SAHLGRENSKA UNIVERSITETSSJUKHUSET VGR

HTA-centrum
Regional activity-based HTA
HTA-report 2026-147

Health Technology Assessment
2026-04-29

Visual AI-based motion monitoring compared with current standards of care for reducing fall and fall-related injuries within health care

Edebo A, Holmquist Henrikson L, Jivegård L, Khan J, Norén P, Petzold M, Svanberg T, Vingare T, Bergh C

Visual AI-based motion monitoring compared with current standards of care for reducing fall and fall-related injuries within health care

[Visuell AI-baserad rörelsemonitorering jämfört med standardvård för att förebygga fall och fallskador i sjukvården]

Edebo A[1], Holmquist Henrikson L[2], Jivegård L[1], Khan J[1], Norén P[3], Petzold M[1], Svanberg T[4], Vingare T[5], Bergh C[1*]

[1] Center for Health Technology Assessment, Sahlgrenska University Hospital, Gothenburg, Region Västra Götaland, Sweden

[2] Department of Emergency Medicine and Geriatrics, Sahlgrenska University Hospital, Gothenburg, Region Västra Götaland, Sweden

[3] Department of Physical Therapy and Occupational Therapy, Sahlgrenska University Hospital, Gothenburg, Region Västra Götaland, Sweden.

[4] Medical Library, Sahlgrenska University Hospital, Gothenburg, Region Västra Götaland, Sweden

[5] Department of Digitization, Head Office, Gothenburg, Region Västra Götaland, Sweden

*Corresponding author

Published 2026-04-29

2026:147

Table of contents

1 Abstract

Background: Falls are common among older adults and represent a major cause of injury, loss of independence, reduced quality of life, and mortality. Healthcare-associated fall injuries occurred in 0.7% of care episodes at Swedish acute care hospitals. In Swedish inpatient care, all patients over the age of 65, as well as those with risk conditions, undergo a fall risk assessment upon admission. Currently used methods to prevent falls within inpatient care in Region Västra Götaland,e.g. bed-exit alarms, bed rails, lighting solutions, and non-slip socks, or one-to-one observation, are limited in their ability to prevent falls. Systems based on artificial intelligence may predict risk-related behaviours and alert staff before a fall occurs.

Question at issue: Does visual AI-based motion monitoring of patients' movements using sensors mounted on the ceiling or walls compared to standard care reduce the risk of falls and fall-related injuries in patients with an increased risk of falling, and what are the experiences of patients and staff?

Methods: Systematic literature searches in Medline, Embase, and the Web of Science Core Collection were performed in May 2025. Citation searching for relevant reports was also performed, as well as searching relevant websites of manufacturing companies and Swedish HTA organisations. Publication type was not limited to peer-reviewed scientific journals but could also include conference abstracts and reports from manufacturing companies and other grey literature. Screening of abstracts and critical appraisal of selected articles followed standard methodology. The results of each study were summarised by outcome. Meta-analyses were not possible due to discrepancies in study designs and outcome reporting. The certainty of evidence for each outcome was assessed using the GRADE approach.

Results: We included thirteen studies, presented in ten reports: nine cohort studies, including eight before-and-after studies and one with a stratified parallel control group, and four case series. These studies compared visual AI-based motion monitoring with standard care, the latter mostly without a more specific definition, or no monitoring, aiming to reduce falls and fall-related injuries during hospital admission. Four studies used the QUMEA system (QUMEA AB). Studies were in general poorly reported, lacked strict controls, four were only presented in a workshop paper, three were only reported as abstracts, and studies had varying degrees of problems with directness, risk of bias, and precision. Mortality and patient experience were not reported. Comparing AI vs standard care, unweighted mean rate ratios of 0.48 and 0.71 for rate of falls per admission and rate of falls per 1000 patient days were reported, thus in favour of the intervention. Similarly, unweighted mean rate ratios of 0.32 and 0.67 were shown for rate of fall-related injuries per admission and rate of fall-related injuries/1000 patient days, respectively. The certainty of evidence was very low for all reported outcomes: falls and fall-related injuries during hospital admission, accuracy, length of admission, staff workload and staff experiences.

Economic aspects: The VGR analysis is the only health economic study available and is based on a before-and-after design, as is the rest of the literature, thus of low quality.

The total annual cost of implementing this AI technology in VGR (120 wards, 2400 beds) is estimated at SEK 10.8 million, corresponding to 4,495 SEK per inpatient bed per year. Benefits (fewer resource needs) would primarily be attributable to a reduced number of fall-related injuries and elimination of one-to-one observations. Since our analysis showed no reliable effects on benefits, we applied this knowledge in a base-case scenario. In the base scenario, no benefits were assumed. It is therefore not possible to assess whether this AI technology is economically sustainable. This report also includes a sensitivity analysis of potential economic benefits and savings.

Ethical aspects: Improved patient benefit from AI-based visual-based falls prevention in patients with increased risk of falls could not be demonstrated. From the perspective of needs and solidarity, those with the greatest needs should be prioritised over those with lesser needs. Falls in hospitals can be very severe events, thus, according to the principle of need and solidarity, costly interventions may be acceptable. It may be an unacceptable risk to replace one-to-one observation with a technique not proven to be superior for preventing fall-related injuries, especially in the most vulnerable patients. Given the lack of evidence of improved patient benefit and the cost of AI-based visual fall-prevention techniques, the principle of cost-effectiveness may not be met.

Conclusion: Visual AI-based monitoring to reduce falls and fall injuries in health care has been studied only in low-quality studies. Therefore, no conclusions can be drawn regarding patient benefits or cost-effectiveness, despite indications of reduced falls and fall injuries. The technique requires controlled studies of acceptable quality to evaluate safety, effectiveness, and costs.

2 Populärvetenskaplig sammanfattning – Plain language summary in Swedish

Frågeställning: Kan visuell, AI-baserad monitorering av patientens rörelsemönster genom sensorer i tak och väggar minska risken för fall och fallskador hos patienter med ökad risk för fall jämfört med standardåtgärder och hur ser upplevelserna ut för patienter och personal?

Bakgrund: Fallolyckor är vanligt förekommande bland äldre och leder ofta till skador, minskad livskvalitet och i värsta fall död. Risken ökar med ålder och skörhet. En svensk undersökning visar att cirka 0,7 procent av alla sjukhusvistelser resulterar i en fallskada. För att minska fallrisken rekommenderas att patienter över 65 år, eller med annan förhöjd risk, får en fallriskbedömning vid inläggning. Dagens förebyggande åtgärder – som sänglarm, sänggrindar, belysning, antihalksockor och tillsyn eller vak är ibland otillräckliga eller inte tillräckligt effektiva. I takt med att befolkningen åldras ökar behovet av nya metoder för att förebygga fall och fallskador. Nya AI-baserade system syftar till att förutse riskbeteenden och larma personal innan en fallolycka sker.

Metod: Systematiska litteratursökningar genomfördes i flera databaser i augusti 2025. Med hjälp av etablerade metoder identifierades de vetenskapliga artiklar som kunde bidra till att besvara den aktuella frågan. Även konferensabstrakt och rapporter från företag och organisationer inkluderades om de uppfyllde frågeställningen. De enskilda studierna granskades, resultaten summerades och tillförlitligheten av de sammanlagda resultaten bedömdes.

Resultat: Totalt inkluderades tretton studier, vars resultat hämtades ur tio publikationer. Nio kohortstudier, inkluderande åtta före-efter studier och en stratifierad studie med parallella interventions- och kontrollgrupper samt fyra fallserier inkluderas. Dessa studier jämförde AI-baserad rörelsemonitorering med "standard behandling", oftast utan att den senare specificerades närmare, eller ingen monitorering, i avsikt att reducera fall och fallskador på sjukhus. Fyra studier använde QUMEA-systemet. Studierna var generellt dåligt rapporterade, saknade relevanta kontrollgrupper och tre studier var endast rapporterade i form av ett abstrakt. Dödsfall rapporterades inte. En minskning av andelen fall rapporterades i 30% och 52%, räknat per 1000 vårddagar och per patientinläggningar när alla studier lades samman. Andelen fallskador minskade på motsvarande sätt till 33% och 68%. Tillförlitligheten är mycket låg för samtliga rapporterade utfall: fall, fallskador, sjukhusvistelsens längd, precision, personalens arbetsinsats och upplevelser. Sammanställningar i form av meta-analyser var inte möjligt att göra och det var heller inte möjlighet att dra någon slutsats om tekniken ifråga.

Ekonomiska aspekter: Den totala kostnaden per år för att införa AI-teknologin i VGR (120 vårdavdelningar och 2 400 vårdplatser) beräknades till 10,8 miljoner kronor. Det motsvarar cirka 4 495 kronor per vårdplats och år. I basscenariot antogs inga nyttor, eftersom vetenskapliga artiklar, avseende effekten av AI på fall och fallskador, är av för låg kvalitet för att kunna dra några konklusioner. Den här rapporten innehåller även en känslighetsanalys av de potentiella ekonomiska nyttor och besparingar

Etiska aspekter: Eftersom endast studier av låg kvalitet fanns tillgängliga, går det inte att bedöma om AI-baserad rörelsemonitorering i avsikt att förhindra fall och fallskador har effekt, är säkert och kostnadseffektivt jämfört med de metoder som används dag. Enligt de etiska principerna ska de patienter som har störst behov prioriteras framför de med lägre behov. Eftersom fallolyckor på sjukhus kan vara väldigt allvarliga, även resultera i död, så kan åtgärder som förhindrar fall, enligt prioriteringsprincipen, tillåtas vara kostsamma. Det kan anses vara icke acceptabelt att till extra vulnerabla patienter ersätta extra vak med en teknik som inte bevisat sig vara överlägsen i att förhindra fall och fallskador. Eftersom effekten av AI monitorering inte går att bedöma uppfylls inte kostnadseffektivitetsprincipen. Risken för integritetsintrång behöver beaktas.

Slutsats: AI-baserad rörelsemonitorering för att förebygga fall och fallskador inom sjukvården har endast studerats i studier av låg kvalitet. Dessa indikerar en minskning i såväl fall som fallskador, men resultatens tillförlitlighet är mycket låg. Tekniken behöver studeras i kontrollerade studier av högre kvalitet för att säkerhet och effektivitet ska kunna bedömas samt om kostnaderna är rimliga utifrån svenska prioriteringsprinciper.

The above summaries were written by representatives from HTA-centrum. The HTA report was approved by the regional board for quality assurance of activity-based HTA.

