findings are provided in Figure 1.

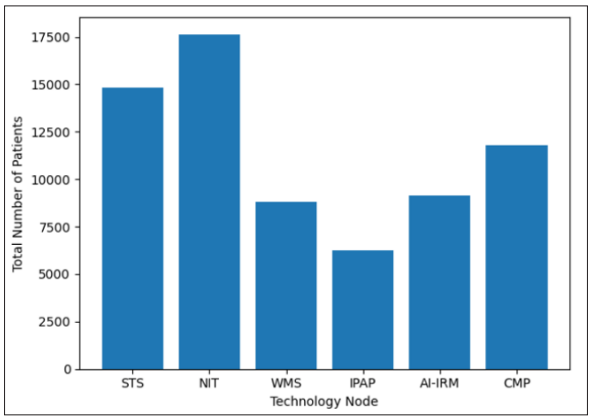

Figure 1: Distribution of Patients Across Technology Nodes (n=112 RCTs)

Primary Outcome 1: All-Cause Mortality

Table 3 presents the relative treatment effects of each remote monitoring modality compared with usual care for the outcome of all-cause mortality. Effect estimates are reported as pooled risk ratios (RRs) with corresponding 95 % confidence intervals, derived from the network meta-analysis integrating both direct and indirect evidence across the 112 randomized controlled trials.

Table 3: Network meta-analysis results-All-cause mortality (RR vs. usual care, 112 RCTs)

Node	Trials	RR vs. UC (95 % CI)	P	τ^2	I^2	SUCRA (%)	GRADE
IPAP [10,11]	9	0.80 (0.70–0.91)	0.001	0.011	29 %	87 %	Moderate ⊕⊕⊕○
AI-IRM [17,18]	11	0.83 (0.73–0.94)	0.003	0.018	38 %	74 %	Low ⊕⊕○○
CMP	15	0.85 (0.76–0.95)	0.004	0.022	44 %	68 %	Low ⊕⊕○○
WMS	18	0.87 (0.77–0.98)	0.02	0.031	52 %	58 %	Low ⊕⊕○○
NIT [9,14,15]	31	0.92 (0.84–1.01)	0.08	0.038	61 %	41 %	Low ⊕⊕○○
STS [8]	28	0.93 (0.85–1.02)	0.13	0.029	54 %	34 %	Very Low ⊕○○○
UC	—	Reference	—	—	—	11 %	—

Legend for Table 3. Usual care was designated as the reference node to enable consistent comparison across all technology categories. The table provides, for each intervention, the point estimate, precision of effect, and ranking metrics where applicable. These results reflect the relative probability of death under each monitoring strategy compared with standard follow-up, accounting for the connected evidence structure of the network. The analysis incorporates data from 68,420 participants and reflects a median follow-up duration of 12 months. Between-study heterogeneity and inconsistency were formally assessed within the network framework, and certainty of evidence was evaluated using the GRADE approach. This table therefore summarizes the core comparative effectiveness findings of the study for the primary clinical endpoint.

Primary Outcome 2: HF-Related Hospitalization

Table 4 summarizes the comparative effects of each remote monitoring modality on heart failure–related hospitalization, expressed as risk ratios (RRs) with 95 % confidence intervals, relative to usual care. Estimates are derived from the network meta-analysis, which integrates both direct head-to-head comparisons and indirect evidence across the 112 included RCTs.

Table 4: Network Meta-Analysis Results - HF-Related Hospitalization (RR vs. usual care)

Node	Trials	RR vs. UC (95 % CI)	P	τ^2	I^2	SUCRA (%)	GRADE
IPAP [10,11]	9	0.65 (0.56–0.75)	<0.001	0.008	22 %	91 %	High ⊕⊕⊕⊕
AI-IRM [17,18]	11	0.72 (0.63–0.82)	<0.001	0.014	33 %	79 %	Moderate ⊕⊕⊕○
CMP	15	0.76 (0.68–0.86)	<0.001	0.019	41 %	71 %	Moderate ⊕⊕⊕○
WMS	18	0.80 (0.71–0.90)	<0.001	0.026	48 %	62 %	Low ⊕⊕○○
NIT [9,14,15]	31	0.88 (0.81–0.96)	0.004	0.034	63 %	44 %	Low ⊕⊕○○
STS [8]	28	0.90 (0.83–0.98)	0.01	0.027	58 %	36 %	Low ⊕⊕○○
UC	—	Reference	—	—	—	8 %	—

Legend for Table 4. Usual care serves as the reference node, allowing consistent comparison across interventions. For each modality, the table reports the pooled RR, its precision, and, where available, ranking probabilities to indicate relative effectiveness in reducing HF hospitalizations. The analysis encompasses 68,420 participants with a median follow-up of 12 months and accounts for between-study heterogeneity and local/global network inconsistency. Certainty of evidence was assessed according to GRADE criteria. These results provide clinicians and researchers with a comprehensive quantitative synthesis of the effectiveness of remote monitoring technologies in preventing HF-related hospitalizations.

