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RESEARCH ARTICLE

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Estimation of the maximum potential cost saving from reducing serious adverse events in hospitalized patients

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Abstract

Purpose: The increasing use of advanced medical technologies to detect adverse events, for instance, artificial intelligence-assisted technologies, has shown promise in improving various aspects within health care but may also come with substantial expenses. Therefore, understanding the potential economic benefits can guide decision-making processes regarding implementation. We aimed to estimate the potential cost savings associated with reducing length of stay and avoiding readmissions within the framework of an artificial intelligence-assisted vital signs monitoring system.

Methods: We used data from Danish national registries and coarsened exact matching to estimate the difference in length of stay and probability of readmission among adult in-hospital patients exposed to and not exposed to serious adverse events. We used these estimates to calculate the maximum potential savings that could be achieved by early detection of adverse events to reduce length of stay and avoid readmissions.

Results: Patients exposed to serious adverse events during admission had 2.4 (95% CI: 2.4–2.5) additional hospital bed days and had 14% (95% CI 11%–17%) higher odds of readmissions compared with patients not exposed to such events. A base case scenario yielded maximum potential savings if one patient avoided a serious adverse event of EUR 2040 due to reduced length of stay and EUR 43 due to avoidance of readmissions caused by serious adverse events.

Conclusion: Reductions in serious adverse events are associated with decreased healthcare costs due to reduced length of stay and avoided readmissions. Artificial intelligence-assisted vital signs monitoring systems are one potential approach to

reduce serious adverse events, however, the ability of this technology to reduce adverse events remains unclear. Comprehensive prospective analyses of such systems including the intervention and implementation costs are necessary to understand their full economic impact.

KEYWORDS
artificial intelligence, continuous vital signs monitoring, cost savings, health economic, serious adverse events

Editorial Comment

The cost of adverse events in hospitals has been estimated in a Nordic hospital context. The results provide support for further studies on how to prevent adverse events.

1 | INTRODUCTION

Worldwide, healthcare systems are increasingly challenged by ageing populations,[1–4] shifting burden of disease,[5,6] medical staff shortages,[7–10] and increasing healthcare costs.[4] This is further compounded by the continuous introduction of increasingly advanced medical technologies, which presents its own set of challenges as well as adds to the financial burden.[3,11] However, concurrently, there is hope that these technologies can also help address some of the challenges faced by the healthcare system. Novel advanced medical technologies include, for instance, artificial intelligence (AI), and the rapid advances in this area raise many expectations and hopes for future healthcare provision. AI has the potential to improve efficiency and equity, reduce errors, and enhance the quality of care provided to patients; for example, AI can be used to help diagnose diseases, predict patient outcomes, and identify treatments that are most likely to be effective.[12–18] Additionally, AI can help healthcare systems better manage resources and holds the potential to reduce overall costs.[14,15] Despite the inherent challenges of AI technologies (such as ethical and legal issues), the use of AI in health care is expected to continue to grow and has the potential to revolutionize the way health care is delivered in the years to come.

One example of AI-supported healthcare technology is AI-assisted continuous vital signs monitoring (CVSM) systems; such an innovative clinical support system should integrate vital signs measurements from continuous patient monitoring devices[19–21] with AI algorithms. This allows for automatic detection and prediction of physiological deterioration in hospitalized patients. In case of vital signs deterioration, the hospital staff is alerted by real-time alarms suggesting medical attention and interventions if required. By detecting vital sign deviations that are associated with imminent serious adverse events (SAEs) at an earlier stage than hitherto, treatment can be initiated earlier, which may entail a shorter treatment process and hence, decrease the number of bed days. Continuous vital sign monitoring at the general ward without AI interpretation has shown promising results, as supported by a meta-analysis and a recent large propensity-matched study, showing reduced length of stay (LOS), intensive care unit transfer, and specific complications.[22,23] At the same time, resources may be freed because the monitoring is done automatically. Importantly, by only alerting in cases with proven relation to clinically relevant outcomes, the risk for false alerts and alert fatigue is reduced. Altogether, this may translate into new and more efficient workflows and decreased healthcare costs. In this way, these kinds of technologies hold the potential to address some of the challenges faced by health systems in many parts of the world.

On the other hand, the implementation of new AI technology may represent a significant cost to health systems, and an important question to answer is therefore what potential benefits the introduction of new and advanced technologies may generate. Information about the potential benefits can inform decision-making regarding adoption and may affect the willingness to invest in the technology.[24]

1.1 | Aim

The aim of this paper is to estimate the costs of SAEs among hospitalized patients in Danish hospitals. Costs are calculated based on the difference in LOS between patients exposed and not exposed to SAE during admission and the probability of readmission given the exposure to an SAE during primary admission.