Ylva Carlsson
Head of HTA-centrum of Region Västra Götaland, Sweden, 2026-04-29

Regional board for quality assurance of activity-based HTA

Carlsson, Ylva	MD, Associate professor
Falk Erhag, Hanna	RN, Senior university lecturer
Hongslo Vala, Cecilie	MSc, PhD
Larsson, Anders	MD, PhD
Larsudd-Kåverud, Jennie	MD, PhD
Linden, Karolina	RNRM, Associate professor
Rylander, Christian	MD, Adjunct professor
Schwarz, Anneli	PhD, Speech therapist
Sjögren, Petteri	DDS, PhD
Steingrimsson, Steinn	MD, Associate professor
Wallerstedt, Susanna	MD, Professor
Wartenberg, Constanze	Psychologist, PhD
Wijk, Helle	RN, Professor

DDS Doctor of dental surgery
MD Medical doctor
PhD Doctor of Philosophy
RN Registered Nurse
RNRM Registered Nurse Registered Midwifery

3. Summary of findings (SoF)

Table 1a

Outcomes	Study design Number of studies	Relative effect (unweighted mean, range)	Absolute effect (range)	Certainty of evidence*Grade
Incidence of falls per 1000 patient days during hospital admission	4 cohort studies (6 cohorts) 6 case series	Incidence rate ratio = 0.71 (0.43 - 1.07)[a]	Incidence rate I=2.84 - 6.65[a] C= 4.1 - 11.72[a]	⊕OOO[1]
Rate of falls per hospital admission	2 cohort studies	Rate ratio = 0.48 (0.36 - 0.63)[a]	I=0.55 - 2.8[a] C=0.88 - 7.7[a]	⊕OOO[2]
Incidence of fall injuries per 1000 patient days during hospital admission	1 cohort study (3 cohorts)	Incidence rate ratio = 0.67 (0.58 - 0.77)[a]	I= 0.32 - 0.89[a] C= 0.55 - 1.16[a]	⊕OOO[1]
Rate of fall injuries per hospital admission	2 cohort studies	Rate ratio = 0.32 (0.22 - 0.48)[a]	I= 0.055 - 1.1[a] C= 0.252 - 2.3[a]	⊕OOO[2]

Table 1b

Outcomes	Study design Number of studies	Relative effect	Absolute effect	Certainty of evidence*Grade
Sensitivity, specificity, PPV and NPV for detection of falls	2 case series	Sens = 0.8 [b] Spec = n.r. [b] PPV = 0.96 [b] NPV = n.r. [b] Sens = 0.7 [c] Spec = 1.0 [c] PPV = 0.01 [c] NPV = 1.0 [c]		⊕OOO

Table 1 c Survey findings

Outcomes	Study design Number of studies	Relative effect	Absolute effect	Certainty of evidence*Grade
Staff workload	1 case series [d] (survey)		Intervention helps to manage time and prioritize work	⊕OOO
Staff experience	5 case series [e] (surveys)		+ Early intervention. + Quiet environment. (-) False alarms (-) Stress due to alarms	⊕OOO

Footnotes: I = intervention group. C=control group. [a)] Results expressed as unweighted mean (range). [b)] Coahran 2018 [c)] Eichenbrenner 2024. [d)] Wright 2022 regarded as case series whereas survey was conducted only after intervention. [e)] Slutrapport 2024, Potter 2017, Wright 2022 regarded as case series for this outcome whereas surveys were conducted only after intervention.

1) Serious imprecision, serious study limitations, some uncertainty regarding directness
2) Some imprecision, serious study limitations, some uncertainty regarding directness

* Certainty of evidence

High certainty ⊕⊕⊕⊕: We are very confident that the true effect lies close to that of the estimate of the effect.

Moderate certainty ⊕⊕⊕O: We are moderately confident in the effect estimate. The true effect is likely to be close to the estimate of the effect, but there is a possibility that it is substantially different to the estimate of the effect.

Low certainty ⊕⊕OO: Confidence in the effect estimate is limited. The true effect may be substantially different from the estimate of the effect.

Very low certainty ⊕OOO: We have very little confidence in the effect estimate. The true effect is likely to be substantially different from the estimate of effect.

4 Abbreviations and acronyms

AI = Artificial intelligence

HTA = Health Technology Assessment

NPV=negative predictive value

PPV=positive predictive value

P= Population

I = Intervention

C = Comparison

O= Outcome

SBU= The Swedish Agency for Health Technology Assessment and Assessment of Social Services

SKL = Sveriges Kommuner och Landsting

WHO = World Health Organisation

5 Background

Disease/disorder of interest and its degree of severity
Falls are common among older adults and globally represent a major cause of injury, loss of independence, reduced quality of life, and mortality. In Sweden, fall accidents result in more than 100,000 emergency department visits annually (Socialstyrelsen, 2025). The World Health Organisation's (WHO) definition of a fall is: "an event which results in a person coming to rest inadvertently on the ground or floor or other lower level. Falls, trips and slips can occur on one level or from a height" (WHO, 2021). Falls are the second leading cause of injury and mortality in the world, and people aged 60 and over have the highest risk of death or serious injury from falls. Globally, a third of people aged 65 years and older fall at least once per year, with 5% of these falls resulting in a fracture (WHO, 2021). The frequency of falls increases with age and frailty level (WHO, 2007).

In addition to underlying fall risks, several factors can further increase the likelihood of falling during a hospital stay, including acute illness, delirium, medication, recovery from surgery, extended periods of immobility or bed rest and being in an unfamiliar place (WHO, 2021).

Given the substantial burden of fall-related harm, there is a strong need for cost-effective fall-prevention strategies in hospital care to reduce patient injuries and support safe, sustainable use of healthcare resources.

Prevalence and incidence
It is common for individuals with a known risk of falls to sustain fall-related injuries in connection with hospital admission, typically during the initial phase of the hospital stay or in association with a change of environment (Sveriges Kommuner och Landsting;SKL, 2011; Skog, 2016). Common risk factors include advanced age, cognitive impairment, reduced mobility, and medications that affect balance or cognitive function (Heikkilä et al., 2023). Activities associated with falls most frequently include transfers to and from the bed or chair, walking, and using the toilet. Fall rates are highest during periods when patients are most active, such as in the morning and afternoon, although many falls also occur at night (SKL, 2011; Skog, 2016). The majority of in-hospital falls that result in injury are unwitnessed.

A medical record review conducted by SKL, evaluating healthcare-associated injuries occurring in Swedish acute care hospitals, found that fall-related injuries occurred in 0.7% of 12,590 reviewed care episodes in 2016 (SKL, 2018).

Present treatment
The "World guidelines for falls prevention and management for older adults: a global initiative" (Montero-Odasso et al., 2022) recommend performing a multifactorial fall risk assessment in all hospitalised older adults >65 years of age. For Swedish inpatient care the Swedish manual for inpatient care (Vårdhandboken, 2021) recommends that all patients over the age of 65, as well as adults with neurological or cognitive conditions, undergo a fall risk assessment upon admission and whenever

their condition changes in order to identify whether fall-prevention measures are needed and which measures should be implemented. Those interventions must be individualised and multifactorial, and this is best achieved through interdisciplinary teamwork.

In Region Västra Götaland, the current standard of care used to prevent falls includes bed-exit alarms, bed rails, lighting solutions, and non-slip socks. When required, patients are also provided with mobility aids, supervision, and, if necessary, one-to-one observation. However, existing measures, except for one-to-one observation, cannot detect imminent falls, which limits their ability to prevent them. In some cases, the devices in use may even exacerbate injuries; for example, raised bed rails can trap extremities and increase the height from which a patient may fall.

Healthcare services are struggling to maintain adequate staffing levels, and the additional shifts required for one-to-one observation is resource demanding. Aside from one-to-one observation, there are currently few tools that enable staff to work proactively in patients at very high risk of falling. In the context of an ageing population, there is a growing need for assistive technologies to help preventing falls and fall injuries.

Thus, there is a clear need for cost-effective fall prevention strategies in hospital care, to reduce patient harm and optimise the resource-efficient use of nursing staff time.

The normal pathway through the healthcare system and the current wait time for medical assessment/treatment
All patients aged 65 and older, as well as those with neurological or cognitive conditions, should be assessed for fall risk as soon as possible after arriving at the hospital, preferably within two hours. The fall-risk assessment is carried out by asking the following two questions:

• Ask the patient or a relative: Has the patient fallen at any time during the past year?

• Ask yourself as healthcare staff: Is there a risk that the patient may fall during the hospital stay if no preventive measures are implemented?

A "yes" to either question indicates an increased risk of falling, and a plan to prevent falls should be created and documented in the medical record. Preventive interventions must be individualised and multifactorial, and this is best achieved through teamwork. Fall-risk assessments and follow-ups of implemented preventive measures should be performed regularly during the hospital stay, as the patient's condition may change rapidly. If a fall occurs, the event and its circumstances must be documented, the causes analysed, and the fall-prevention plan updated accordingly.

Number of patients per year who undergo the current treatment regimen
No generalisable information is available on the number and proportion of patients at increased risk of falls and therefore in need of preventive strategies. According to the "World Guidelines for Falls Prevention and Management", all older adults should be considered as high risk and a standard comprehensive assessment followed by multidomain interventions should be considered (Montero-Odasso et al., 2022).

Present recommendations from medical societies or health authorities
See the present treatment in the Background section.

6 Health Technology at issue: AI-based motion monitoring

The technology under assessment is an AI-based visual motion monitoring system for patient rooms. In this context, "AI-based" refers to the use of trained algorithms that analyse and classify movement data captured by the sensor system to identify predefined movement patterns associated with an increased risk of falling. In this report, AI-based motion monitoring is defined as a contact-free, room-covering sensor solution that continuously records patients' movement patterns.

Use of the system is preceded by a fall risk assessment in accordance with local routines. For patients at an increased risk of falling, AI-based motion monitoring can be used as part of the preventive measures. Once a decision has been made to monitor a patient, the staff selects a monitoring level, that is, the types of movements to which the system should respond, for example, rising up in bed, sitting on the edge of the bed, or standing up. These settings determine which events generate alerts and alarms.

The technology to be used in Region Västra Götaland from the company QUMEA is based on ceiling-mounted sensors that register movement throughout the patient room. In the QUMEA system, movement data are captured using radar-based sensors rather than cameras, thereby avoiding video recording and reducing privacy concerns. The collected information is processed by an algorithm that identifies movement patterns corresponding to the selected monitoring levels. When predefined criteria are met, an alarm is sent to the mobile devices of healthcare staff. The proactive approach implies that, based on these alarms, health care professionals perform bedside checks to assess the situation and, when needed, act before a fall occurs. Multiple algorithms are used to distinguish the patient from other movements in the room, interpret posture and movement, and determine when monitoring should be active or paused, for example, when healthcare staff is present.

