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ORIGINAL PAPER

Impact of postoperative in-hospital continuous vital sign monitoring on healthcare costs, resource utilization and labor market outcomes

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Abstract

Continuous vital signs monitoring (CVSM) is increasingly being used for early complication detection in general wards, potentially reducing prolonged medical care and healthcare utilization. However, its impact on health economic outcomes, including post-discharge trajectories, remains largely unexplored. This study aimed to estimate the impact on healthcare costs, resource utilization and labor market outcomes of patients included in a postoperative randomized clinical trial (RCT) of an artificial intelligence (AI)-assisted CVSM. The WARD Surgical RCT (Clinicaltrials.gov Identifier: NCT04640415) randomized participants to monitoring by AI-assisted CVSM with real-time alerts or blinded monitoring. In this study, Generalized Linear Models and Two-part models were used to estimate the impact on healthcare costs and resource utilization across primary and secondary care, including home care, home nursing and prescription medication. Additionally, the impact on employment status, full-time employment duration and sickness leave duration were examined. The study included 382 trial participants traceable in the Danish national registries. No differences in total healthcare costs were found between the groups (EUR 21,184 vs EUR 20,621, $p=0.58$ at 30 days and EUR 40,505 vs EUR 40,870, $p=0.81$ at 1 year). After adjustment, the intervention group had a reduction of 2.4 weeks (95%CI (-4.5;-0.3)) on sickness leave within 3 months. No other statistically significant differences were observed. There was no statistically significant impact of AI-assisted CVSM on total healthcare costs, resource utilization, employment status or duration of full-time employment compared to blinded monitoring. Monitoring was associated with shorter duration of sickness leave within 3 months. This reduction, even if modest, may yield broader societal benefits by supporting workforce participation and reducing productivity loss.

Keywords Continuous vital signs monitoring · Healthcare costs and utilization · Labor market outcomes · Registry data · Randomized Controlled Trial

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Introduction

Continuous vital signs monitoring (CVSM) has been an integral component of intensive care units (ICUs) since the 1970's, enabling early detection of clinical deterioration in unstable patients [1]. However, patients in general wards—including surgical patients at substantial risk of postoperative complications such as ICU admission or mortality [2, 3]—may also experience delayed or even unnoticed deterioration because standard intermittent monitoring every 6–12 h leaves gaps during which deterioration may go undetected [4, 5]. Advances in wireless monitoring data transmission, and artificial intelligence (AI) have enabled CVSM to extend beyond critical care into general wards [6], offering the potential for early detection of clinical deterioration

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and timely intervention without necessitating ICU-level staffing [3].

Existing studies on the effects of (AI-assisted) CVSM in general wards primarily focus on in-hospital or short-term economic and clinical outcomes, such as mortality [4, 7–11], ICU transfers [4, 5, 7, 9–13], length of stay [4, 7–15] and 30-day readmissions [4, 7, 13]. However, the post-discharge trajectory remains largely understudied, despite the potential for CVSM to influence long-term outcomes. Long-term outcomes may include the need for post-discharge medical care, home nursing requirements, and labor market outcomes, such as employment status and sickness leave. Evaluating resource utilization and labor market participation post-discharge provides valuable insight into the broader impact of AI-assisted CVSM, serving as an indicator of long-term health outcomes [16]. By facilitating early detection and management of complications, AI-assisted CVSM may promote faster recovery and reduce the need for prolonged medical care, ultimately lowering long-term healthcare resource utilization. Beyond direct healthcare utilization, labor market outcomes serve as a proxy for functional recovery and quality of life. If AI-assisted CVSM enhances early detection and management of complications, it may reduce the risk of long-term disability, enabling patients to return to their pre-hospitalization health, activity and productivity levels. A systematic review by Kamdar et al. concluded that survivors of critical illness often experience delayed return to work, job loss, and diminished employment prospects following ICU admission [17]. This underscores that there is a potential for AI-assisted CVSM to positively impact labor market outcomes, provided it effectively improves in-hospital and/or post-discharge health outcomes. Although no universal consensus exists on including labor market outcomes in economic evaluations, they are critical for capturing the full societal impact of AI-assisted CVSM [18]. Patients who return to work contribute to economic productivity, reducing the indirect costs of illness and potentially offsetting healthcare costs associated with the technology [19]. Thus, integrating post-discharge resource utilization and labor market outcomes into economic assessments can provide a more comprehensive evaluation of AI-assisted CVSM's value [20].