2 | METHODS

The study is part of the Wireless Assessment of Respiratory and circulatory Distress (WARD) project—an ongoing innovation project developing an AI-assisted CVSM solution[19,20] founded at Bispebjerg Hospital, Rigshospitalet, and the Technical University of Denmark. A clinical trial of the intervention is ongoing at the time of writing. A recent publication from the project has demonstrated a significant reduction in alerts whilst maintaining sensitivity of responsiveness.[25]

2.1 | Data and identification of cases

We used national registry data on inpatient admissions in Danish general public hospitals in the years 2017–2018 available from the National Patient Registry (NPR). The NPR includes information on

different types of hospital admissions, including diagnoses, treatments, and surgeries. We included all types of hospital departments and all types of diagnoses. Admissions were defined as inpatient stays with a minimum length of 12 h. Patients identified with admission during 2017–2018 were then linked to additional registries containing sociodemographic characteristics of the Danish population using the central personal registration number, which is unique for every Danish citizen.

Patients were excluded if they were under 18 years of age, had missing information, or if they were not traceable in the population registries. If sociodemographic characteristics were missing for the relevant year, we retrieved the most recent data available up to 2 years prior. If no data was available within this timeframe, the patient was marked as having missing information and was, hence, excluded.

Readmissions were identified as any emergency admission within 30 days from previous discharge date. After identifying primary admissions and readmissions, we applied a washout period of 30 days meaning that any acute admission during January 2017 preceding an admission within 30 days was excluded. In this way, we avoided counting readmissions in the beginning of the study period as a primary admission. Primary admissions can be both emergency and planned admissions, whereas readmissions can only be emergency admissions. Patients can have multiple primary admissions and readmissions during the period.

SAEs were defined according to international criteria for each complication in a prespecified compendium used for each chart review. The overall definition of SAEs was according to International Conference on Harmonization-GCP criteria.[26] Cases were identified as patients exposed to an SAE during their primary admission. SAEs were defined according to the WARD project, and conditions were translated to ICD10 codes in collaboration with a clinician (see Table S1 in Supplementary Information for a full list of SAEs and ICD10 codes). In total, SAEs used for analysis comprised 29 different conditions.

2.2 | Matching and matching variables

To identify a suitable control group, we used coarsened exact matching (CEM). The basic idea of CEM is to first coarsen the variables on which the match should be made and then to make exact matches based on the discrete categories of the coarsened variables.[27]

Matching variables included age (10-year intervals), sex (male/female), year of admission (2017/2018), main diagnosis (first character in ICD10 block code), education (5 categories), socioeconomic classification (6 categories), current marital status (4 categories), ethnic origin (3 categories), comorbidities (none/some) according to the Charlson's Comorbidity Index (CCI) using a 5-year look-back period and surgery during primary admission (yes/no). These variables were assumed to be related to the outcome (LOS and readmission) regardless of their relation to the exposure (SAE during primary admission). As there were more patients in the control group than in the case group, we normalized the distribution by weighting the subsequent regressions. Cases received a weight of 1 and controls received a weight based on how many cases they matched: $((\text{treatnment\_}n)/(\text{control\_}n))/((\text{total\_control\_}n)/(\text{total\_treatment\_}n))$.

CCI was constructed based on recorded diagnoses for the past 5 years from date of primary admission. This means that patients can have different CCI's if they have more primary admissions during the period. In our primary analysis, we excluded myocardial infarction and transient ischemic attack from CCI because these two conditions are considered SAEs according to the WARD project.[1] The calculation of CCI is based on Quan et al.[28,29]

2.3 | Outcomes

Our analyses included two outcomes of interest: LOS and readmission. LOS is calculated based on information on date and time for both admission and discharge and reported as number of bed days. Readmission is defined as any emergency admission within 30 days from previous discharge date. If two contacts have fewer than 4 hours between discharge of the first and admission of the next, they are treated as one admission. This means that an admission is only considered a readmission if it happens more than 4 hours after discharge of the previous admission (and less than 31 days from next admission). In the analysis of readmission, we excluded all patients who died during their primary admission or within 30 days from discharge as we cannot know whether these patients would have been readmitted or not.

2.4 | Statistical analyses and robustness checks

For assessment of imbalance between the groups before and after matching, we calculated the L1 imbalance measure. This measure ranges between 0 and 1, with 1 indicating complete imbalance.

Subsequently, baseline patient characteristics of patients exposed to SAE and not exposed to SAE during admission were compared before and after matching. Categorical variables were compared using a Pearson's chi-squared test and continuous variables were compared using a two-sample *t*-test. As for comparison after matching, we compared the weighted characteristics of the groups.