For comparison, several other technical and organisational methods are currently used to prevent falls within health care, such as alarm mats, simple motion sensors, bed rails, anti-slip aids, and increased observation, including one-to-one supervision. These methods are often limited to a specific part of the room, and alarms are usually triggered only once the patient has already initiated a transfer or is in a high-risk situation. One-to-one supervision requires staff to be physically present with the patient for extended periods of time and is resource intensive.

In this Health Technology Assessment (HTA), the introduction of AI-based motion monitoring is compared with current practices and technologies for fall prevention in inpatient care. The technology is intended to replace existing alarm-based aids and to reduce the need for continuous manual observation, with the aim of maintaining or improving patient safety in situations of increased fall risk. The main rationale for introducing the technology is to reduce the number of fall and fall-related injuries. The system does not require individual training or calibration for each patient. Instead, the algorithms are trained during system development to recognise general movement patterns, and monitoring is configured by staff by selecting appropriate monitoring levels.

7 Focused question

Question(s) at issue:
Does visual AI-based motion monitoring of patients' movements using sensors mounted on the ceiling or walls reduce the risk of falls and fall-related injuries in patients with an increased risk of falling compared to standard care, and what are the experiences of patients and staff?

PICO	
P	Adult patients within hospital care with an increased risk of falls
I	Visual AI-based motion monitoring of patients' movements by sensors on the ceiling or walls
C	No motion monitoring, standard treatment (bed-exit alarms, bed rails, lighting solutions, and non-slip socks, or one-to-one observation)
O	<u>Critical for decision-making</u> Mortality, related to fall injury Fall injury (stratified by seriousness if possible) (main outcome) Fall <u>Important for decision-making</u> Sensitivity and specificity, PPV and NPV for detection of falls Length of stay Workload for staff Patient experience Staff- experience

<u>Eligibility criteria</u>

Study design:
Randomised controlled trials
Non-randomised controlled studies
Case series

Publication type:
Peer-reviewed reports and grey literature including conference abstracts and publications from industry

Language:
English, Swedish, Norwegian, Danish

Publication date: 2014-

8 Method

Systematic literature search (Appendix 1)

In August 2025, one of the authors; a medical librarian with several years of experience of systematic review searching, performed systematic searches in Medline (OvidSP), Embase (OvidSP), and the Web of Science Core Collections. Searches were based on searches performed in a report by HTA Region Värmland (2024), with slight modifications including removal of limits to randomised controlled trials. The search strategies were peer-reviewed by another senior medical librarian prior to execution using the PRESS Checklist (PRESS, 2016). Websites of Swedish national and regional HTA organisations, as well as known companies manufacturing similar devices, were visited. A citation search of relevant reports was performed in Web of Science. Search strategies, eligibility criteria and a graphic presentation of the selection process are presented in Appendix 1. Two authors independently of one another screened the obtained abstracts to decide eligibility for full-text retrieval. All abstracts were screened using the Rayyan tool (Ouzzani et al., 2016). Any disagreements were resolved by consensus. All full-text reports were read by at least two authors, independently of one another, and it was finally decided in a consensus meeting including all authors, which reports should be included in the assessment.

Critical appraisal and certainty of evidence

Characteristics of the included studies are presented in Appendix 2. The excluded studies and the reasons for exclusion are presented in Appendix 3. Included studies were critically appraised using an adjusted checklist from the Swedish Agency for Health Technology Assessment and Assessment of Social Services (SBU) for assessment of nonrandomised controlled studies. Data were extracted by at least two authors and summarised for each outcome in Appendix 4. No meta-analyses were performed. A summary graph with only estimates of fall and fall-related injuries is presented. The certainty of evidence for each outcome was assessed using the GRADE approach for cohort studies (Atkins et al., 2004, GRADE Working group). A summary of the results per outcome and the associated certainty of evidence are presented in the Table of Summary-of-findings.

Ongoing research

A search in Clinicaltrials.gov (Nov 18, 2025) identified 1,148 studies, using the field Other terms and the search terms: *((artificial intelligence OR AI OR natural language processing OR machine learning OR deep learning OR neural network OR algorithm) AND ((fall OR falls OR bed) AND (detect OR detection OR prevent OR prevention OR exit OR exits OR reduce OR reduction OR monitor OR monitoring)) OR (QUMEA OR Verso vision OR Cuviva OR Silvershield OR Pontosense) OR (intelligent AND (sensor OR sensors OR sensing OR program OR programs OR system OR systems)) AND (hospital OR hospitals OR hospitalized OR hospitalised OR inpatient OR inpatients OR ward OR wards))***.**

9 Results

Search results and study selection (Appendix 1)

The literature search identified 2,939 records after removal of duplicates. DedupEndNote (Lobbestael, 2023) was used for deduplication. After reading the abstracts, 2,892 records were excluded. 47 reports were sought for retrieval. Two reports could not be retrieved, and 34 reports were excluded after full-text reading. Ten reports, including thirteen studies, among which four were only presented in a workshop paper and three as abstracts, were finally included in the assessment (Appendix 2). One health economics study was used for the economic aspects.

Included studies

The PICO of this HTA was fulfilled in nine non-randomised cohorts with results reported after intervention with a stratified parallel control group in one and before and after intervention in eight, reported in five different publications (Slutrapport Innovationsprojekt Fallprevention, 2023; Gervasi et al., 2025, Jones et al., 2021; Potter et al., 2017; Wright et al., 2022; Kramer et al., 2020).

The cohort studies reported in Slutrapport Innovationsprojekt Fallprevention (2023) and Gervasi et al. (2025) had several study limitations. Jones et al. (2021) had some problems with directness, study limitations, and precision. Potter et al. (2017) had some problems with directness, major problems with study limitations, and some problems with precision. Wright et al. (2022) had some problems with study limitations and serious imprecision.

The publication by Kramer et al. (2020) was a workshop summary with results from five cohort studies, including data from the aforementioned cohort study by Jones et al. (2021), and had some problems with directness, serious study limitations as well as serious imprecision.

Four additional case series were included (Coahran, 2018; Eichenbrenner, 2024; Hasemann, 2024; Ryser, 2024), of which the latter three were published in abstract form.

Thus, in total thirteen studies were included: nine cohort studies, including eight before-and-after studies and one with a stratified parallel control group, and four case series.

Results per outcome

Outcomes critical for decision making

Mortality was not reported

Falls during hospital admission
Rate of falls observed during visual monitoring in the "Intervention (I)-group" compared to no monitoring or ordinary setting with extra personnel in the "Comparison (C)-group" was reported by six of the included nine cohort studies (Slutrapport Innovationsprojekt Fallprevention, 2023; Gervasi et al., 2025; Jones et al. 2021; Potter et al., 2017; Wright et al., 2022; and in group A of Kramer, et al., 2020) in two different, non-directly comparable ways, i.e., rate of admissions with falls and rate of admissions with falls per admission days. All studies had problems with directness, study limitations, and/or precision.

Rate of admissions with falls per total admissions was reported in Slutrapport Innovationsprojekt Fallprevention (2023) with n=363 patients in the I-group and n=1,047 patients in the C-group. A rate ratio between the Intervention and Control groups of 0.36 in favour of the former was shown (fig. 1).

In the study by Jones et al. (2021), results were reported as total falls per 1000 admissions with n=151 in the I-group and n=221 in the C-group. The results showed no significant difference in incidence rate between the intervention and the observation groups, with a rate ratio of 0.63 (fig. 1).

Gervasi et al. (2025), Potter et al. (2017), and Wright et al. (2022) reported rate of admissions with falls per admission days. In the study by Gervasi et al. (2025), including n=228 in the I-group and n=352 in the C-group, the incidence rate ratio was 0.43 (95% CI: 0.12 – 1.24), p=n.s. In the study by Potter et al. (2017), neither the number of included patients nor the p-values were reported. Three different cohorts that fulfilled the PICO could be extracted, comparing intervention and observation groups and incidence rate ratios of 1.01, 0.68, and 1.07 calculated, respectively (fig. 1). Wright et al. (2022) showed an incidence rate ratio of 0.57 when comparing the I-group to the C-group (fig. 1).

Group A of Kramer et al. (2020) reported results after intervention in more than 700 patients. An incidence rate ratio of 0.74 could be calculated from extracted results but no p-values were reported (fig. 1).

Thus, five before-and-after studies and one with parallel groups including eight different cohorts showed mean rate ratios of 0.48 and 0.71 concerning the rate of falls per admission and the rates of falls/1000 patient-days, respectively (fig. 1).

The three other cohorts presented in Kramer et al. (2020); Kramer B (n=n.r.), Kramer C (n=650) and Kramer D (n= approx. 10,000) reported a decrease respectively by 52.2%, 54% and 46% in unattended falls after intervention.

Three case series reported falls during hospital admission, Coahran et al. (2018) (n=6), Eichenbrenner et al. (2024) (n=119) and Haseman et al.(2024) (n=119). Coahran et al. (2018) reported five unattended falls during 267 "device" nights. Eichenbrenner et al. (2024) and Haseman et al. (2024) reported from the same patient group that 33 unattended falls had occurred and that the frequency of falls was twice as high without monitoring, respectively.

Conclusion: It is uncertain whether AI-based monitoring compared to no monitoring or ordinary settings with extra personnel decreases the risk of unattended falls during hospital admission (very low certainty of evidence, GRADE ⊕OOO).

Fall-related injury during hospital admission

Fall-related injuries were reported in three different cohort studies (Slutrapport Innovationsprojekt Fallprevention, 2023; Jones et al., 2021; Potter et al., 2017) in two different, non-directly comparable ways, i.e., rate of admissions with falls and rate of admissions with falls per admission days. All studies had problems with directness, study limitations, and/or precision.

Rate of admissions with fall-related injuries per total admissions was reported in Slutrapport Innovationsprojekt Fallprevention (2023) with n=363 patients in the I-group and n=1,047 patients in the C-group. Fall-related injuries were less frequent in the intervention group, and a rate ratio could be calculated to 0.48 (p=not reported) (fig. 1).

The study by Jones et al. (2021) reported results as total fall-related injuries per 1000 admissions with n=151 in the I-group and n=221 in the O-group. The results showed a lower rate of fall-related injuries in the intervention group and a rate ratio of 0.22 (p=0.025) (fig. 1).

In the study by Potter et al. (2017), the number of included patients was not reported, and results were reported as the rate of admissions with fall-related injuries per admission days. Three different cohorts that fulfilled the PICO could be extracted, with incidence rate ratios of 0.58, 0.77, and 0.67 calculated respectively (fig. 1).

Thus, three before-and-after studies including five different cohorts showed mean rate ratios of 0.32 and 0.67 concerning rate of fall related injuries per admission and rate of fall related injuries/1000 patient days, respectively (fig. 1).