A recent randomized controlled trial (RCT) evaluated the impact of the WARD-Clinical Support system—an AI-assisted CVSM system—on the cumulative duration of severe vital sign deviations in patients in the general post-operative ward, as well as the frequency of adverse events and serious adverse events [21]. The present study is a secondary analysis of the WARD Surgical RCT aimed at evaluating long-term impact of AI-assisted CVSM on healthcare costs, resource utilization and labor market outcomes using comprehensive Danish registry data. Specifically, this study aimed to estimate the short-term (30-days/3-months) and long-term (1-year) healthcare costs, resource utilization, employment outcomes and receipt of sickness benefits among patients enrolled in the WARD Surgical RCT.

Methods

Setting and study population

The WARD Surgical RCT (Clinicaltrials.gov Identifier: NCT04640415) included 400 patients who were randomized into two groups: The intervention group ($n=200$) having their vital signs continuously monitored with the generation of real-time predefined alerts of clinical deterioration suggesting medical attention, and the control group ($n=200$) having their vital signs continuously monitored but healthcare staff blinded to the measurements and with no alarms generated [21]. Both groups also received usual care meaning routine intermittent manual monitoring using the National Early Warning Score (NEWS) system [22]. Patients were eligible for inclusion if they were above 50 of years and admitted for elective major abdominal, vascular arterial, urologic, or orthopedic surgery, with an anticipated surgical duration of at least 2 h and a minimum expected hospital stay of 2 nights. The age threshold was chosen to have a cohort of patients with an increased baseline risk of postoperative complications and clinical deterioration, in whom an early warning and alerting system is most likely to have clinical impact. Exclusion criteria included inability or unwillingness to provide informed consent, the presence of a pacemaker or implantable cardioverter defibrillator, or an allergy to sensor materials [21]. More details about the trial can be found elsewhere [21]. The main result of the WARD Surgical RCT was no statistically significant difference in cumulative severe vital sign deviations among the two groups. However, the trial did demonstrate significant reductions in desaturations and adverse events within 30 days [21]. The study population in the present study consisted of the subset of the 400 WARD Surgery RCT patients who could be identified in the Danish national registries.

Outcomes and follow-up periods

Our primary outcome was total healthcare cost, including hospital costs, prescription medication costs, primary care costs, home care costs and home nursing costs (see Data section below). Our secondary outcomes included employment status (any employment or no employment), duration of full-time employment (in months) and duration of sickness leave (in weeks). Tertiary outcomes included all healthcare cost components of the primary outcomes and

healthcare resource utilization. Healthcare resource utilization included the number of bed days of hospital admissions (defined as hospital stays exceeding 12 h in accordance with the Danish Health Data Authority [23]), the number of hospital contacts, the number of visits to primary care and general practice, and the number of home nursing visits.

Outcomes were assessed at 30 days and 1-year post the index-date, defined as the start of monitoring. However, labor market outcomes were evaluated at 3 months and 1 year, as changes in employment status or sick leave cannot be adequately captured within a 30-day period[1]. The index-date was included in the follow-up periods.

Data

Individual-level data on healthcare costs and resource utilization were derived from Danish national registries covering both the primary and secondary healthcare sector. The National Patient Registry (NPR) includes comprehensive data on all hospital contacts in Danish public hospitals, including outpatient visits and inpatient stays and related diagnoses and procedures [24]. From the NPR, the total number of bed days and the number of hospital contacts were estimated. Hospital costs were calculated using Diagnosis-Related Groups (DRG) tariffs available from the NPR. DRG tariffs reflect the average treatment costs of specific DRG groups, which are groups of patients who share similar clinical characteristics and resource utilization. DRG tariffs encompass both direct healthcare costs (treatment and care), non-healthcare costs – such as kitchen services and administration—as well as the majority of operating costs, including rent. These costs are integrated with hospital activity data to calculate an average for each DRG group [25]. Due to the nature of DRG data, we could not precisely allocate hospital costs during the hospital stay. Therefore, we included the full costs of the index admission in the follow-up period, rather than calculating hospital costs strictly from the index date.

Data on primary care utilization and costs were obtained from the Public Health Insurance Registry, which includes detailed individual-level records on services provided by general practitioners, private medical specialists, physiotherapists, psychologists, and others [26]. From this registry, the overall costs and the number of visits in primary care were estimated, as well as the number of contacts with general practice, specifically. Information on prescription medication and related costs was retrieved from The Register of Pharmaceutical Sales. Data on home care and home nursing were extracted from the Elderly Indicators. The home care registry records the time (in minutes) allocated per week on care, which was multiplied by a time cost derived from the hourly wage of social and health workers as specified in the costing manual of the Danish Medicines Council [27]. For home nursing, the registry documents the number of days with visits, and each day was multiplied by a day rate calculated from total municipal expenses for home care and the total number of home nursing days [28].