We used generalized linear models (GLM) to estimate the excess bed days of patients exposed to an SAE. We report the results using both GLM with identity link and gamma distribution and GLM with log link and gamma distribution. In the primary analysis, we adjusted for main diagnosis (first two characters of the code block), hospital, death during admission, and all matching variables.

For estimation of the probability of readmission given SAE exposure during primary admission, we used a logistic regression model. In the primary analysis, we adjusted for main diagnosis (first two characters of the code block), hospital, and all matching variables.

In the primary analysis, exposure to SAE is first treated as a binary variable (indicating any SAE or no SAE) and subsequently as a

categorical variable. The categories of SAEs are provided in Table S2 in Supplementary Information.

We performed a series of robustness checks to verify the stability of our results. We repeated our analyses on a sample with CCI containing all diagnoses and a sample excluding those patients who died during their primary admission. The latter was only performed for the analysis of LOS as the analysis of readmission already excluded all patients who died during primary admission or within 30 days from discharge.

An overview of all models run can be found in Supplementary Information; Table S3 shows all GLM models run in the analysis of LOS and Table S4 shows all logistic regression models run in the analysis of readmission.

All data analysis was performed using Stata V.17 and significance level was set to 0.05.

2.5 | Costs of SAEs

In order to calculate the costs associated with SAEs and determine the potential savings achievable by reducing them, we estimated the cost of readmission and the cost of a bed day with SAE. Costing was done from a health-system perspective and took a deterministic analytic approach. The available cost data does not provide exact treatment costs for individual hospital contacts. Instead, we employed Diagnosis-Related Groups (DRG) tariffs as a proxy for estimating the treatment costs of SAEs. DRG tariffs represent the average treatment costs of specific DRG groups[2] and include both direct healthcare (treatment and care, including intensive care, radiology, etc.) and direct non-healthcare costs (kitchen, laundry, administration, etc.) as well as most operating costs (e.g., rent). Costs are then linked to activity data to derive an average across for each particular DRG group.[30] DRG prices of hospital admissions are available from the DRG-coded NPR.

Because no single estimate of an additional bed day exists, we used three alternative approaches for estimating the cost of a bed day with SAE (summarized in Table 1).

The first approach was to utilize the per diem rate which is the tariff paid for hospital stays with a duration above than the trim point[3]. In Denmark, the per diem rate is EUR 293.29 (2022 prices).[31] However, this value is likely to underestimate the actual cost of a bed day since the per diem rate represents a day for a patient who has completed his/her treatment. Hence, this rate is typically used for patients who are waiting to move on to another option, which may not accurately reflect the circumstances of a day with an SAE.

The second approach, therefore, was to calculate the costs of an additional bed day on the basis of the DRG tariff of the primary admissions of patients exposed to SAE. We calculated the average price per day by dividing the cost of the primary admissions divided by the observed LOS across all patients. The average daily cost based on this approach was EUR 1224.17. However, as the DRG tariff of the primary admission incorporates both primary and secondary diagnoses, isolating the costs specifically attributable to SAEs during the primary admission was not feasible. Consequently, our final approach was to base our calculation on the DRG tariffs of the readmissions caused by SAEs. In this approach, we calculated the cost of an additional bed day as the total DRG tariffs of the readmissions divided by the number of bed days of readmissions. This allowed us to derive an average cost per readmission as well as an average cost per day attributable to SAEs. Using this approach, the average price of readmission among patients exposed to SAE during their primary admission was found to be EUR 4495.68, and the average price per bed day EUR 839.92. This last approach served as our base case.

Ultimately, this allowed us to estimate the costs of SAEs for three different scenarios. The three scenarios are summarized in Table 1. In all scenarios, the costs of readmission due to SAE are the same (EUR 4495.68).

All costs have been adjusted to 2022 price levels and converted to Euros (1 EUR = 7.45 DKK). A CHEERS checklist has been completed.[32]

TABLE 1 Scenarios and associated average daily cost estimates for calculation of costs of SAE.

Scenarios	Average daily cost	Reference
Scenario 1 (base case)	EUR 651.42	DRG tariffs of readmissions
Scenario 2	EUR 293.29	Per diem rate
Scenario 3	EUR 976.76	DRG tariffs of primary admissions

3 | RESULTS

3.1 | Matching results

The pooled population comprised 881,228 adult patients of which 153,878 (17.5%) experienced at least one SAE and 727,350 did not. The matching process successfully matched 147,598 (95.9% of available patients) patients exposed to SAE with 516,821 (71.1% of available patients) patients not exposed to SAE. Matching markedly reduced initial imbalance in characteristics between the two groups. Due to the large sample size, mean age and socioeconomic classification remained statistically significantly different, however, these differences were minimal in absolute terms. Table 2 presents the (uncoarsened) characteristics of the two groups before and after matching. Distribution and differences in main diagnosis are provided in Supplementary Information (Table S5). L1 balance measures before and after matching are reported in Table S6 in Supplementary Information.