Conclusion: It is uncertain whether AI-based monitoring compared to no monitoring or ordinary setting with extra personnel decreases the risk of injurious falls during hospital admission (very low quality of evidence, GRADE ⊕OOO).

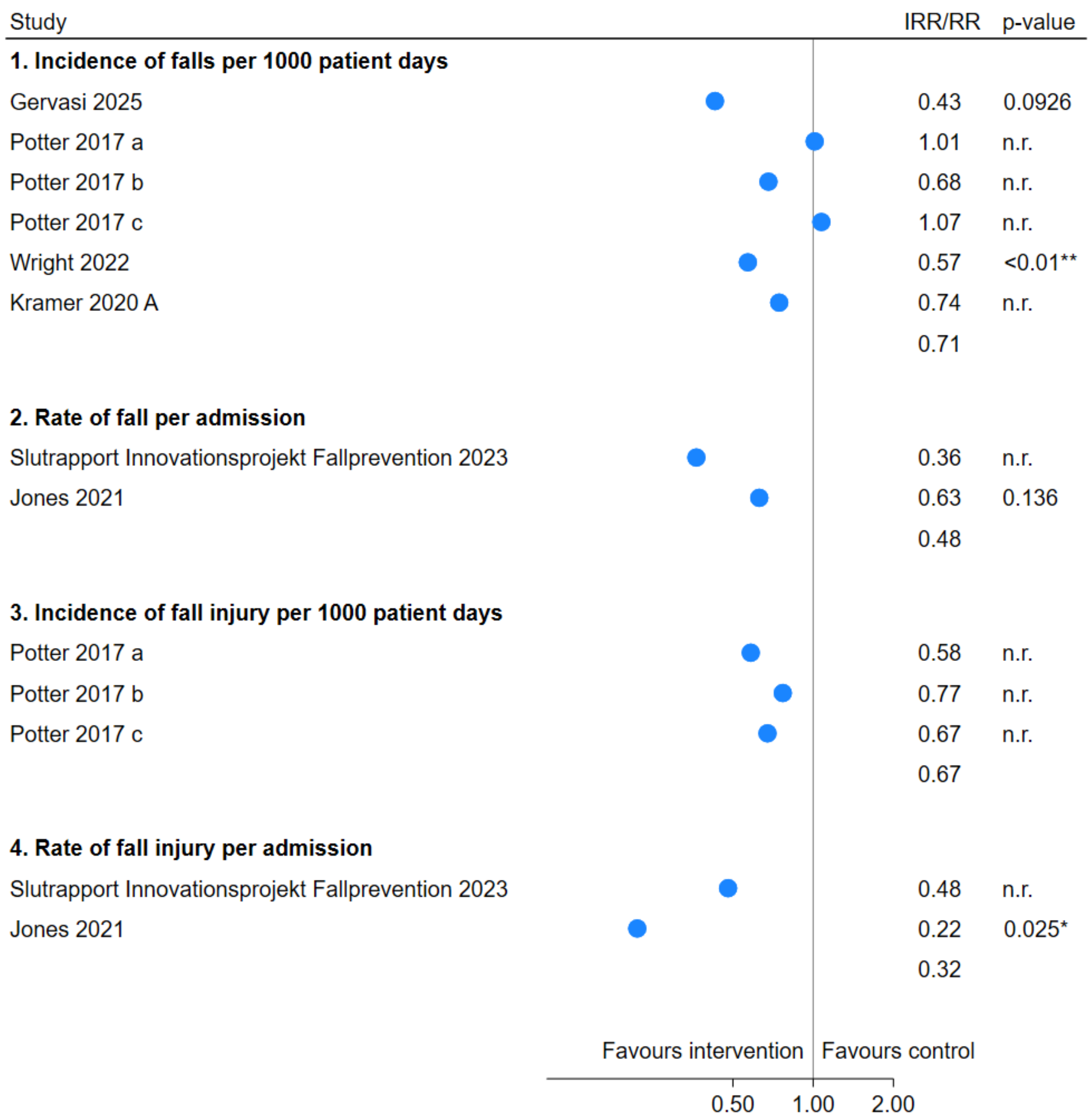


Figure 1. Incidence rate ratios between intervention and control group with unweighted mean incidence rate ratio calculated per outcome regarding falls and fall injuries. P-values noted when reported. Note that only 2 of these 13 estimates of risk ratios are reported to be statistically significant, one for fall injuries and one for falls.

n.r.=not reported

Outcomes important for decision making

Patient experience was not reported.

Length of admission was not reported.

Sensitivity, specificity, positive predictive value and negative predictive value for detection of falls

Two case series, Coahran et al. (2018) (n=6) and Eichenbrenner et al. (2024) (n=119) reported sensitivity and positive predictive value for detection of falls, the latter additionally reported specificity and negative predictive value. Coahran et al. (2018) reported a sensitivity of 0.8 and a positive predictive value of 0.01 for detection of unattended falls during 267 “device” nights. Eichenbrenner et al. (2024) reported a sensitivity of 0.7, specificity of 1.0, a positive predictive value of 0.96 and a negative predictive value of 1.0 for detection of falls.

Staff workload

One case series reported on the outcome of staff workload based on a staff survey conducted during the cohort study of above reported outcomes, Wright et al. (2022) (n =12). In the survey it was concluded that AI-based monitoring compared to no monitoring or ordinary settings with extra personnel help staff to manage time and prioritise work.

Staff experience

Four case series reported on staff experiences. In Coahran et al. (2018) , staff interviews showed both appreciation towards AI-based monitoring, i.e., enhanced patient safety, and frustration with malfunctioning systems. In Potter et al. (2017) , group discussions revealed that AI-based monitoring created a quieter care environment, although the increased number of alarms could result in alarm fatigue. In Ryser et al. (2024) , survey responses showed that the majority trusted AI-based monitoring, although false alarms could be a problem. In Slutrapport Innovationsprojekt Fallprevention (2023) , survey responses revealed general support for the fall sensor system, i.e., quick start-up and hygienic advantages); although high noise levels and alarms sent to all nursing staff on the ward were concerning, and interviews revealed advantages, i.e., reduced response times and better nighttime patient control; as well as challenges, i.e., technical issues, inadequate training, and stress from false alarms.

10 Ethical aspects

As only very low certainty evidence was available, improved patient benefit from AI-based visual-based falls prevention in patients with increased risk of falls could not be demonstrated. From the perspective of needs and solidarity, those with the greatest needs should be prioritised over those with lesser needs. Given that falls in hospitals can be very severe events and even result in death, the principle of needs and solidarity suggests that costly interventions may be acceptable. However, given the lack of evidence of improved patient benefit, the principle of cost-effectiveness may not be met. It may be an unacceptable risk to replace one-to-one observation with a technique not proven to be superior for preventing falls and fall-related injuries, especially in the most vulnerable patients. The principle of human dignity, which emphasises respect for patients' integrity, autonomy, individuality, and rights, must be upheld. Since the studied technologies detect patient movements by constant surveillance, it is imperative that monitoring and remote tracking preserve patients' privacy and confidentiality. The principle of autonomy holds that patients should have the right to participate in decisions regarding their care and should thus receive information about the use of motion monitoring techniques.

11 Organisational aspects

Time frame for the putative introduction of the new health technology

Introduction of AI-based motion monitoring in Region Västra Götaland commenced in the autumn of 2025, when the system from the company QUMEA was implemented in 20 inpatient wards across the region. Thus, the examined technique is already undergoing implementation. The present HTA report will contribute to the visualization of knowledge gaps and to further development within this area. Based on the current installation rate, it is estimated that 40–50 wards per year can be equipped with the technology. The regional goal is to include approximately 120 wards within the coming years.

Several preparatory steps are required before a ward can begin using the technology. These include the procurement of sensors, installation of electrical and network connections, physical mounting of the devices, and subsequent calibration to ensure proper functioning in each specific room. In parallel, managers and clinical staff must receive training and information on the new workflows and alarm procedures associated with AI.

Present use of the technology in other hospitals in Region Västra Götaland

Within Region Västra Götaland, local implementation strategies have varied, but the technology is primarily used for patients identified through fall risk assessment as requiring enhanced monitoring. Overall, both within Region Västra Götaland and nationally, the technology is being adopted in a stepwise fashion, often starting with high-risk wards, with the aim of reducing falls and supporting staff through more proactive monitoring.

Consequences of the new health technology for personnel

According to the report Slutrapport innovationsprojekt fallprevention (2023), the greatest advantages are the ability to prevent falls and the system's early warnings. The staff feel that they do not need to perform supervision as frequently because the system informs them what is happening in the room. They find that the system starts quickly and is more hygienic than other fall-prevention equipment. What has been perceived as negative is that the noise level becomes high when the system triggers frequent alarms, and that all warnings are sent to all staff regardless of which team they belong to.

Staff undergo a two-step training process. First, all employees complete a digital introduction covering the purpose, functionality, and central safety aspects of the system. This is followed by an on-site practical training session of approximately one hour in connection with the implementation.

Consequences for other clinics or supporting functions at the hospital or in Region Västra Götaland

Theoretical potential cost savings for X-ray, treatment of fractures, etc., are not available. In the VGR project, no serious fall injuries, such as fractures, occurred. No other consequences are expected.

12 Economic aspects

The economic analysis of the AI-based fall-prevention technology aims to estimate the costs of implementing and operating the technology, as well as any potential reduction in costs due to possibly reduced need for resources (benefits). The inputs to the technology were identified within an innovation project at Region Västra Götaland (Nyttokalkyl, Västra Götalandsregionen, 2024a, 2024b). Further analysis was conducted to convert capital costs, defined as inputs with a useful life of more than one year, into equivalent annual costs. These costs were adjusted for time differences by applying a 3% discount rate over their expected lifetime, in accordance with Drummond et al. (2015). Capital input included investments in technology, training, and other resources with benefits extending beyond one year. Under the innovation project, data were collected from two hospital departments and extrapolated to 120 hospital departments in Region Västra Götaland in Sweden (Nyttokalkyl, Västra Götalandsregionen, 2024a, 2024b).

We calculate a base-case scenario and a sensitivity analysis. Because the scientific articles reviewed concerning efficacy of AI-technology on prevention of falls and fall-related injuries were of too low quality for any conclusions to be drawn (GRADE ⊕OOO), no benefits were assumed in the base-case analysis (Table 2), and only the costs of the AI technology are presented.

However, it seems important to conduct a sensitivity analysis using hypothetical scenarios that apply different levels of benefit, since reductions in care-days due to fewer fall injuries and decreased one-to-one patient observations may generate financial benefits for VGR. In this analysis, for calculating the benefits from the reduced fall injuries and reduced one-to-one patient observations, we considered 10% to 100% (with 10% intervals) of the hypothetical full potential of the AI technology.