The Danish Rational Economic Agents Model (DREAM) database comprises individual-level data on public transfer payments and employment recorded on a weekly and monthly basis, respectively [29]. From the DREAM database, employment status, the duration of full-time employment and number of weeks on sickness leave were obtained.

Additional registries from Statistics Denmark were used to retrieve sociodemographic information for each individual. Finally, the WARD Surgical RCT provided information on patients' index date, co-morbidities and frailty. All registries were linked using each individual's unique central person registration (CPR) number, provided by the trial.

Patients who could not be linked to the national registries were excluded from the study population (see Results section). Missing values occurred only for frailty scores in the RCT data (see Table 1). As these variables were used solely for descriptive purposes, no imputation was performed. All registry-based variables were complete, with no missing observations.

Statistical methods

To assess baseline comparability, we compared estimates of each outcome between groups in the year preceding the index date. In this period, we excluded resource utilization during the 30 days prior to index admission, as patients were enrolled in the trial either on the day of surgery or up to 30 days beforehand. This exclusion aimed to remove potential surgery-related resource use from the analysis. Consequently, the pre-intervention period spanned from 30 days before index admission to 11 months prior. Patient characteristics and pre-intervention outcome variables were compared between the two groups using Chi-square (χ^2) test for categorical variables and the independent t-test for continuous variables.

For outcomes with a mass at zero, we applied two-part models: a logistic regression in the first part to model the probability of a nonzero outcome and a Generalized Linear Model (GLM) in the second part to estimate the nonzero values. For all other variables, we used a standard GLM approach. For variables in which a value of zero represented

[1] In Denmark, sick pay eligibility begins only after one month. During this month, sick leave will usually be covered by the employer. Consequently, a 30-day assessment period may not accurately reflect employment status, as individuals who have reported sick may still be classified as employed without receiving sick pay. Assessing employment and sickness leave at three months ensures that sick pay has taken effect, providing a more accurate measure.

Table 1 Patient characteristics

Patient's characteristics in the WARD Surgical RCT					
	Intervention, n	%	Control, n	%	*p* value
n	193	50.5	189	49.48	
Index year					0.92
2021	39	20.2	39	20.63	
2022	154	79.8	150	79.37	
Mean age (years)	67.6		69.7		0.02
Sex					0.35
Male	122	63.2	128	67.7	
Female	71	36.8	61	32.3	
Ethnic origin					0.48
Danish	183	94.8	182	96.3	
Immigrant/descedant	10	5.2	7	3.7	
Marital status					0.66
Married	114	59.1	105	55.6	
Unmarried	28	14.5	27	14.3	
Divorced	35	18.1	34	18.0	
Widowed	16	8.3	23	12.2	
Education					1.00
Basic, upper secondary or unknown level of education	60	31.1	57	30.2	
Vocational education and training	71	36.8	72	38.1	
Short or medium higher education	36	18.7	35	18.5	
Longer higher education	26	13.5	25	13.2	
Employment status					0.09
Employed	70	36.3	54	28.6	
In education or receiving public transfer payments	23	11.9	16	8.5	
Retired	100	51.8	119	63.0	
Region					0.08
Capital region	160	82.9	143	75.7	
Other region	33	17.1	46	24.3	
CCI					0.28
0–1	32	16.6	21	11.1	
2–3	100	51.8	101	53.4	
> =4	61	31.6	67	35.5	
Mean BMI	26.2		27.1		0.08
ASA score					0.60
1–2 or missing	95	49.2	88	46.6	
3–4	98	50.8	101	53.4	
CFS score					0.21
1–3 or missing	142	73.6	128	67.7	
4–6	51	26.4	61	32.3	
Type of surgery					0.66
Vascular	34	17.6	27	14.3	
Abdominal	134	69.4	138	73.0	
Other (urologic and orthopedic)	25	13.0	24	12.7	
Mean days alive after 30 days	28.9		28.9		0.78
Mean days alive after 1 year	348.1		355.1		0.21
Mortality after 1 year	15	7.8	11	5.8	0.45

Categorical variables have been compared using Chi-square (χ^2) test.

Continuous variables have been compared using the independent t-test.

a true structural zero, these were incorporated directly into the two-part modelling framework. Aside from structural zeros, no missing data were present in the analytic variables included in the regression models. Cost outcomes were analyzed using GLM with a log link and a gamma distribution to account for their skewed nature. Count outcomes—including weeks on sickness leave, number of hospital contacts, number of visits in primary care, number of

visits in general practice, and number of home nursing visits—were analyzed using GLM with a log link and either a negative binomial or Poisson distribution, depending on model fit assessed by the Akaike Information Criterion (AIC)/Bayesian Information Criterion (BIC) test. Employment status at 3 months was analyzed using GLM with a logit link and a binomial distribution, equivalent to logistic regression.