As shown in Table 2, after matching, the mean LOS was 8.0 days for patients exposed to an SAE during admission and 4.4 days for patients not exposed to SAE during admission (p <.001). Additionally, 8.4% of patients exposed to SAE during admission were readmitted

TABLE 2 Baseline patient characteristics between patients exposed to SAE during admission and patients not exposed to SAE during admission before matching and weighted characteristics after matching.

	Before matching					After matching				
	No SAE	%	Any SAE	%	*p*-value	No SAE	%	Any SAE	%	*p*-value
n	727,350		153,878			516,821		147,598		
Year of admission					.157					1.000
2017	435,547	59.9	92,444	60.1		312,821	60.5	89,338	60.5	
2018	291,803	40.1	61,434	39.9		204,000	39.5	58,260	39.5	
Sex					<.001					1.000
Male	316,484	43.5	80,844	52.5		272,056	52.6	77,696	52.6	
Female	410,866	56.5	73,034	47.5		244,765	47.4	69,902	47.4	
Mean age (years)	59.0		72.0		<.001	72.1		72.3		<.001
Highest level of education					<.001					0.999
Primary school	252,453	34.7	66,766	43.4		228,143	44.1	65,155	44.1	
General upper secondary education	31,430	4.3	3286	2.1		10,686	2.1	3053	2.1	
Vocational upper secondary education	8197	1.1	1055	0.7		3430	0.7	998	0.7	
Vocational education and training (VET)	251,444	34.6	54,616	35.5		186,880	36.2	53,351	36.2	
Short higher education	24,217	3.3	4088	2.7		11,264	2.2	3217	2.2	
Medium higher education	96,715	13.3	16,104	10.5		52,400	10.1	14,984	10.2	
Bachelor degree	9688	1.3	734	0.5		2297	0.4	637	0.4	
Long higher education	50,407	6.9	6967	4.5		20,886	4.0	5977	4.1	
PhD	2799	0.4	262	0.2		834	0.2	226	0.2	
Employment status/social support					<.001					.026
Employed	238,012	32.7	22,941	14.9		75,147	14.5	21,461	14.5	
In education	28,326	3.9	1356	0.9		4076	0.8	1164	0.8	
Unemployed	6314	0.9	602	0.4		1681	0.3	523	0.4	
Sickness benefits/leave/education allowance	8814	1.2	754	0.5		1278	0.3	365	0.3	
Disability pension	62,643	8.6	10,685	6.9		34,695	6.7	10,146	6.9	
Social pension	313,654	43.1	109,768	71.3		374,924	72.5	107,126	72.6	
Early retirement	11,318	1.6	2275	1.5		7840	1.5	2187	1.5	
Social security benefit	42,629	5.9	4090	2.7		14,172	2.7	3767	2.6	
Others out of work	15,640	2.2	1407	0.9		3008	0.6	859	0.6	
Marital status					<.001					1.000
Married	330,376	45.4	69,184	45.0		235,626	45.6	67,292	45.6	
Unmarried	185,628	25.5	20,160	13.1		64,726	12.5	18,485	12.5	
Divorced	112,639	15.5	25,287	16.4		83,130	16.1	23,741	16.1	
Widowhood	98,707	13.6	39,247	25.5		133,339	25.8	38,080	25.8	
Ethnic origin					<.001					1.000
Danish	661,451	90.9	145,712	94.7		496,687	96.1	141,848	96.1	
Immigrant	56,813	7.8	7568	4.9		19,301	3.7	5512	3.7	
Descendant	9086	1.3	598	0.4		833	0.2	238	0.2	
Surgery during admission					<.001					1.000
No	402,465	55.3	119,452	77.6		404,089	78.2	115,403	78.2	
Yes	324,885	44.7	34,426	22.4		112,732	21.8	32,195	21.8	
Mean CCI	0.5		0.7		<.001	0.7		0.7		.693
Readmission					<.001					<.001
No	675,268	92.8	140,951	91.6		475,730	92.1	135,199	91.6	
Yes	52,082	7.2	12,927	8.4		41,091	8.0	12,399	8.4	

(Continues)

TABLE 2 (Continued)

	Before matching					After matching				
	No SAE	%	Any SAE	%	*p*-value	No SAE	%	Any SAE	%	*p*-value
Mean LOS (days)	4.0		8.1		<.001	4.4		8.0		<.001

Note: Main diagnosis is provided in Supplementary Information. Percentages are within-characteristic (column) percentages, and the *p*-values are the results of a test of differences between the No SAE and Any SAE samples conducted before and after matching.

within 30 days; among patients not exposed to SAE, 8.0% were readmitted (p <.001).