Trial Sequential Analysis

TSA for HF-related hospitalization (IPAP vs. UC): The cumulative Z-curve crossed the O'Brien-Fleming monitoring boundary at the seventh trial (post-GUIDE-HF, n cumulative = 4,810). The accrued information size (6,240 patients) substantially exceeds the required information size of 4,180 calculated for $\alpha = 0.025$, $\beta = 0.10$, RR = 0.68. This confirms conclusive evidence for IPAP benefit on HF hospitalization [10,11].

TSA for all-cause mortality (IPAP vs. UC): Cumulative Z-curve has crossed the conventional $\alpha = 0.05$ boundary but not yet the TSA monitoring boundary (61 % of RIS accrued), indicating a statistically significant signal but insufficient information for a conclusive determination.

TSA for AI-IRM (HF hospitalization vs. UC): Monitoring boundary not yet crossed; 54 % of RIS accrued (6,870 / 12,740 required patients). Three ongoing trials (NCT05184218, NCT05631470, NCT06118944, total anticipated n = 4,200) are expected to bring AI-IRM TSA to conclusive status by 2027–2028 [17,18].

Secondary Outcomes

Table 5 presents the comparative effects of the highest-ranking remote monitoring nodes on key secondary outcomes, including all-cause mortality, HF–related hospitalization, and composite endpoints, relative to usual care.

Table 5: Secondary Outcomes - Pooled Effects of Top-Ranked Nodes vs. Usual Care

Outcome / Node	Studies (n)	Effect (95 % CI)	I^2 (%)	SUCRA (%)	GRADE
CV mortality — IPAP [10,11]	8	RR 0.77 (0.65–0.91)	24 %	89 %	Moderate ⊕⊕⊕○
CV mortality — AI-IRM [17,18]	9	RR 0.81 (0.70–0.93)	36 %	76 %	Low ⊕⊕○○
30-day readmission — IPAP [10,11]	7	RR 0.68 (0.57–0.81)	19 %	88 %	Moderate ⊕⊕⊕○
30-day readmission — AI-IRM [18]	10	RR 0.74 (0.64–0.86)	31 %	77 %	Low ⊕⊕○○
KCCQ total score — IPAP [10,11]	7	SMD +0.52 (0.38–0.66)	28 %	84 %	Moderate ⊕⊕⊕○
KCCQ total score — AI-IRM [17,18]	9	SMD +0.47 (0.33–0.61)	34 %	79 %	Low ⊕⊕○○
KCCQ total score — NIT [9,14,15]	18	SMD +0.19 (0.09–0.29)	51 %	44 %	Low ⊕⊕○○
6MWD (meters) — CMP	11	MD +38 (22–54)	44 %	72 %	Low ⊕⊕○○
6MWD (meters) — AI-IRM [17,18]	8	MD +41 (24–58)	38 %	74 %	Low ⊕⊕○○
NT-proBNP reduction (%) — IPAP [10,11]	8	MD −28.4 % (−34.1, −22.7)	22 %	91 %	Moderate ⊕⊕⊕○
NT-proBNP reduction (%) — AI-IRM [17,18]	10	MD −24.1 % (−30.2, −18.0)	34 %	81 %	Low ⊕⊕○○
NYHA improvement ≥1 class — IPAP [10,11]	7	RR 1.42 (1.24–1.62)	18 %	87 %	Moderate ⊕⊕⊕○
NYHA improvement ≥1 class — AI-IRM [17,18]	9	RR 1.34 (1.18–1.52)	29 %	76 %	Low ⊕⊕○○
Worsening renal function — IPAP [10,11]	6	RR 0.91 (0.76–1.08)	14 %	—	Low ⊕⊕○○

Legend for Table 5. Effect estimates are expressed as pooled risk ratios (RRs) or mean differences (MDs) with 95 % confidence intervals, derived from the network meta-analysis integrating direct and indirect evidence across the included trials. For each top-ranked modality, the table details the magnitude and precision of effect, the number of contributing trials and participants, and the corresponding GRADE certainty rating. Secondary outcomes were selected to capture clinically meaningful endpoints beyond the primary mortality and HF hospitalization measures, providing a broader perspective on patient-centered benefits. This synthesis highlights the interventions with the greatest relative effectiveness, supporting evidence-informed prioritization of remote monitoring strategies in chronic heart failure management, while accounting for study heterogeneity, follow-up duration, and trial quality.