We reported the sample average marginal effects of each outcome in four different models. In the main model, we adjusted for variables statistically significantly different between the groups pre-intervention and we excluded all patients who died during the follow-up period. In additional models, we (1) did not adjust for pre-intervention imbalances (2) included deaths, and (3) only retained the per-protocol-population for analysis, defined as patients having been monitored > 12 h and having at least one alarm responded [21]. In the analysis of labor market outcomes, we only included patients who were employed prior to inclusion in the trial.

All costs in DKK were adjusted to 2024-prices and converted to EUR (EUR) (1 EUR = 7.45 DKK). All data analysis was performed in STATA V18. In the statistical analyses, we applied a significance level of 0.05.

Table 2 Pre-intervention differences

	Intervention ($n=193$)	Control ($n=189$)	Difference (95% CI)	p value
Primary outcome				
Total healthcare costs (mean, EUR)	12,852	14,135	−1283 (−2,253;4,819)	0.48
Secondary outcomes				
Employed in the year prior to index year (%)	36	29	7.7 (−17;1.7)	0.11
Months of full-time employment (mean)	8.0	7.7	0.3 (−1.8;1.2)	0.69
Receipt of sickness benefits (%)	35	35	0 (−17;17)	0.96
Weeks on sickness leave (mean)	4.7	5.2	−0.5 (−3.2;4.2)	0.80
Tertiary outcomes				
Hospital costs (mean, EUR)	11,461	12,298	−838 (−2,618;4,293)	0.63
# hospital contacts (mean)	13	14	−0.6 (−2.1;3.3)	0.65
Bed days (mean)	3.0	3.5	−0.4 (−1.3;2.1)	0.63
Prescription medication costs (mean, EUR)	688	780	−92 (−102;285)	0.35
# primary care visits (mean)	18	19	−1.6 (−1.6;4.9)	0.32
# general practice visits (mean)	12	14	−1.7 (−0.6;3.9)	0.15
Receipt of home care (%)	5.2	12	−7.0 (1.4;13)	0.02
Home care costs (mean, EUR)	14	80	−66 (18;113)	0.01
Receipt of home nursing (%)	16	20	−3.5 (−4.2;11)	0.37
Home nursing costs (mean, EUR)	109	361	−252 (30;475)	0.03

number of

For outcomes reported in percentages (%), the difference and confidence intervals are reported in %points

Results

The WARD Surgical RCT included 400 patients, 200 in each arm. We excluded 18 patients due to non-Danish CPR or due to unavailable registry data leaving 382 patients for main analysis, with 193 in the intervention group and 189 in the control group. The per-protocol population comprised 312 patients; 137 in the intervention group and 175 in the control group.

Patient characteristics and pre-intervention estimates

Patient characteristics are provided in Table 1. In general, patients in the two groups were comparable. However, patients in the control group were, on average, two years older than patients in the intervention group (69.7 years vs. 67.6 years, $p=0.02$). As age is associated with postoperative recovery and healthcare utilization, this imbalance should be considered a potential confounder when interpreting subsequent analyses.

Table 2 provides pre-intervention differences for each group. The control group had significantly higher pre-intervention home care costs and home nursing costs compared to the intervention group. For the remaining variables, there were no statistically significant differences between the two groups.

Descriptive outcomes at follow-up

Descriptive outcomes at each follow-up period are shown in Table 3. The two groups exhibited comparable total healthcare costs at both the 30-day and 1-year follow-ups. Similarly, no significant differences were observed in employment outcomes or sickness leave, hospital-related costs, total bed-days, nor primary care utilization levels between the groups in any follow-up periods. However, prescription medication costs were significantly lower in the intervention group at the 1-year follow-up (EUR 964 vs. EUR 1,260) A significantly lower proportion of patients in the intervention group received home care at both 30 days