3.2 | Distribution of SAEs

The distribution of SAEs is shown in Tables S7 and S8 in Supplementary Information. Of those exposed, 82.7% of patients were exposed to one SAE during admission, and <0.1% suffered from more than 8. The most frequent type of SAE was circulatory (38.2%), followed by respiratory (22.0%) and infectious (23.4%) SAEs.

3.3 | Primary analysis

Patients exposed to an SAE during admission had an average excess LOS of 2.4 days (95% CI: 2.4–2.5 days) (Table 3) corresponding to a 68% longer hospital stay among patients suffering from an SAE compared to patients not suffering from an SAE (see Table S9 in Supplementary Information for results of GLM log-gamma model). Moreover, all categories of SAEs were significantly associated with additional bed days, ranging from 1.1 days (95% CI: 1.1–1.2 days) for circulatory SAEs to 5.3 days (95% CI 5.0–5.5 days) for neurologic SAEs. Finally, patients exposed to an SAE during admission had 14% higher odds of being readmitted. This result was also highly statistically significant. However, the odds ratio (OR) varied depending on the type of SAE, ranging from 0.93 (95% CI 0.86–0.99) for neurologic SAEs to 1.42 (95% CI 1.30–1.55) for "other" SAEs. All estimates were statistically significant at the 5% level.

3.4 | Robustness checks

Our robustness analyses examined how the estimates varied with alternative model specifications (described in Supplementary Information Table S3) consistently demonstrated highly statistically significant estimates of excess bed days associated with SAE exposure ranging from 2.4 to 3.2 days, see Figure 1 (estimates in Table S9–S11 in Supplementary Information). In all scenarios, neurologic and "other" SAEs were associated with longest LOS; neurologic SAEs between 5.2 and 5.8 days and 'other' SAEs between 5.2 and 7.3 days. Circulatory SAEs were associated with fewest excess days, between 1.2 and 1.7 days, see Table S12–S14 in Supplementary Information.

The OR for readmission was 1.14 and this estimate did not change when adjusting only for main diagnosis and hospital or when including CCI with all diagnoses, see Figure 2 (estimates in Table S15 in Supplementary Information, model descriptions in Table S4). The range of OR across different types of SAEs also remained stable; between 0.93 for neurologic SAEs and 1.45 for "other" SAEs (see Table S16 in Supplementary Information).

TABLE 3 Results of the primary analysis of length of stay and readmissions.

	Excess bed days	OR for readmission
	n = 664,419	n = 616,416
Exposed to any SAE	2.4 (2.4; 2.5)	1.14 (1.11; 1.17)
Exposed to neurologic SAE	5.3 (5.0; 5.5)	0.93 (0.86; 0.99)
Exposed to respiratory SAE	2.8 (2.7; 3.0)	1.14 (1.09; 1.19)
Exposed to circulatory SAE	1.1 (1.1; 1.2)	1.20 (1.16; 1.24)
Exposed to infectious SAE	2.9 (2.8; 3.0)	1.07 (1.03; 1.12)
Exposed to 'other' SAE	5.2 (4.8; 5.6)	1.42 (1.30; 1.55)

Note: 95% confidence intervals in parentheses.

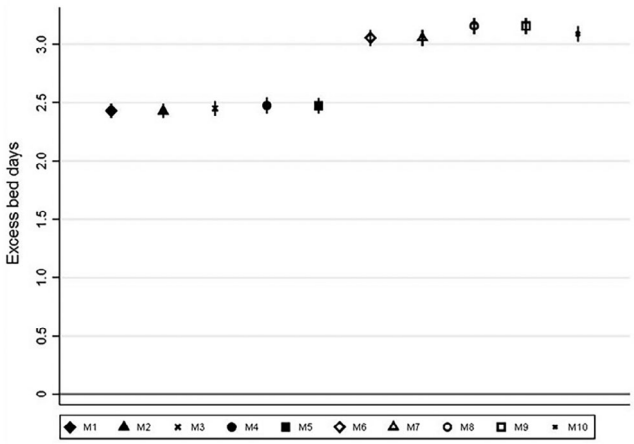

FIGURE 1 Coefficient plot for the analysis of excess bed days due to SAE exposure (binary SAE) during primary admission. Y-axis represents excess bed days. The markers represent the coefficient of each model and its 95% confidence interval. Model descriptions. 1 (main model): Adjusted for hospital, main diagnosis, death during admission, and all matching variables. M2: M1 incl. CCI with all diagnoses. M3: M1 excl. all deaths. M4: M1 excl. death during admission. M5: M4 incl. CCI with all diagnoses. M6: M1 excl. all matching variables. M7: M6 incl. CCI with all diagnoses. M8: M1 excl. death during admission and all matching variables. M9: M8 incl. CCI with all diagnoses. M10: M8 excl. all deaths. See also description of all models in Supplementary Information Table S3.