The total annual cost of the technology amounted to SEK 10.8 million, of which vendor costs accounted for 65% (SEK 7 million), which includes the costs of purchasing and installing sensors, maintenance and so forth, followed by technology investment costs of 18% (SEK 1.9 million), and training costs of 17% (SEK 1.8 million). No benefit was assumed in this base-case, which means that the net total annual benefits of the investment in AI-technology were estimated to SEK 10.8 million and 4,495 SEK per inpatient bed. Based on the available scientific evidence, this technology is not economically viable.

Table 2. Yearly costs of AI-Based-Fall-Prevention in 120 Hospital-Departments in the Västra Götaland Region in 2025

Costs/benefits	Description	Cost per year (SEK)	Share (%) of total
Costs	1) Hospital technology investment	1,948,801	18.1%
	2) Vendor cost	7,000,000	64.9%
	3) Training	1,838,365	17.0%
	Total costs	***10,787,166***	***100.0%***
Benefits	4) Saving from reduced care-days due to fewer fall injuries	-	
	5) Reduced costs of one-to-one patient observation	-	
	Total benefits	**-**	
Total net benefits		**-10,787,166**	
Cost per Inpatient bed per year		4,495	
Benefits per Inpatient bed per year		-	
Net benefits per inpatient bed day		**- 4,495**	

Notes:

1) Installation of network outlets and cable routing per care station costs 5,000 SEK. Installation of sensors and cable routing per care station, totaling 120 hospital departments. The lifetime of this setting is eight years, and 3% discounting rate has been applied.
2) Vendor costs (including costs of sensors, maintenance, etc.) are a flat-rate amount for each year.
3) Contains staff-time of 50 nurses and assistant nurses of each department for training (reallocation of staff time within the departments), and considering the effect of training remains three years with a discounting rate of 3%.
4) Based on three extra hospital days (data not available, estimated by the VGR project group) related to each fall injury, 100% scenario. However, no benefit is applied in the base case scenario.
5) Reduced need for one-to-one patient observations due to AI-technology installation in 120 hospital departments. 145 hours (18 episodes per month with 8 hours of observation) at SÄS and 80 hours (10 episodes and 8 hours per month) at SU were included. Thus, the reduced hours per two departments were estimated to 202,5 hours per month (see Nyttokalkylen 2024). In total: 12 x 202,5 x 60=145 800 hours. 300 SEK per hour (salary per hour for nurse assistant) gives 300x 145 800=43.7 million for 120 wards. It is assumed that the rate of patients with increased fall risk, and the use of one-to-one patient observation are the same in the 120 hospital departments as in the two departments at SÄS and SU. Of these hours, in the 100% scenario, all were carried out by hourly staff or the staff from recruitment firms. Here, no benefit is applied in the base-case scenario due to a lack of evidence in the reviewed literature.

The sensitivity analysis illustrates how the total annual net benefit changes as realised benefits range from 10% to 100% of the full potential of the AI technology, where the total annual saved costs of care-days were estimated to SEK 57.2 million and for saved one-to-one bed observations to 43.7 million. If we assume that 50% of reduced one-to-one patient observations are performed by hourly staff or hired from recruitment firms and 50% are performed by ordinary staff, the total benefits would be estimated to SEK 21.8 million. A lower benefit realisation level, e.g., 10% for both benefit sources (reduced care days and reduced one-to -one observations) (presented in Table 2), shows a total benefit of SEK 5.7 million from reduced care days and

SEK 4.4 million from reduced one-to-one patient observations, respectively. Under this assumption, the net annual benefit remains negative at SEK 690 000, indicating that the technology is not economically viable at this level of benefit realisation.

The analysis further suggests that the break-even point can be reached when approximately 10.7% of the estimated total benefits are realised. Above this threshold, this investment in AI technology becomes economically favorable in the present model.

Table 3. Sensitivity analysis - changes in net benefits due to changes in total benefits at different levels (0-100%)

(A)Reduced benefits*	(B) Benefits from reduced care-days **	(C) Benefits from reduction in one-to-one observation ***	(B+C) Total benefits	(D) Total costs	(B+C)-D Net benefits
0%	0	0	0	10,787,166	- 10,787,166
10%	5,722,570	4,374,000	10,096,570	10,787,166	- 690,596
20%	11,445,140	8,748,000	20,193,140	10,787,166	9,405,974
30%	17,167,710	13,122,000	30,289,710	10,787,166	19,502,544
40%	22,890,280	17,496,000	40,386,280	10,787,166	29,599,114
50%	28,612,850	21,870,000	50,482,850	10,787,166	39,695,684
60%	34,335,420	26,244,000	60,579,420	10,787,166	49,792,254
70%	40,057,990	30,618,000	70,675,990	10,787,166	59,888,824
80%	45,780,560	34,992,000	80,772,560	10,787,166	69,985,394
90%	51,503,130	39,366,000	90,869,130	10,787,166	80,081,964
100%	57,225,700	43,740,000	100,965,700	10,787,166	90,178,534

Note:

* Benefit levels (0% to 100%) from reduced care-days due to fewer fall injuries and reduced one-to-one observations by hourly staff or hired staff from recruitment firms.
** See note [4)] under Table 2, thus, at 100% level, 3 extra care days per fall injury.
*** See note [5)] under Table 2, thus at 100% level, all extra hours are paid by extra personnel.

If 1.5 extra hospital days per fall injury is applied (no serious injuries, such as fractures, occurred during the test period, poor information on the type of injuries is available) and 50% for extra personnel due to one-to-one observation, this would give a total benefit of SEK 38.6 million yearly. It should be emphasized that, except for 50% reduction of one-to-one observations, calculated benefits are hypothetical since no information on type of fall injuries is available and thus no costs for fall injuries can be assessed.

Further, it needs to be stressed that there is a lack of evidence for superiority in the main outcomes of the systematic review.

Present costs of currently used technologies

The current technology entails costs related to healthcare staff time (assistant nurses) required to manage bed alarm mats. Each mat requires approximately 9.3 minutes of handling time, totaling 68.4 hours annually across two hospital departments. When extrapolated to 120 hospital departments in VGR, this resulted in total annual assistant nurse salary costs of approximately SEK 1.2 million.

The frequency of and costs for false alarms are not available. Alarms are sent to various ward personnel, and should false alarms be frequent, this would be associated with high costs.

Available economic evaluations or cost advantages/disadvantages

No other health economic studies were identified in the literature.

13 Discussion

Summary of main results: This HTA analysis compared visual AI-based motion monitoring with "standard care", the latter mostly without a more specific definition, aiming at reducing falls and fall-related injuries during hospital admissions. Nine cohort studies, including eight before-and-after studies and one with a stratified parallel control group, and four case series were included. Four of the studies used the QUMEA system.

Mortality and patient experience were not reported. Although most studies reported reduced unattended fall rates, the certainty of evidence was assessed as very low due to problems with directness, risk of bias, and precision. Studies were generally poorly reported, lacked strict control groups, and several studies were reported only as abstracts. Certainty of evidence was very low also for all reported outcomes: falls, fall-related injuries during hospital admission, accuracy, staff workload, and staff experience. An observation to note based on this HTA analysis, is the high risk of false alarm as described in one study, where only just above 1% were related to actual falls. Different settings, AI-based technologies, and reporting standards precluded meta-analysis and further limited the possibility for conclusions about the effectiveness of AI-based fall prevention compared to other methods. The uncertain evidence also affects the economic analysis of the base-case scenario, in which the technology is not economically viable.

Overall completeness and applicability of evidence
This HTA analysis shows that it is uncertain whether AI-based motion monitoring affects the rate of falls and fall-related injuries compared with other techniques. More research, including well-designed randomised clinical trials and non-randomized controlled studies, is needed to establish the effectiveness, safety, and cost-effectiveness of the technology.

Agreements and disagreements with other studies and reviews
No systematic review with the present PICO was identified. In a non-systematic review by Ahmed et al. (2024), radar point cloud processing for assessing human movements in health care and assisted living domains was studied. As one part of that review, radar-based sensors for motion monitoring using 3-D point clouds were studied. Accuracy for fall detection ranging from 75% to 99.5% was reported. The two studies reporting accuracy parameters in our present HTA (Coahran et al., 2018, Eichenbrenner et al., 2024) showed sensitivity of 0.8 and 0.7, respectively. Reported positive predictive values were very different: 0.96 and 0.01 respectively.

Lee et al. (2025), in a recent systematic review, studied digital healthcare approaches to fall detection and prevention. Their review included detection systems using inertial, pressure, radar, or multimodal sensors, thus employing technologies not included in our present HTA. Nevertheless, the technologies studied did not consistently reduce falls or injurious falls. Results were inconsistent, with some studies even showing an increased rate of falls. Frequent false alarms contributed to alarm fatigue. Lee et al. (2025) concluded that detection systems improve surveillance but currently offer limited preventive effects, whereas prediction models failed to establish clinical benefits.

In summary, visual-based motion monitoring technologies combined with AI could have the potential to recognize potentially dangerous situations and inform the staff when patients need help. The currently available technologies are, however, insufficiently studied. The risk of frequent false alarms and subsequent alarm fatigue may constitute a significant problem.

14 Future perspectives

Scientific knowledge gaps

Only before-and-after studies and case series were identified. There is a high need for well-performed controlled studies of this AI technology for the investigation of safety, efficacy, and costs and consequences for healthcare personnel.

Ongoing research (from clinicaltrials.gov)

Three ongoing studies were relevant for the present PICO.

NCT05391334, started 2022-11-01 in Basel, Switzerland with estimated completion 2024-06-30. The study compares the effectiveness of contact mats with AI-based visual motion monitoring using the QUMEA technique on, e.g., falls and nurses' workload in patients with delirium in an acute care specialised delirium unit. The study protocol does not mention whether the study is randomised. The study status is unknown; last update was 2023-05-11.

NCT04393272 is an observational study in a geriatric clinic in St. Gallen, Switzerland first posted 2020-05-11. It evaluates three-dimensional (3-D) sensor technology and, for the outcome falls, compared with falls detected by nursing staff members. Study status is unknown; last update was 2022-08-25.

NCT06339125 compares computer visualisation and AI interpretation of patient motion with two other techniques and no intervention respectively. Estimated study start was 2025-05 and outcomes include falls, falls with injuries and nurse perceptions. The study was posted 2024-04-01 to be performed in Massachussetts General Hospital but has not yet started recruiting.