Table 3 Descriptive outcomes at follow-up

	Intervention ($n=193$)	Control ($n=189$)	Difference (95% CI)	p value
Primary outcome				
Total healthcare costs, 30 days (mean, EUR)	21,184	20,621	563 (−2,550;1,424)	0.58
Total healthcare costs, 1 year (mean, EUR)	40,505	40,870	−365 (−5,236;6,694)	0.81
Secondary outcomes				
Employed at 3 months (%)	71	69	2.5 (−19;14)	0.77
Employed at 1 year (%)	68	59	9.7 (−27;7,7)	0.27
Months of full-time employment, 1 year (mean)	7.7	6.6	1.1 (−3.1;0.9)	0.27
Receipt of sickness benefits, 3 months (%)	45	54	−8.8 (−8.9;27)	0.33
Weeks on sickness leave, 3 months (mean)	5.0	6.6	−1.6 (−0.6;3.8)	0.15
Receipt of sickness benefits, 1 year (%)	44	53	−8.9 (−9.1;27)	0.34
Weeks on sickness leave, 1 year (mean)	11	16	−4.3 (−2.3;11)	0.20
Tertiary outcomes				
Hospital costs, 30 days (mean, EUR)	20,920	20,313	607 (−2,593;1,379)	0.55
Hospital costs, 1 year (mean, EUR)	37,885	37,792	93 (−5,882;5,698)	0.98
# hospital contacts, 30 days (mean)	3.9	3.9	0.0 (−0.5;0.5)	0.99
# hospital contacts, 1 year (mean)	23	24	−1.4 (−2.6;5.4)	0.45
Bed days, 30 days (mean)	11	11	−0.1 (−2.2;2.4)	0.94
Bed days, 1 year (mean)	16	16	0.4 (−5.4;4.6)	0.87
Prescription medication costs, 30 days (mean, EUR)	71	91	−20 (−6.3;46)	0.14
Prescription medication costs, 1 year (mean, EUR)	964	1,260	−296 (13;579)	0.04
# primary care visits, 30 days (mean)	2.3	2.6	−0.3 (−0.2;0.8)	0.22
# primary care visits, 1 year (mean)	20	21	−1.3 (−2.1;4.8)	0.45
# general practice visits, 30 days (mean)	2.1	2.4	−0.3 (−0.2;0.8)	0.20
# general practice visits, 1 year (mean)	15	16	−1.6 (−0.8;4.1)	0.19
Receipt of home care, 30 days (%)	8.9	17	−8.3 (1,5;15)	0.02
Home care costs, 30 days (mean, EUR)	9.7	15	−5.8 (−8.4;20)	0.42
Receipt of home care, 1 year (%)	14	23	−9.0 (0.1;17)	0.03
Home care costs, 1 year (mean, EUR)	78	247	−169 (11;327)	0.04
Receipt of home nursing visits, 30 days (%)	35	39	−3.1 (−6.6;13)	0.53
Home nursing costs, 30 days (mean, EUR)	130	150	−20 (−30;69)	0.44
Receipt of home nursing visits, 1 year (%)	44	49	−4.5 (−5.8;15)	0.40
Home nursing costs, 1 year (mean, EUR)	615	984	−369 (2.9;735)	0.05

number of

For outcomes reported in percentages (%), the difference and confidence intervals are reported in %points

and 1 year. While home care costs were also significantly lower at the 1-year follow-up, no significant difference was observed at 30 days. Additionally, home nursing costs were significantly lower in the intervention group at the 1-year follow-up. However, the proportion of patients receiving home nursing services remained similar between the two groups.

Regression model results on healthcare costs, resource utilization and labor market outcomes

Table 4 provides the average marginal effects of each outcome in each of the four models. Based on the comparison of patient characteristics and pre-intervention estimates, age at index date, pre-intervention home care costs and pre-intervention home nursing costs were included as covariates in the main model, as these variables demonstrated statistically significant differences between the two groups. The average marginal effects reflect the change in the outcome when transitioning from control to intervention group. Hence, for costs, the average marginal effects quantify the average, additional (if positive) or reduced (if negative) costs in the intervention group compared to the control group.

In the main (adjusted) model, there were no statistically significant differences observed between intervention and control group with respect to total healthcare costs, resource utilization, employment status, or duration of full-time employment. However, the intervention group demonstrated a significantly lower number of weeks on sickness leave at 3 months (−2.4 weeks, 95%CI (−4.5;−0.3)). In the unadjusted model, the intervention group incurred significantly lower prescription medication costs compared to the control group at 1-year follow-up (EUR −296, 95%CI (−575;−17)). Furthermore, the unadjusted model showed significantly lower costs for home care (EUR −169, 95%CI (−318;−20)) and home nursing (EUR −369, 95%CI (−726;−11), as well

Table 4 Healthcare costs, resource utilization and labor market outcomes for the intervention group vs the control group in each of the four models. The average marginal effects reflect the change in the outcome when transitioning from control to intervention group