3.5 | Estimation of costs

In our base case scenario, assuming a decrease in LOS of 2.4 days, the maximum potential savings from avoidance of one SAE due to lower LOS amounted to EUR 2040.16 (95% CI: 1988.89–2091.07) calculated as 839.92 EUR * 2.4 days.[4] Scenario 2 yielded maximum potential savings of EUR 712.40 (95% CI: 694.50–730.18) and in scenario 3, the maximum potential savings increased to EUR 2973.50 (95%CI: 2898.78–3047.71). The results of the three scenarios are summarized in Table 4.

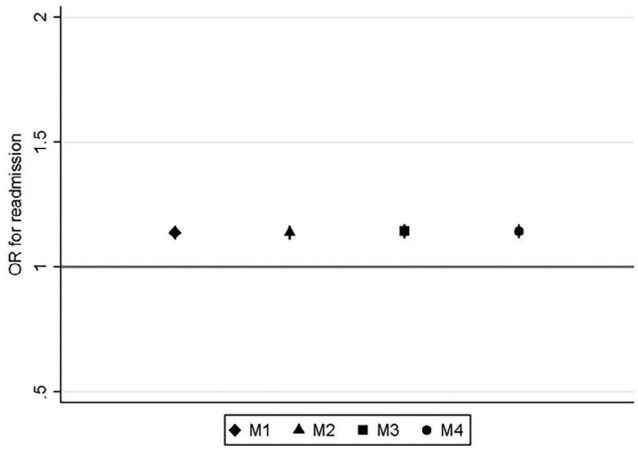

FIGURE 2 Coefficient plot for robustness checks of the analysis of readmission given SAE exposure (binary SAE) during admission. *Y*-axis represents OR. The markers represent the OR of each model and its 95% confidence interval. Model descriptions. M1 (main model): Adjusted for hospital, main diagnosis, and all matching variables. M2: M1 incl. CCI with all diagnoses. M3: M1 excl. main diagnosis. M4: M3 incl. CCI with all diagnoses. See also description of all models in Supplementary Information Table S4.

As for the maximum potential savings due to avoiding readmissions caused by SAE, the absolute predicted probabilities of readmission among the full sample and cases were 7.66% and 8.62%, respectively. These estimates were derived from the logistic regression model. This corresponded to an absolute difference of 0.95% yielding maximum savings of EUR 42.81 per patient with SAE (0.0095 * 4495.68 EUR) if readmissions could be avoided.

To illustrate the potential impact in a clinical setting, a hospital department with 7000 yearly admissions and an SAE rate of 17.5% (as in our sample) would result in 1225 patients exposed to SAE annually. In the most optimistic case where all of these SAEs could be avoided, the department could—in our base case scenario—save EUR 2,499,191 per year from shorter LOS of patients avoiding longer LOS due to SAEs. If all additional readmissions caused by SAEs could be avoided, the departments would save EUR 52,447.32. In total, this would amount to EUR 2,551,639 to be potentially saved by preventing SAEs and thereby shortening LOS and avoiding readmissions to the greatest degree possible.

Table 5 summarizes the maximum savings that can be achieved by avoiding SAEs through shortening LOS and avoiding readmissions among patients exposed to SAE during admission, as well as the intermediate calculations of the illustrative example. Results are presented for each of the three scenarios. These results should be interpreted as an upper bound; if for example only half of the cases can be prevented through early detection, only half of the cost would be saved.

TABLE 4 Maximum potential savings due to shortening LOS.

	Average daily costs, EUR (2022)	Maximum savings, EUR (2022)	Lower CI, EUR (2022)	Higher CI, EUR (2022)
Base case	651.42	1582.30	1542.54	1621.79
Scenario 2	293.29	712.40	694.50	730.18
Scenario 3	976.76	2372.54	2312.92	2431.75

TABLE 5 Expected maximum savings related to decreasing LOS and avoiding readmissions caused by SAEs.