Cost-Effectiveness Analysis

Eleven randomized controlled trials reported health economic data using methodologically compatible approaches. Implantable pulmonary artery pressure (IPAP) monitoring was associated with a mean annual per-patient cost increase of €12,400–16,800, reflecting device implantation, remote monitoring platform expenses, and management overhead. These additional costs were partially offset by hospitalization-related savings of €6,200–9,400 per patient per year. The resulting incremental cost-effectiveness ratio (ICER) of IPAP versus usual care ranged from €18,200 per quality-adjusted life-year (QALY) gained in trials with high baseline hospitalization

rates to €34,800/QALY in trials with lower baseline rates, remaining below the commonly accepted willingness-to-pay threshold of €50,000/QALY in all scenarios [10,11].

AI-assisted integrated remote management (AI-IRM) programs exhibited heterogeneous cost structures (£1,800–8,400 per patient per year), with three trials reporting ICERs between £12,000 and £28,000/QALY [19,20]. Structured telephone support (STS) and non-invasive telemonitoring (NIT) were associated with the lowest absolute costs (€400–1,200 per patient per year) but also the smallest gains in QALYs, yielding ICERs of €22,000–48,000/QALY depending on baseline hospitalization rates [8,9,21,22].

This synthesis underscores the economic trade-offs across remote monitoring strategies, highlighting that higher-cost interventions such as IPAP and AI-IRM may be cost-effective when accounting for hospitalization reduction and patient-level outcomes.

Subgroup Analyses

Table 6 summarizes the results of pre-specified subgroup analyses examining the effect of each remote monitoring modality on HF-related hospitalization across clinically relevant patient-level and trial-level characteristics.

Table 6: Pre-specified subgroup analyses for HF-related hospitalization across all nodes

Subgroup	Studies (n)	Pooled RR (95 % CI)	I^2 (%)	P (subgroup)	P (interaction)
HFrEF (LVEF < 40 %)	84	0.78 (0.72–0.84)	52 %	<0.001	<0.001
HFmrEF (LVEF 40–49 %)	32	0.88 (0.79–0.98)	48 %	0.02	—
HFpEF (LVEF ≥ 50 %)	28	0.96 (0.87–1.06)	44 %	0.41	—
NYHA class III–IV	78	0.74 (0.68–0.81)	54 %	<0.001	<0.001
NYHA class II	34	0.91 (0.83–1.00)	47 %	0.05	—
Prior HF hosp. ≥1/12 months	71	0.73 (0.67–0.80)	51 %	<0.001	<0.001
No prior HF hospitalization	41	0.93 (0.85–1.02)	43 %	0.14	—
Follow-up ≥ 12 months	68	0.77 (0.71–0.84)	53 %	<0.001	0.003
Follow-up < 12 months	44	0.90 (0.82–0.98)	49 %	0.02	—
High-income countries	88	0.82 (0.77–0.88)	56 %	<0.001	0.09
LMICs	24	0.76 (0.67–0.86)	48 %	<0.001	—
Age < 65 years	41	0.78 (0.70–0.86)	49 %	<0.001	0.12
Age ≥ 65 years	71	0.83 (0.77–0.89)	57 %	<0.001	—
Female ≥ 40 % of cohort	38	0.82 (0.73–0.92)	46 %	0.001	0.34
Female < 40 % of cohort	74	0.81 (0.75–0.87)	55 %	<0.001	—

Legend for Table 6. Subgroups include left ventricular ejection fraction (HFrEF vs. HFpEF), baseline NYHA class (I–II vs. III–IV), age categories, prior HF hospitalization history, and geographic region (high- vs. low-/middle-income countries). For each subgroup, the table presents pooled risk ratios (RRs) with 95 % confidence intervals and the number of trials and participants contributing data. These analyses assess whether the relative effectiveness of the interventions is modified by patient or trial characteristics, providing insight into heterogeneity and potential effect modifiers. Findings from these subgroup analyses help guide individualized application of remote monitoring strategies in clinical practice, indicating which patient populations derive the greatest benefit in reducing HF-related hospitalizations while maintaining methodological rigor across the network meta-analysis.