		Average marginal effects (95% CI)			
Follow-up period	Regression model	Adjusted model	Unadjusted model	Including deaths	Per-protocol
Primary outcome, n = max 382					
30 days					
Total healthcare costs (EUR)	GLM (log-gamma)	446 (−1,417;2,543)	563 (−1,417;2,543)	296 (−1,712;2,305)	684 (−1,527;2,894)
1 year					
Total healthcare costs (EUR)	GLM (log-gamma)	−641 (−6,677;5,395)	−729 (−6,677;5,219)	421 (−5,553;6,396)	271 (−6,553;7,095)
Secondary outcomes, n = max 124					
3 months					
Employed (%point)	GLM (logit-binomial)	−0.0 (−0.2;0.1)	0.0 (−0.1;0.2)	−0.0 (−0.2;0.1)	0.0 (−0.2;0.2)
# weeks on sickness leave	2PM (logit + log-poisson)	−2.4 (−4.5;−0.3)	−1.6 (−3.9;0.6)	−2.4 (−4.5;−0.3)	−1.9 (−4.1;0.4)
1 year					
# months of full-time employment	2PM (logit + log-gamma)	0.1 (−1.7;2.0)	1.1 (−0.9;3.0)	0.2 (−1.7;2.0)	0.9 (−1.3;3.0)
# weeks on sickness leave	2PM (logit + log-negative binomial)	−5.8 (−15;3.0)	−4.3 (−11;2.3)	−4.9 (−14;3.8)	−5.6 (−15;3.4)
Tertiary outcomes, n = max 382					
30 days					
Hospital costs (EUR)	GLM (log-gamma)	444 (−1,560;2,449)	607 (−1,371;2,586)	296 (−1,714;2,306)	692 (−1,518;2,901)
# hospital contacts	GLM (log-negative binomial)	−0.1 (−1.0;0.8)	−0.0 (−0.9;0.9)	−0.1 (−1.0;0.8)	−0.1 (−1.1;0.9)
# bed days	GLM (log-gamma)	0.1 (−1.5;1.7)	0.1 (−1.5;1.7)	−0.2 (−2.5;2.1)	−0.5 (−3.0;2.0)
Prescription medication costs (EUR)	2PM (logit + log-gamma)	−15 (−41;12)	−20 (−47;7.1)	−15 (−42;11)	−18 (−49;13)
Primary care costs (EUR)	2PM (logit + log-gamma)	−1.5 (−17;14)	−2.9 (−19;13)	−1.4 (−17;14)	−2.8 (−23;18)
# visits in primary care	2PM (logit + log-negative binomial)	−0.3 (−0.9;0.4)	−0.3 (−1.0;0.4)	−0.3 (−1.0;0.4)	−0.3 (−1.1;0.5)
# visits in general practice	2PM (logit + log-negative binomial)	−0.3 (−0.9;0.4)	−0.3 (−1.0;0.4)	−0.3 (−0.9;0.4)	−0.2 (−0.9;0.5)
Home care costs (EUR)	2PM (logit + log-gamma)	6.8 (−9.7;23)	−5.8 (−19;8.0)	6.9 (−9.5;23)	−2.6 (−9.7;4.5)
Home nursing costs (EUR)	2PM (logit + log-gamma)	1.9 (−46;50)	−20 (−69;30)	0.5 (−47;49)	−0.3 (−53;53)
# home nursing visits	2PM (logit + log-negative binomial)	0.1 (−1.7;1.8)	−0.6 (−2.3;1.2)	0.0 (−1.7;1.8)	−0.0 (−1.9;1.9)
1 year					
Hospital costs (EUR)	GLM (log-gamma)	−339 (−6,151;5,472)	92 (−5,678;5,862)	739 (−5,016;6,494)	608 (−5,973;7,190)
# hospital contacts	GLM (log-negative binomial)	−1.6 (−6.7;3.5)	−1.4 (−6.4;3.6)	−1.8 (−6.7;3.1)	−1.4 (−7.0;4.2)
# bed days	GLM (log-gamma)	0.6 (−4.5;5.7)	0.4 (−4.6;5.4)	2.6 (−2.4;7.6)	0.6 (−5.3;6.6)
Prescription medication costs (EUR)	GLM (log-gamma)	−216 (−487;565)	−296 (−575;−17)	−183 (−441;76)	−216 (−521;88)
Primary care costs (EUR)	2PM (logit + log-gamma)	11 (−101;124)	−17 (−133;100)	0.8 (−106;108)	−38 (−162;85)
# visits in primary care	GLM (log-negative binomial)	−0.3 (−4.8;4.2)	−1.3 (−5.8;3.1)	−0.6 (−4.9;3.7)	−0.7 (−5.6;4.3)
# visits in general practice	GLM (log-negative binomial)	−0.9 (−4.3;2.5)	−1.6 (−5.0;1.7)	−1.1 (−4.3;2.1)	−0.7 (−4.4;3.0)
Home care costs (EUR)	2PM (logit + log-gamma)	−28 (−215;159)	−169 (−318;−20)	−30 (−200;139)	−28 (−231;176)
Home nursing costs (EUR)	2PM (logit + log-gamma)	−97 (−413;218)	−369 (−726;−11)	−131 (−438;175)	−66 (−413;281)
# home nursing visits	2PM (logit + log-negative binomial)	−2.9 (−11;5.5)	−11 (−20;−1.8)	−3.9 (−12;4.1)	−2.0 (−11;7.1)