Maximum savings per patient exposed to SAE	Scenario 1 (base case)	Scenario 2	Scenario 3
Savings per patient exposed to SAE due to decreased LOS	1582 EUR	712 EUR	2372 EUR
Savings per patient exposed due to avoided readmissions	15 EUR	15 EUR	15 EUR
Illustrative example			
Number of yearly admissions	7000	7000	7000
Number of patients exposed to SAE	1225 (17.5%)	1225 (17.5%)	1225 (17.5%)
Excess probability of readmission due to SAE	0.95%	0.95%	0.95%
Number of readmissions to be avoided (1225 patients * 0.95%)	12 patients	12 patients	12 patients
Total savings due to decreased LOS (savings per patient * 1225 patients)	1,938,317 EUR	872,688 EUR	2,906,365 EUR
Total savings due to avoided readmissions (14.77 EUR * 1225 patients)	18,094 EUR	18,094 EUR	18,094 EUR
Total savings	1,956,411 EUR	890,781 EUR	2,924,459 EUR

4 | DISCUSSION

There are currently high expectations for the potential of AI-assisted CVSM systems to identify patients at risk of SAEs which could theoretically reduce the occurrence of such events. However, so far clinical evidence demonstrating that AI-assisted CVSM systems can be successful in avoiding or reducing SAEs through early detection has not yet been produced. In the absence of such evidence, this study aimed to identify the maximum potential economic benefits, should AI-assisted CVSM systems show to be successful in early detection and avoidance of SAEs. Our results also apply to reductions in SAEs stemming from other types of technologies or interventions aimed at reducing SAEs.

The maximum potential benefit of avoiding SAEs using AI-assisted CVSM systems was estimated to be associated with a decrease of LOS of 2.4 days and 14% lower odds of being readmitted within the following 30 days. Distinguishing between different types of SAEs, the excess bed days ranged between 1.1 for circulatory SAEs day and 5.3 days for neurologic SAEs, and OR for readmission varied between 0.93 for neurologic SAEs and 1.42 for other SAEs. All results were statistically significant and supported by various robustness checks. If targeting all patients and achieving complete avoidance of SAE, the potential benefit is a decrease in LOS of 2.4 days and avoidance of all related readmissions, which would translate into potential cost savings of EUR 2040 due to decreased LOS and EUR 43 due to avoided readmissions per patient, respectively, for patients currently experiencing SAE.

It should be noted that these estimates are the upper bound of the cost savings that could be expected as a result of applying a detection tool to all patients and would lead to the prevention of all SAEs. It is unlikely that this kind of monitoring system will completely eliminate the excess bed days and readmissions caused by SAEs. Therefore, our estimates should be interpreted as the maximum potential savings that could be expected; hence, in reality, the estimate will most likely be lower. However, our estimate provides a benchmark to which the costs of new technologies can be compared alongside information about the expected effectiveness in preventing events. Moreover, although this kind of technology is relatively easily implemented and easily applied to most kinds of patients, some patient groups might be more relevant to target than others. Thus, if the technology was targeted to high-risk groups (i.e., major surgery or admittance for severe chronic obstructive pulmonary disease) and was effective at preventing events in these groups the estimate for this subgroup could be different.

It is well recognized that (S)AEs in hospitals constitute a serious threat to patient safety and remain an increasing problem of global concern; adverse events cause (potentially avoidable) harm to patients and impose significant costs on individuals, healthcare systems, and economies.[33] In 2017, OECD estimated patient harm to be the 14th leading cause of the global disease burden[34] and according to Harvard Global Health Institute, AEs are likely to become one of the 10 leading causes of death and disability globally.[35] Moreover, OECD estimates that 15% of total hospital activity and costs in the OECD countries are directly related to AEs[34] and that preventable patient harm accounts for around 8.7% of health expenditure.[33]