Planned study in VGR

SAFE (Safe AI-assisted Fall Prevention through Evidence) is a multicentre, multimethod research project investigating AI-assisted fall prevention across all hospitals in Region Västra Götaland (VGR). The project examines how AI can support fall prevention work in hospital settings by studying the implementation of the QUMEA sensor-based AI system. Data are collected through interviews with healthcare professionals and patients, and retrospective analyses of electronic health records at predefined measurement points to capture changes over time. It will translate empirical findings into practical implementation guidance tailored to hospital environments. The project will run between 2026 and 2028. The research project focuses on several areas: the implementation of AI-assisted fall prevention; its alignment with existing work practices; its effects on nursing workload and the work environment; patient-reported experiences among individuals with elevated risk of falling; and its impact on fall incidence and other clinical outcomes. Although the SAFE project will provide an increased understanding of AI as a tool in fall prevention strategies to increase patient safety in hospital care, it will most likely not fill the knowledge gaps identified in this HTA report.

15 Participants in the project

The question was nominated by

Thomas Brezicka, MD, Chief Medical Officer, PhD, Region Västra Götaland Department of Quality and patient safety, Sahlgrenska University Hospital, Gothenburg, Sweden

Participating healthcare professionals

Lena Holmquist Henrikson, Consultant Geriatrician, Department of Emergency Medicine and Geriatrics, Sahlgrenska University Hospital, Gothenburg, Region Västra Götaland, Sweden
Paulina Norén, Specialist in Occupational Therapy, Department of Physical Therapy and Occupational Therapy, Sahlgrenska University Hospital, Gothenburg, Region Västra Götaland, Sweden.

Tore Vingare, Strategist, Department of Digitization, Head Office, Gothenburg, Region Västra Götaland, Sweden

Participants from HTA-centrum

Christina Bergh, Professor Emerita, Department of Obstetrics and Gynecology, Sahlgrenska Academy, Gothenburg University and Senior Consultant, Region Västra Götaland, Sahlgrenska University Hospital, HTA-centrum, Gothenburg, Sweden

Anders Edebo, MD, Consultant General Surgeon, Chief Medical Officer, PhD, Region Västra Götaland, Sahlgrenska University Hospital, HTA-centrum, Gothenburg, Sweden

Lennart Jivegård, MD, Consultant Vascular Surgeon, PhD, Associate Professor, Region Västra Götaland, Sahlgrenska University Hospital, HTA-centrum, Gothenburg, Sweden

Participants from Medical Library

Therese Svanberg, Medical Librarian, Region Västra Götaland, Sahlgrenska University Hospital, Medical Library, Gothenburg, Sweden

External reviewers

Katarina Wilhelmsson, MD, Consultant Geriatrics, Associate Professor, Institute of Neuroscience and Physiology, Department of Psychiatry and Neurochemistry, Sahlgrenska Academy, University of Gothenburg, Gothenburg, Sweden.
Region Västra Götaland, Sahlgrenska University Hospital, Department of Acute Medicine and Geriatrics

Sophia Frantz, MD, Consultant Nuclear Medicine and Clinical Physiology, Department of Translational Medicine, Lund University, Malmö, Sweden.
Project Manager, Department of Research, Development, Education and Innovation, HTA Syd, Skåne University Hospital, Lund, Sweden

Declaration of interests

No conflict of interest was reported.

Project time

The HTA was accomplished during the period of 2025-05-23 to 2026-04-24.
Literature searches were conducted 2025-08-22.

Components of this Health Technology Assessment

- ✓ Description of methods
- ✓ PICO
- ✓ Full literature search
- ✓ Flowchart
- ✓ Selection based on relevance
- ✓ Quality assessment
- ✓ Data tabulation
- ✓ Evidence synthesis
- ✓ Meta-analysis
- ✓ Certainty of evidence by GRADE
- ✓ Summary
- ✓ Economical aspects
- ✓ Organisational aspects
- ✓ Ethical aspects
- ✓ Ongoing studies
- ✓ Excluded articles
- ✓ Participation of experts
- ✓ External review
- ✓ Knowledge gaps identified
- ✓ Conflict of interest reported

Appendix 1: PICO, study selection, search strategies, and references

Question(s) at issue:
Does visual AI-based motion monitoring of patients' movements using sensors mounted on the ceiling or walls reduce the risk of falls and fall-related injuries in patients with an increased risk of falling compared to standard care, and what are the experiences of patients and staff?

PICO: (*P=Patient I=Intervention C=Comparison O=Outcome*)

PICO	
P	Adult patients within hospital care with an increased risk of falls
I	Visual AI-based motion monitoring of patients' movements by sensors on the ceiling or walls
C	No motion monitoring, standard treatment (bed-exit alarms, bed rails, lighting solutions, and non-slip socks, or one-to-one observation)
O	**Critical for decision-making** Mortality, related to fall injury Fall injury (stratified by seriousness if possible) (main outcome) Fall **Important for decision-making** Sensitivity and specificity, PPV and NPV for detection of falls Length of stay Workload for staff Patient experience Staff's experience

Eligibility criteria

Study design:
Randomised controlled trials
Non-randomised controlled studies
Case series

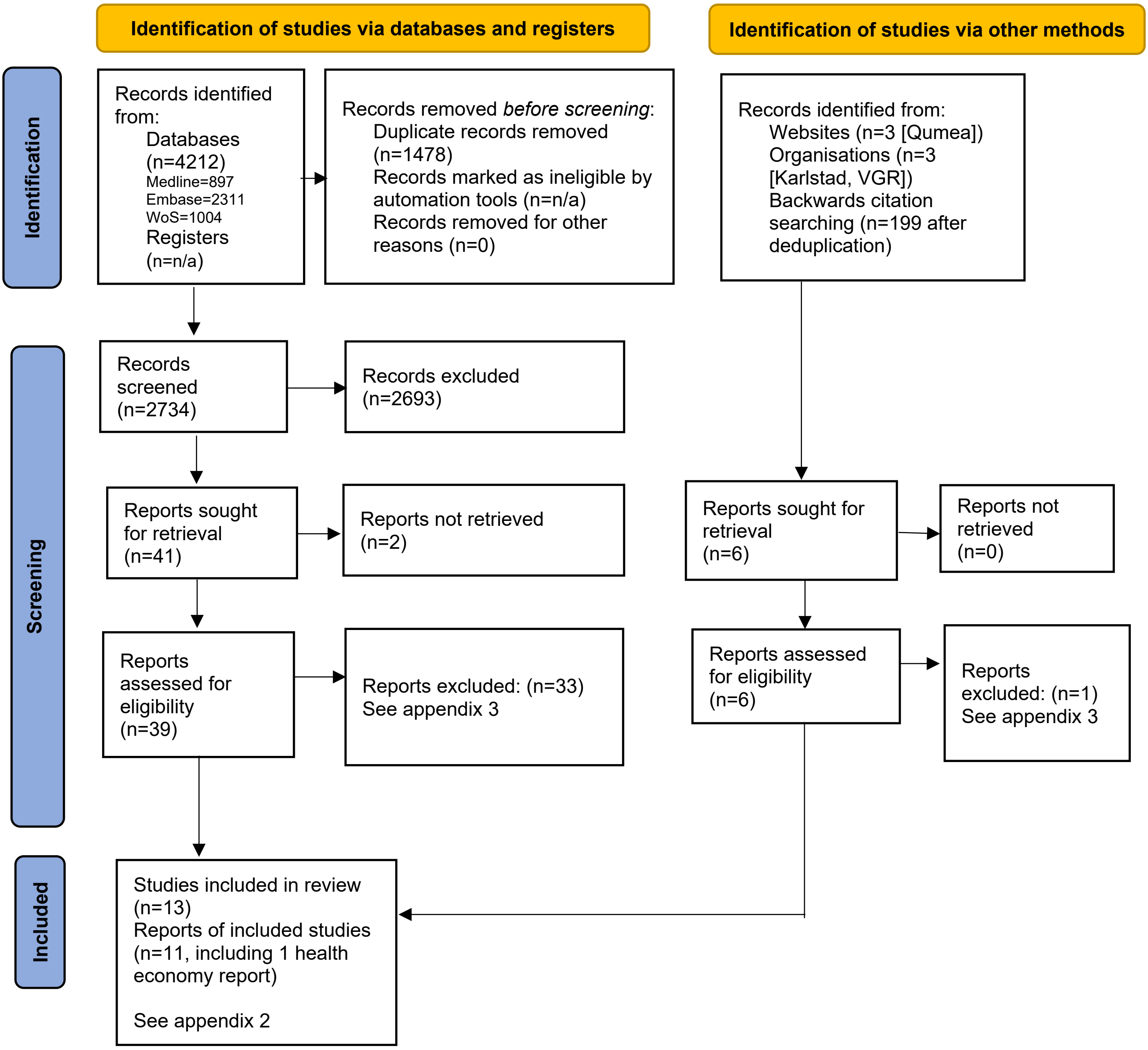
Publication type:
Peer-reviewed reports and grey literature including conference abstracts and publications from industry

Language:
English, Swedish, Norwegian, Danish

Publication date: 2014-

Selection process – flow diagram

PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers and other sources



From: Page et al., 2021

Search strategies

Database: Ovid MEDLINE(R) ALL (OvidSP)
Date: 22 Aug 2025
No. of results: 897

#	Searches	Results
1	Accidental Falls/pc or (fall* adj5 prevent*).ti,ab,kf. or (reduc* adj2 fall*).ti,ab,kf. or bed fall*.ti,ab,kf. or get out of bed.ti,ab,kf. or bed-egress.ti,ab,kf. or (bed adj4 exit*).ti,ab,kf. or (bed adj4 detect*).ti,ab,kf. or (fall adj4 detect*).ti,ab,kf.	22273
2	exp Artificial Intelligence/ or artificial Intelligence.ti,ab,kf. or AI.ti,ab,kf. or natural language processing.ti,ab,kf. or machine learning.ti,ab,kf. or deep learning.ti,ab,kf. or neural network*.ti,ab,kf. or algorithm*.ti,ab,kf.	825562
3	(QUMEA or Verso vision or Cuviva or Silvershield or Pontosense).ti,ab,kf.	2
4	exp Monitoring, Physiologic/ or (detect* or monitor* or (fall* adj6 intervention*)).ti,ab,kf.	4126201
5	((sensor* or sensing or program* or system or systems) and intellig*).ti,ab,kf.	56484
6	2 or 3 or 4 or 5	4775021
7	exp Hospitals/ or Hospitalization/ or Institutionalization/ or Inpatients/ or hospital$1.ti,ab,kf. or hospitali?ation.ti,ab,kf. or institutionali?ation.ti,ab,kf. or inpatient*.ti,ab,kf. or ward.ti,ab,kf. or wards.ti,ab,kf.	2028144
8	1 and 6 and 7	1353
9	limit 8 to yr="2014 -Current"	925
10	limit 9 to (danish or english or norwegian or swedish)	897