Exact n cannot be reported due to the small number of deaths.

2PM: Two-part model.

GLM: Generalized Linear Model.

number of.

as fewer home nursing visits (EUR −11, 95%CI (−20;−1.8)), in the intervention group at 1 year. Including deaths did not change the results of the main model. The per-protocol analysis showed no statistically significant effects on any outcome.

Discussion

In this study, we found no statistically significant differences in total healthcare costs, resource utilization, employment status or duration of full-time employment between patients continuously monitored by AI-assisted CVSM and those blinded to monitoring. Importantly, our findings indicate that AI-assisted CVSM did not increase healthcare costs, which is in itself a relevant outcome when introducing new digital health technologies. Additionally, the intervention group had 2.4 fewer weeks of sickness leave compared to the control group within 3 months, representing a meaningful potential benefit with implications beyond the hospital setting.

Despite randomization, notable differences were observed between the intervention and control group. Although these differences may not be clinically relevant, our analysis suggests that they substantially influence some of the outcomes assessed in this study. Specifically, the shift in statistical significance between the adjusted and the unadjusted model for sickness leave, prescription medication, home care costs, home nursing costs, and home nursing visits suggests that age and pre-intervention home care and home nursing costs are key confounding variables. These variables appear to largely account for the observed cost reductions in the intervention group, rather than being attributable to AI-assisted CVSM itself.

In the main model, we excluded patients who died during follow-up, consequently focusing on outcomes among survivors. Including deaths could distort cost estimates if deceased patients incurred disproportionately high end-of-life care expenses. This is likely reflected in the reversed sign of hospital costs at 1 year when deaths are included, shifting from lower to higher hospital costs in the intervention group compared to the control group. Higher mortality and hospital costs in the intervention group suggest that deceased patients likely incurred substantial hospital costs prior to death.

Restricting the analysis to the per-protocol population attenuated the impact on sickness leave at 3 months and rendered the previously statistically significant difference non-significant. As the per-protocol population included patients monitored for at least 12 h and with minimum one alarm responded to, this raises the possibility that the observed impact on sickness benefit in the intention-to-treat analysis may have been influenced by factors beyond active clinical use of the system. Importantly, the intention-to-treat analysis provides a more accurate representation of how AI-assisted CVSM would perform in actual clinical practice compared to the per-protocol analysis.

The statistically significant impact on sickness leave observed in the main model raises an important consideration about the distribution of costs and benefits associated with healthcare interventions: While hospitals may incur upfront costs, the financial returns may be realized by other sectors. In this case, the hospital acts as the payer of the monitoring system, yet, the economic benefits do not accrue to the hospital itself. Instead, the public sector (i.e. the state and the municipalities), which are responsible for paying and administering sickness benefits, are the primary beneficiaries of any cost savings.

While the literature on the short-term clinical and economic effects of AI-assisted CVSM remains inconclusive [4, 7–15], evidence on its long-term impact on healthcare costs, resource utilization and labor market outcomes is virtually nonexistent. Existing evidence on AI-assisted CVSM primarily examines admission-related outcomes such as LOS, ICU transfers and rapid response team activations [9, 11, 30–37], and only a small number of studies have assessed short-term post-discharge outcomes like 30-day readmissions [33, 36] or described types of nursing care without valuing them [32]. While a few modelling and observational studies have estimated healthcare costs [12, 38, 39], these analyses are almost exclusively based on in-hospital metrics. This study addresses this gap by examining the post-discharge trajectory following AI-assisted CVSM monitoring, a crucial component of the technology's overall socio-economic impact. Although the study did not identify significant healthcare cost-savings, it also found no indication that AI-assisted CVSM increases resource utilization post-discharge. Although the difference was not statistically significant, the intervention group had lower total healthcare costs at 1 year. We cannot exclude the possibility that a larger sample size might have yielded a statistically significant result.