Previous studies have estimated the economic implications of SAEs and AEs, including both LOS and costs of care.[22,31–34] These studies have demonstrated relatively different results due to differences in methods but also in setting and included AEs. For instance, Hauck et al. examined incremental LOS due to six specific patient safety incidents and estimated excess bed days ranging from 11.2 to 21.2 days.[38] The authors included six patient incidents in the analysis; death in low-mortality Healthcare Resource Groups, pressure ulcer, central line infection, postoperative hip fracture, deep-vein thrombosis/pulmonary embolism, and postoperative sepsis. They were all considered preventable and selected due to their significant interest among both the public, policymakers, and academics, and because a translation into the English coding system was already available.[38] While deep vein thrombosis and (postoperative) sepsis were also considered in our analysis, the remaining indicators were not. Tessier et al. also studied excess bed days among patients suffering from harmful events and concluded that the incremental LOS varied between 0.4 and 24.2 days.[37] For definition of harmful events, the authors used the hospital harm framework proposed by the Canadian Institute for Health Information. This framework includes 31 groups of harmful events, which are all considered potentially preventable.[37] Comparing the 31 conditions in this framework with the 29 used in our study reveals an overlap of only five (six[5]) conditions. Hoogervorst-Schilp et al. estimated both incremental LOS and associated costs and found that patients exposed to AEs stayed 5.11 days longer and cost EUR 2600 more than patients not exposed to AEs.[36] Moreover, a study by Kjellberg et al. focused on acute patients and concluded that acute patients exposed to AE had higher mean costs of EUR 9509.[24] In the two studies by Hoogervorst-Schilp et al. and Kjellberg et al., AEs were identified by scanning patient records using a trigger tool (16 trigger words in Hoogervorst-Schilp et al. and 42 trigger words in Kjellberg et al.) but it is not clear how these trigger words translate to the specific AEs, making a direct comparison difficult.

While some of the results from the aforementioned studies indicate longer LOS and more expensive AEs than what we have observed, it is important to note that our study includes a diverse sample of patients and a relatively extensive list of SAEs. As a result, our findings can be regarded as conservative or cautious in nature. Moreover, the fact that we included a rather long list of SAEs makes our results general and transferable to other detection tools aiming at detecting a broad range of SAEs and preventing them from escalating. Thus, our results provide insight into the potential for a tangible and existing technology but are equally relevant for similar systems. This information can aid in the decision-making processes around purchasing and implementing this kind of system—processes that undoubtedly will emerge as these kinds of technologies are developed, tested, and released onto the market.

4.1 | Limitations

This study has some limitations. First, available data did not allow us to distinguish between serious and non-serious AEs meaning that some of the included SAEs may not actually be serious in a clinical

sense. However, the general consensus is that not all AEs are reported to the national mandatory system[35] and hence, it is most likely that the complications we have identified in the registries lean towards the more severe end. Second, we were not able to obtain data on exact treatment costs of SAEs which would, obviously, have been our preferred option. Third, in order to identify SAEs we relied on data from the Danish national registries and although the reliability of this data is generally deemed high, a more sensitive approach would have been individual review of medical records, or—even better—prospective daily assessments. This would likely have resulted in higher frequency of SAE, and thus also a larger potential saving per patient. Fourth, the definition of readmission might be challenged; we cannot know with certainty if the readmission is actually related to the primary admission, or due to a new cause, and using a 30-day cutoff is somewhat arbitrary. However, this definition is widely used in the literature, as well as in the WARD project's study protocols. Finally, although we included a long list of potential confounding variables for matching, we cannot leave out the possibility of residual confounding, for example, by body mass index.

5 | CONCLUSION

Patients exposed to an SAE during hospital admission spend 2.4 days longer in hospital and have 14% higher odds of being readmitted within 30 days compared to patients not exposed to an SAE. The maximum cost savings that can be achieved by avoiding one SAE is EUR 2040 due to shortening LOS and EUR 43 due to avoiding readmissions. Having access to this information can inform decisions about investing in AI-assisted technologies and similar technologies or interventions aimed at reducing SAEs.

AUTHOR CONTRIBUTIONS

All authors have contributed sufficiently to take responsibility for it. All authors reviewed the manuscript and 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, figure and table preparation, writing the manuscript text, and critical revision of paper. LS contributed to concept and design of the paper and critical revision of the paper. EKA contributed to concept and design of the paper, writing the manuscript, critical revision of paper, obtaining funding, and supervision. CSM contributed to concept and design of the paper, writing the manuscript, critical revision of the paper, obtaining funding, and supervision. SRK contributed to concept and design of the paper, acquisition of data, analysis, and interpretation of data, writing the manuscript, critical revision of paper, and supervision. JK contributed to concept and design of the paper, acquisition of data, analysis, and interpretation of data, critical revision of paper, and supervision.

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DATA AVAILABILITY STATEMENT

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

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ENDNOTES

[1] The two conditions were myocardial infarction (translated to DI21) and transient ischemic attack (translated to DG459). Practically, this means excluding DI21* and DG459 but keeping all other codes under DG45, i.e. DG450*, DG451*, DG452*, DG453* and DG458*.

[2] Groups of patients who are similar in terms of clinical characteristics and resource use.

[3] The trim point is calculated as the third quartile of bed days plus 1.5 times the difference between first and the third quartile for each DRG group.

[4] Confidence interval is calculated based on the confidence interval from the main GLM identity-gamma model.

[5] We include surgical site infection, Tessier et al. included post-procedural infections.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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