Database: Embase 1974 to 2017 January 09 (OvidSP)
Date: 22 Aug 2025
No. of results: 2311

#	Searches	Results
1	falling/ or (fall* adj5 prevent*).ti,ab,kf. or (reduc* adj2 fall*).ti,ab,kf. or bed fall*.ti,ab,kf. or get out of bed.ti,ab,kf. or bed-egress.ti,ab,kf. or (bed adj4 exit*).ti,ab,kf. or (bed adj4 detect*).ti,ab,kf. or (fall adj4 detect*).ti,ab,kf.	69944
2	exp Artificial Intelligence/ or artificial Intelligence.ti,ab,kf. or AI.ti,ab,kf. or natural language processing.ti,ab,kf. or machine learning.ti,ab,kf. or deep learning.ti,ab,kf. or neural network*.ti,ab,kf. or algorithm*.ti,ab,kf.	964431
3	(QUMEA or Verso vision or Cuviva or Silvershield or Pontosense).ti,ab,kf.	3
4	exp physiologic monitoring/ or (detect* or monitor* or (fall* adj6 intervention*)).ti,ab,kf.	5344808
5	((sensor* or sensing or program* or system or systems) and intellig*).ti,ab,kf.	66324
6	2 or 3 or 4 or 5	6088785
7	exp hospital/ or hospitalization/ or institutionalization/ or hospital patient/ or aged hospital patient/ or hospital$1.ti,ab,kf. or hospitali?ation.ti,ab,kf. or institutionali?ation.ti,ab,kf. or inpatient*.ti,ab,kf. or ward.ti,ab,kf. or wards.ti,ab,kf.	3930025
8	1 and 6 and 7	3630
9	limit 8 to (conference abstracts or embase or medline or "preprints (unpublished, non-peer reviewed)")	3428
10	limit 9 to yr="2014 -Current"	2386
11	limit 10 to (danish or english or norwegian or swedish)	2311

Database: Web of Science Core Collection
Entitlements: - WOS.SCI: 1970 to 2025, - WOS.AHCI: 1975 to 2025, - WOS.BHCI: 2005 to 2025, - WOS.BSCI: 2005 to 2025, - WOS.ESCI: 2020 to 2025, - WOS.ISTP: 1990 to 2025, - WOS.SSCI: 1970 to 2025, - WOS.ISSHP: 1990 to 2025
Date: 22 Aug 2025
No. of results: 1004

#	Search Query	Results
1	TS=("accidental fall*" OR (fall* NEAR/4 prevent*) OR (reduc* NEAR/1 fall*) OR "bed fall*" OR "get out of bed" OR "bed-egress" OR (bed NEAR/3 exit*) OR (bed NEAR/3 detect*) OR (fall NEAR/3 detect*))	26342
2	TS=("artificial intelligence" OR AI OR "natural language processing" OR "machine learning" OR "deep learning" OR "neural network*" OR algorithm*)	4256627
3	TS=(QUMEA or "Verso vision" or Cuviva or Silvershield or Pontosense)	2
4	TS=((detect* or monitor* or (fall* NEAR/5 intervention*)))	7113845
5	TS=(((sensor* OR sensing OR program* OR system OR systems) AND intellig*))	376505
6	#5 OR #4 OR #3 OR #2	10671550
7	TS=(hospital OR hospitals OR hospitalization OR hospitalisation OR institutionalization OR institutionalisation OR inpatient* OR ward OR wards)	1728445
8	#1 AND #6 AND #7	1328
9	#1 AND #6 AND #7 Timespan: 2014-01-01 to 2025-09-01	1004

The websites listed below were visited February 2025.
One relevant report was identified.

Source	Search terms / Browsing	No. of results	No. of relevant results
SBU www.sbu.se	Fallprevention AI	3 20	1 1
CAMTÖ https://www.regionorebrolan.se/sv/forskning/kontakt-och-organisation/hta-enheten-camto/	Browsat		
HTA Region Stockholm https://www.chis.regionstockholm.se/hta/rapporter/	Browsat		
HTA Region Värmland https://www.regionvarmland.se/vardgivarwebben/vard-och-behandling/kunskapsbaserad-halso--och-sjukvard/health-technology-assessment-hta	Browsat		1
Regional samverkansgrupp HTA (tidigare Metodrådet) i Sydöstra sjukvårdsregionen https://sydostrasjukvardsregionen.se/samverkansgrupper/hta/genomforda-bedomningar/	Browsat		
HTA Syd https://vardgivare.skane.se/kompetens-utveckling/sakkunniggrupper/hta-skane/#110365	Browsat		

Vetenskapliga rådet, Region Dalarna https://www.regiondalarna.se/plus/vard/utveckling-och-utbildning/kunskapsstyrning/vetenskapliga-radet/	Browsat		

Citation searching

A backwards and forwards citation search in Web of Science, [15 Oct 2025], resulted in 199 records after deduplication. Relevant reports included in this HTA-report were used as seed references.

Reference lists

Included reports:

Coahran M, Hillier LM, Van Bussel L, Black E, Churchyard R, Gutmanis I, et al. Automated Fall Detection Technology in Inpatient Geriatric Psychiatry: Nurses' Perceptions and Lessons Learned. Can J Aging. 2018;37(3):245-60.

Eichenbrenner. Revolutionizing Fall Detection: Al-Enhanced Accuracy for the Safety of Patients with Delirium. 2024.

Gervasi C, Perego E, Galli F, Torri V, Castoldi M, Bombardieri E. Prevention of falls in hospitalized patients-evaluation of the effectiveness of a monitoring system (Verso Vision) developed with artificial intelligence. Frontiers in Digital Health. 2025;7:1548209.

Hasemann. AI Supported Delirium Management 2.0. 2024.

Jones KJ, Haynatzki G, Sabalka L. Evaluation of Automated Video Monitoring to Decrease the Risk of Unattended Bed Exits in Small Rural Hospitals. J Patient Saf. 2021;17(8):e716-e26.

Kramer JB, Sabalka L, Rush B, Jones K, Nolte T. Automated Depth Video Monitoring For Fall Reduction : A Case Study. 2020 Ieee/Cvf Conference on Computer Vision and Pattern Recognition Workshops (Cvprw 2020). 2020:1188-96.

Potter P, Allen K, Costantinou E, Klinkenberg WD, Malen J, Norris T, et al. Evaluation of Sensor Technology to Detect Fall Risk and Prevent Falls in Acute Care. Jt Comm J Qual Patient Saf. 2017;43(8):414-21.

Ryser. Nurses' Perception of an AI-Sensor Based Bed Exit Warning on a Specialized Unit for Patients with Delirium. 2024.

Slutrapport Innovationsprojekt Fallprevention. Västra Götalandsregionen, 2023.

Wright K, Singh S. Reducing Falls in Dementia Inpatients Using Vision-Based Technology. J Patient Saf. 2022;18(3):177-81.

Health economy report:

Nyttokalkyl för fallprevention. Västra Götalandsregionen, 2024a. https://hittaidiariet.vgregion.se/DocumentHittaDiariet/DownloadDocument/3726887?filename=Rapport%20nyttokalkyl%20fallprevention [citerad 17 april 2026].

Also found at:

Fallprevention med AI-tjänst: nyttokalkyl för AI-baserad fallprevention. Inera, Öppen info: Nyttokalkyler. Västra Götalandsregionen, 2024b. Version 1.1

https://inera.atlassian.net/wiki/spaces/OINK/pages/3838017656/Fallprevention+med+AI-tj+nst [citerad 20 april 2026].

Excluded reports:

Ahmed S, Abdullah S, Cho SH. Advancements in Radar Point Cloud Processing for Macro Human Movements in Healthcare and Assisted Living Domains: A Review. Ieee Sensors Journal. 2024;24(22):36287-305. doi: doi:https://doi.org/10.1109/jsen.2024.3452110.

Asbjorn D, Jim T. Recognizing Bedside Events Using Thermal and Ultrasonic Readings. Sensors. 2017;17(6):09. doi: doi:https://doi.org/10.3390/s17061342.

Azizan A. Challenges and opportunities in sensor-based fall prevention for older adults: a bibliometric review. J Enabling Technologies. 2024;18(4):306-18. doi: doi:https://doi.org/10.1108/jet-02-2024-0011.

Caponi A, Ermini S, Guiducci L, Valli B, Rizzo A. Co-Design of a Patient Fall Risk Prevention Service Powered by Machine Learning. Proceedings of the 4th African Conference for Human Computer Interaction, Africhi 2023. 2023:135-41. doi: doi:https://doi.org/10.1145/3628096.3629047.

Chang YS, Lin GY. Real-time Fall Detection and Reporting System Using the AlphaPose Model of Artificial Intelligence. Sensors and Materials. 2025;37(4):1639-56. doi: doi:https://doi.org/10.18494/sam5419.

Chen LB, Chang WJ, Yang TC. BedEye: A Bed Exit and Bedside Fall Warning System Based on Skeleton Recognition Technology for Elderly Patients. Ieee Access. 2025;13:60403-23. doi: doi:https://doi.org/10.1109/access.2025.3558004.

Chwyl B, Chung AG, Shafiee MJ, Fu YJ, Wong A. DeepPredict: A Deep Predictive Intelligence Platform for Patient Monitoring. 2017 39th Annual International Conference of the Ieee Engineering in Medicine and Biology Society (Embc). 2017:4309-12. doi: doi:https://doi.org/10.1109/embc.2017.8037809.

Daley B, Fetherman B, Turner J. Staffing Utilization and Fall Prevention With an Electronic Surveillance Video System: A Randomized Controlled Study. J Nurs Care Qual. 2021;36(1):57-61. doi: doi:https://doi.org/10.1097/ncq.0000000000000472.

de Frutos JG, Siemon MSN, Nasrollahi K. Fall Detection in Hospital Rooms with Probabilistic Graphical Models. 2024 Ieee Thirteenth International Conference on Image Processing Theory, Tools and Applications, Ipta 2024. 2024. doi: doi:https://doi.org/10.1109/ipta62886.2024.10755628.

Doan TN. An Efficient Patient Activity Recognition using LSTM Network and High-Fidelity Body Pose Tracking. International Journal of Advanced Computer Science and Applications. 2022;13(8):226-33. doi: doi:.

Feld-Glazman R, Trovato E, Kakkanatt A. Reducing Patient Falls on an Acute Inpatient Brain Injury Rehabilitation Unit Through Improved Patient Monitoring. Arch Phys Med Rehabil. 2019;100:e113-e4. doi: doi:https://doi.org/10.1016/j.apmr.2019.08.335.

Haider D, Yang XD, Abbasi QH. Post-surgical fall detection by exploiting the 5 G C-Band technology for eHealth paradigm. Applied Soft Computing. 2019;81. doi: doi:https://doi.org/10.1016/j.asoc.2019.105537.