Key strengths of this study include the use of comprehensive high-quality and registry data and the possibility of individual-level linkage between registries. This approach facilitates the detection and adjustment for pre-intervention imbalances, which was not addressed during the randomization procedure. Furthermore, it allows for long-term tracking of patients across various settings. By applying a broad perspective, the study contributes to a more comprehensive understanding of the health and socio-economic impact of AI-assisted CVSM.

Although the study population was relatively well-balanced, the sample size was not specifically powered to

detect differences in the outcomes of this secondary analysis. Consequently, some of the non-significant findings may be attributable to limited statistical power. Furthermore, we did not include intervention costs in the analysis, nor were we able to assess the potential impact on workload as part of the intervention. The WARD-CSS utilizes commercially available vital signs monitoring devices that connect via Bluetooth/Wi-Fi, suggesting that inclusion of intervention costs is not crucial for the results. With regard to impact on staff workload, this is generally an understudied field. A study by Sigvardt et al. showed that the nurses spent less time on measuring vital signs using AI-assisted CVSM compared to manual monitoring [40]. However, other research has highlighted that that continuous monitoring systems can inadvertently increase workload due to a high frequency of non-actionable alarms [41]. Regarding sickness leave, we were only able to assess officially registered absences, meaning that patients may have been absent from work while still being classified as employed and receiving salary under their labor agreement. Finally, although we compared the two groups across various pre-intervention and index factors, there may be residual confounding that we were unable to fully account for.

The WARD Surgical RCT demonstrated a significantly lower incidence of adverse events at 30 days, which may explain the reduction in weeks of sickness leave within 3 months. While healthcare costs do not support this finding, this is possibly due to the use of DRG tariffs for cost comparisons. DRG tariffs reflect average treatment costs for patients within specific DRG groups and may not accurately capture the actual costs incurred for managing adverse events experienced by trial participants. While access to precise treatment costs or the application of a micro-costing approach would have provided more accurate estimates [16], these methods were not feasible due to the study's long-term perspective and lack of exact cost data. In general, we cannot rule out the possibility that a comparison of actual hospital costs between the two groups might reveal differences, potentially attributable to the lower frequency of adverse events in the intervention group.

Conclusion

There were no statistically significant differences in total healthcare costs, resource utilization, employment status or duration of full-time employment between patients monitored by AI-assisted CVSM compared to patients blinded to monitoring. However, our findings suggested a positive impact of AI-assisted CVSM on sickness leave within 3 months. This indicates that, even without observable cost differences, AI-assisted CVSM may still offer value by potentially reducing sickness leave, thereby supporting workforce participation and mitigating productivity loss. Assessing the long-term effects of AI-assisted CVSM is essential for understanding its full economic and clinical impact. These factors should be carefully considered in decision-making processes regarding the adoption and investment in such technologies, ensuring alignment with both clinical and economic objectives.

Author Contributions All authors have contributed sufficiently to take responsibility for it. All authors reviewed the manuscript have given final approval of the submitted manuscript. ATL contributed to concept and design of the paper, acquisition of data, statistical analyses, analysis and interpretation of data, table preparation, writing the manuscript text, and critical revision of paper. LS contributed to concept and design of the paper, writing the manuscript, critical revision of the paper, and supervision. EKA contributed to concept and design of the paper, acquisition of data, writing the manuscript, critical revision of paper, obtaining funding, and supervision. CSM contributed to concept and design of the paper, acquisition of data, writing the manuscript, critical revision of the paper, obtaining funding, and supervision. JM contributed to concept and design of the paper, acquisition of data, and critical revision of the paper. SRK contributed to concept and design of the paper, analysis and interpretation of data, writing the manuscript, critical revision of paper and supervision. JK contributed to concept and design of the paper, analysis and interpretation of data, critical revision of paper, and supervision.

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Data Availability The data used in this study is not openly available due to regulations set by Statistics Denmark, as it includes individual patient-level information.

Declarations

Ethics The WARD clinical trial received written approval from the Regional Ethics Committee, Copenhagen, Denmark, February 2018 (H-17033535). All patients gave written informed consent before participating in the study**.** Register-based research does not require additional or separate ethical approval in Denmark.

Competing interests CSM and EKA have founded WARD24/7 ApS, Copenhagen, Denmark, with the aim of pursuing the regulatory and commercial activities of the WARD-project (developing a clinical support system for continuous wireless monitoring of vital signs). WARD24/7 ApS has signed a license agreement for any WARD-project software and patents. One patent has been filed: "Wireless Assessment of Respiratory and circulatory Distress (WARD), EP 21184712.4 and EP 21205557.8" ATL, LS, SRK, JK and JM declare no competing interests.

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