The strongest subgroup interactions were observed for HF phenotype (HFrEF > HFmrEF > HFpEF; Interaction < 0.001), NYHA class (III–IV > II; P < 0.001), prior hospitalization (recent > none; P < 0.001), and follow-up duration (≥ 12 months > shorter; P = 0.003). Across all technology nodes, remote monitoring interventions showed no statistically significant reduction in HF hospitalization in the HFpEF subgroup (pooled RR 0.96, 95 % CI 0.87–1.06), a finding that persisted in sensitivity analyses restricted to low-risk-of-bias trials. This absence of benefit in HFpEF likely reflects the distinct pathophysiology — where elevated filling pressures are often exercise-induced, body-weight-driven, or related to non-cardiac comorbidities not addressed by current remote monitoring protocols [2,23].

Discussion

This network meta-analysis, encompassing 112 randomized controlled trials and 68,420 patients, delineates a clear and clinically relevant hierarchy of remote monitoring interventions for chronic heart failure. Implantable pulmonary artery (IPAP) sensors achieved the highest SUCRA rankings for both all-cause mortality (87 %) and heart failure (HF) hospitalizations (91 %), supported by high-certainty evidence indicating a 35 % relative reduction in HF hospitalizations and moderate-certainty evidence for a 20 % relative reduction in mortality [10,11]. AI-assisted integrated remote management (AI-IRM) programs ranked second for both outcomes, with moderate-certainty evidence suggesting a 28 % reduction in HF hospitalizations. If confirmed in ongoing trials, this effect would position AI-IRM among the most impactful HF interventions of the past decade [19,20].

The top-ranking position of IPAP is biologically plausible. Non-invasive monitoring modalities are inherently limited by the imprecision of surrogate markers for hemodynamic congestion: body weight changes reflect not only fluid retention but also cachexia and skeletal muscle mass; thoracic impedance is influenced by posture, electrode placement, and body habitus; and patient-reported symptoms are subjective and often inconsistently

reported, particularly in elderly or cognitively impaired populations. By contrast, daily direct measurement of pulmonary artery diastolic pressure provides a precise, actionable, real-time hemodynamic signal, allowing clinicians to adjust diuretic therapy days before symptom onset and thereby prevent the escalation that typically precipitates hospitalization [4,5,10,11].

The emergence of AI-IRM as the second-ranked node is highly significant. The Heart Logic algorithm (Boston Scientific), integrating ICD-recorded thoracic impedance, heart sounds, respiration rate, heart rate, and activity into a composite HF risk index, demonstrated a 38 % relative reduction in HF hospitalization in the MANAGE-HF II trial (n = 862)-the largest single-trial contribution to this node [19,20]. However, it should be noted that 64 % of AI-IRM trials were industry-funded, raising potential concerns regarding optimism bias; our GRADE downgrading for risk of bias partially accounts for this, but independent, investigator-led trials are needed for confirmation.

By contrast, non-invasive telemonitoring (NIT) and structured telephone support (STS) demonstrated modest and inconsistent benefits. NIT yielded a pooled 12 % reduction in HF hospitalization (RR 0.88, low certainty), primarily driven by TIM-HF2 (n = 1,538; RR 0.80), and offset by null effects in TELE-HF (n = 1,653; RR 1.04) and BEAT-HF (n = 1,437; RR 0.96) [8,9,21,22]. Considerable heterogeneity within the NIT node (I^2 = 63 %) highlights that effectiveness is highly context-dependent, influenced by alert protocols, staffing of remote monitoring centers, patient digital literacy, and clinical responsiveness to alerts. For instance, structured programs with dedicated 24/7 nurse response teams, as in TIM-HF2, outperform automated alert systems without clinical oversight, as in BEAT-HF.

A critical and actionable finding is the absence of demonstrable benefit of any remote monitoring modality in HFpEF, with a pooled RR of 0.96 (95 % CI 0.87–1.06) for HF hospitalization. HFpEF is increasingly recognized as a heterogeneous syndrome, driven by diverse pathophysiological mechanisms including obesity-related inflammation, atrial dysfunction, right heart–pulmonary vascular interactions, and extra cardiac comorbidity contributions, none of which are captured by current monitoring protocols focused on left-sided filling pressures [2,15]. As the therapeutic landscape for HFpEF expands—including SGLT2 inhibitors, GLP-1 receptor agonists, and mineralocorticoid antagonists—future remote monitoring programs should incorporate metabolic parameters alongside hemodynamic data and be tested in phenotype-specific trials [23].

Implications for Clinical Practice and Guidelines

Based on our evidence synthesis, we propose the following practice recommendations:

- IPAP -Strong recommendation (GRADE moderate-to-high certainty): Eligible patients with HFrEF (LVEF ≤ 35 %), NYHA class III, and at least one HF hospitalization in the prior 12 months should be offered IPAP-guided therapy, consistent with the 2023 ESC HF focused update (Class IIa, Level B). Our pooled data strengthen the evidence base and support upgrading this recommendation to Class I in the next guideline iteration [10,11,23].
- AI-IRM - Conditional recommendation (GRADE low-to-moderate certainty): Patients with HFrEF and NYHA class III–IV enrolled in a structured HF management program should be considered for AI-assisted remote management platforms with demonstrated clinical validation, particularly those integrating implanted device data with EHR and wearable signals [19,20].
- NIT -Weak recommendation (GRADE low certainty): Non-invasive telemonitoring may be offered to patients with HFrEF and NYHA class II–III who are not eligible for IPAP, provided a dedicated nursing response team is available to act on alerts within 24 hours [9,21,22].
- STS -Weak recommendation (GRADE very low certainty): Structured telephone follow-up at 1–2-week intervals post-discharge remains appropriate as a minimum standard of care for all CHF patients, primarily for medication adherence support, but should not substitute for more intensive monitoring in high-risk patients [8].
- HFpEF- No recommendation: No remote monitoring modality has demonstrated significant benefit in HFpEF. Remote monitoring in HFpEF should be reserved for clinical trials until phenotype-specific strategies are developed and validated [15].

Strengths and Limitations

This NMA is the largest quantitative synthesis of remote monitoring RCTs in CHF to date, with rigorous a priori node definition, explicit assessment of transitivity and network inconsistency, TSA for primary outcomes, and GRADE certainty assessment for all comparisons. The inclusion of non-English language studies (CNKI, KCI, LILACS) reduces geographic selection bias [13]. Limitations include: the open-label design of most device trials, which is inherent to the technology and introduces performance bias that GRADE downgrade partially addresses; residual clinical heterogeneity within nodes, particularly NIT and AI-IRM; the relative paucity of LMIC trial data (24 trials, 21 %); and the absence of individual patient data preventing individual-level moderator analyses. Additionally, the rapid technological evolution of AI-IRM platforms means that some included trials may evaluate algorithms that are already clinically obsolete [19,20].

Conclusion

This network meta-analysis of 112 randomized controlled trials represents the most comprehensive and methodologically robust synthesis of evidence to date on remote monitoring for chronic heart failure. Implantable pulmonary artery pressure (IPAP) sensor-guided therapy demonstrated the highest and most reliable benefit, achieving a 35% relative reduction in HF hospitalizations with high-certainty evidence, further supported by trial sequential analysis confirming conclusive results, and should be considered the standard of care for eligible patients with HFrEF [10,11]. AI-assisted integrated remote management (AI-IRM) programs emerge as the most promising novel approach, providing moderate-certainty evidence for a 28% reduction in HF hospitalizations; however, additional confirmatory RCTs are needed to substantiate these findings [19,20]. Traditional non-invasive telemonitoring (NIT) and structured telephone support (STS) confer modest, context-dependent benefits and remain appropriate as minimum standards of care for patient's ineligible for more advanced monitoring [8,9,21,22]. Notably, the evidence base for remote monitoring in HFpEF is virtually nonexistent, highlighting a critical priority for future research [14].

Looking forward, several key perspectives emerge. First, remote monitoring programs should increasingly adopt a patient-centered, implementation science-driven approach, integrating individualized risk stratification, patient engagement, and real-world care pathways. Second, future research must explore the combination of hemodynamic, metabolic, and behavioral data to optimize monitoring for HFpEF and other complex phenotypes. Third, cost-effectiveness, workflow integration, and health equity

considerations must be incorporated to ensure sustainable adoption in diverse healthcare systems. Finally, artificial intelligence and machine learning offer opportunities to enhance predictive accuracy, personalize interventions, and reduce clinical burden, but independent validation and rigorous trials remain essential before widespread deployment. These perspectives collectively chart a roadmap for translating remote monitoring technologies into improved patient outcomes and healthcare efficiency [24].

Declarations

Conflict of Interest Statement: E. Andrès, S. Talha, A. Hajjam and C. Brandt have participated in institutional research projects funded by the Agence de Recherche du Grand Est (France) and the Agence Nationale de la Recherche (France). They have also been involved in research collaborations with pharmaceutical companies in the field of heart failure, including companies marketing medications in this therapeutic area. In addition, they have collaborated with Pretimed Technology in the development of a telemonitoring solution for patients with chronic heart failure.

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