Hogan Quigley B, Renz SM, Bradway C. Fall Prevention and Injury Reduction Utilizing Continuous Video Monitoring: A Quality Improvement Initiative. J Nurs Care Qual. 2022;37(2):123-9. doi: doi:https://doi.org/10.1097/ncq.0000000000000582.

Kim JY, Mat N, Kim C, Khan A, Gil HW, Lyu J, et al. Analysis of Near-Fall Detection Method Utilizing Dynamic Motion Images and Transfer Learning. Ieee Access. 2025;13:26398-410. doi: doi:https://doi.org/10.1109/access.2025.3539449.

Lin CJ, Shih CH, Wei TS, Liu PT, Shih CY. Local Object Tracking Using Infrared Array for Bed-exit Behavior Recognition. Sensors and Materials. 2022;34(2):855-70. doi: doi:https://doi.org/10.18494/sam3647.

Mao YJ, Tam AYC, Shea QTK, Zheng YP, Cheung JCW. eNightTrack: Restraint-Free Depth-Camera-Based Surveillance and Alarm System for Fall Prevention Using Deep Learning Tracking. Algorithms. 2023;16(10). doi: doi:https://doi.org/10.3390/a16100477.

Mecocci A, Micheli F, Zoppetti C, Baghini A. Automatic Falls Detection in Hospital-Room Context. 2016 7th Ieee International Conference on Cognitive Infocommunications (Coginfocom). 2016:127-32. doi: doi:.

Mennella C, Maniscalco U, De Pietro G, Esposito M. Advancing AI-driven surveillance systems in hospital: A fine-grained instance segmentation dataset for accurate in-bed patient monitoring. Comput Biol Med. 2025;195:110550. doi: doi:https://doi.org/10.1016/j.compbiomed.2025.110550.

Morawski I, Lie WN, Chiang JC. Action Prediction Using Extremely Low-Resolution Thermopile Sensor Array for Elderly Monitoring. 2021 Ieee International Conference on Image Processing (Icip). 2021:984-8. doi: doi:https://doi.org/10.1109/icip42928.2021.9506024.

Morris ME, Webster K, Jones C, Hill AM, Haines T, McPhail S, et al. Interventions to reduce falls in hospitals: a systematic review and meta-analysis. Age Ageing. 2022;51(5):01. doi: doi:https://doi.org/10.1093/ageing/afac077.

Oliu M, Bozyil R, Siemon M, Martinez-Senent A, Escalera S, Moeslund TB, et al. Fall Detection: Leveraging Depth Information in Bayesian Networks. 2025 Ieee/Cvf Winter Conference on Applications of Computer Vision Workshops, Wacvw. 2025:798-805. doi: doi:https://doi.org/10.1109/wacvw65960.2025.00095.

Pham CT, Visvanathan R, Strong M, Wilson ECF, Lange K, Dollard J, et al. Cost-Effectiveness and Value of Information Analysis of an Ambient Intelligent Geriatric Management (AmbIGeM) System Compared to Usual Care to Prevent Falls in Older People in Hospitals. Applied Health Economics & Health Policy. 2023;21(2):315-25. doi: doi:https://doi.org/10.1007/s40258-022-00773-6.

Rafferty J, Synnott J, Nugent C, Morrison G, Tamburini E. Fall Detection Through Thermal Vision Sensing. Ubiquitous Computing and Ambient Intelligence, Ucami 2016, Pt Ii. 2016;10070:84-90. doi: doi:https://doi.org/10.1007/978-3-319-48799-1_10.

Rantz MJ, Banerjee TS, Cattoor E, Scott SD, Skubic M, Popescu M. Automated fall detection with quality improvement "rewind" to reduce falls in hospital rooms. J Gerontol Nurs. 2014;40(1):13-7. doi: doi:https://doi.org/10.3928/00989134-20131126-01.

Santos LI, D'Angelo M, Cosme LB, de Oliveira HR, Mendes JB, Ekel PY. Swarm intelligence and fuzzy sets for bed exit detection of elderly. Journal of Intelligent & Fuzzy Systems. 2020;39(1):1061-72. doi: doi:https://doi.org/10.3233/jifs-191971.

Sonnby K, Stålhammar M, Molarius A, Hagberg A, Metsini A, Svalstedt M, Fure B. AI-baserade larm för fallprevention inom slutenvården: en systematisk litteratursökning. 2024:21. HTA Region Värmland, 2024.

Sosa MA, Soares M, Patel S, Trujillo K, Ashley D, Smith E, et al. The Impact of Adding a 2-Way Video Monitoring System on Falls and Costs for High-Risk Inpatients. J Patient Saf. 2024;20(3):186-91. doi: doi:https://doi.org/10.1097/pts.0000000000001197.

Tay JL, Xie HT. Novel interventions significantly reduce falls with fractures: A meta-analysis and systematic review. Geriatr Nurs. 2023;52:181-90. doi: doi:https://doi.org/10.1016/j.gerinurse.2023.06.004.

Walzer S, Schon I, Pfeil J, Klemm S, Ziegler S, Schmoor C, et al. Nurses' Perspectives and Experiences of Using a Bed-Exit Information System in an Acute Hospital Setting: Mixed Methods Study. JMIR Formative Research. 2025a;9:e64444. doi: doi:https://doi.org/10.2196/64444.

Walzer S, Schon I, Pfeil J, Merz N, Marx H, Ziegler S, et al. Experiences With an In-Bed Real-Time Motion Monitoring System on a Geriatric Ward: Mixed Methods Study. JMIR Formative Research. 2025b;9:e63572. doi: doi:https://doi.org/10.2196/63572.

Werthen-Brabants L, Bhavanasi G, Couckuyt I, Dhaene T, Deschrijver D. Split BiRNN for real-time activity recognition using radar and deep learning. Sci Rep. 2022;12:7436. doi: doi:https://doi.org/10.1038/s41598-022-08240-x.

Yadav S, Gulia P, Gill NS, Shukla PK, Khan AA, Alharby S, et al. Design of a Lightweight Compressed Video Stream-Based Patient Activity Monitoring System. Cmc-Computers Materials & Continua. 2024;78(1):1253-74. doi: doi:https://doi.org/10.32604/cmc.2023.042869.

Yamauchi Y, Shimoi N. Posture Classification with a Bed-Monitoring System Using Radio Frequency Identification. Sensors. 2023;23(16):21. doi: doi:https://doi.org/10.3390/s23167304.

Yoon H, Shin HC. Detection of Fall Risk Behaviors in Patients with Severe Mobility Issues Using FMCW Radar: Sitting Up and Sitting on the Side of the Bed. Journal of Electromagnetic Engineering and Science. 2024;24(1):65-77. doi: doi:https://doi.org/10.26866/jees.2024.1.r.206.

Other references:

Atkins D, Best D, Briss PA, Eccles M, Falck-Ytter Y, Flottorp S, et al. GRADE Working Group. Grading quality of evidence and strength of recommendations. BMJ. 2004;328(7454):1490-4. doi: 10.1136/bmj.328.7454.1490.

[Checklist from SBU regarding non-randomised controlled studies. (Modified) Version 2014]. [Internet]. [downloaded 2025-10-15]. Available from: https://mellanarkiv-offentlig.vgregion.se/alfresco/s/archive/stream/public/v1/source/available/sofia/su4372-1728378332-748/surrogate/Granskningsmall%20f%c3%b6r%20icke-randomiserade%20studier%20med%20kontrollgrupp%202024-01-24.%20PS.pdf

Drummond MF, Sculpher MJ, Claxton K, Stoddart GL, Torrance GW. Methods for the economic evaluation of health care programmes. Oxford: Oxford University Press; 2015.

Fall och fallskador : åtgärder för att förebygga. Stockholm: Sveriges kommuner och landsting; 2011.

GRADE Working Group. [Internet]. [Place unknown]: GRADE Working Group, c2004-2021 [cited 2021 Feb 13]. Available from: http://www.gradeworkinggroup.org

Heikkilä A, Lehtonen L, Junttila K. Fall rates by specialties and risk factors for falls in acute hospital: A retrospective study. J Clin Nurs. 2023;32(15-16):4868-77. doi: 10.1111/jocn.16594.

Lee A, Lee H, Lee SH. Digital Healthcare Approaches for Fall Detection and Prediction in Older Adults: A Systematic Review of Evidence from Hospital and Long-Term Care Settings. Medicina (Kaunas). 2025;61(11). doi: 10.3390/medicina61111926.

Lobbestael G. DedupEndNote (Version 1.0.0): [Computer software]; 2023 [Available from: https://github.com/globbestael/DedupEndNote]. [Deduplication date 2025-08-22]

Montero-Odasso M, van der Velde N, Martin FC, Petrovic M, Tan MP, Ryg J, et al. World guidelines for falls prevention and management for older adults: a global initiative. Age Ageing. 2022;51(9). doi: 10.1093/ageing/afac205.

Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan-a web and mobile app for systematic reviews. Syst Rev. 2016;5(1):210.

Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. Bmj. 2021;372:n71.

Skog A. Fall och fallskador inom slutenvården – en kartläggning. Göteborg: Sahlgrenska Universitetssjukhuset; 2016.

Socialstyrelsen. Fallolyckor [Internet]. Stockholm. [citerad 25 mars 2026]. https://www.socialstyrelsen.se/kunskapsstod-och-regler/omraden/aldre/stod-i-arbetet--vard-och-omsorg-for-aldre-personer--utifran-amnesomraden/fallolyckor/

Socialstyrelsen. Fallprevention–en Kostnadseffektiv Åtgärd? Hälsoekonomiska Beräkningar AV Fallpreventiva Åtgärder För Äldre. Stockholm Socialstyrelsen; 2022. https://www.socialstyrelsen.se/contentassets/a14087b2443142d5b91b21454daf22e8/2022-5-7923.pdf

Sveriges Kommuner och Landsting (SKL). Vårdskador i svensk akutsjukvård – resultat från journalgranskning 2016.

Vårdhandboken. Fallprevention – översikt. Stockholm: Inera; 2021. Tillgänglig från: https://www.vardhandboken.se/vard-och-behandling/basal-och-preventiv-omvardnad/fallprevention/oversikt/

World Health Organization. Step safely: strategies for preventing and managing falls across the life-course: World Health Organization; 2021.

World Health Organization. WHO Global report on falls prevention in older age. Geneva; 2007.

Project: AI-based motion monitoring

Appendix 2. Characteristics of included studies

Author year country	Study design	Length of follow-up	Study groups; intervention vs control	Patients (n)	Mean age (years)	Male (%)	Outcome variables
Slutrapport Innovationsprojekt Fallprevention 2023 Sweden	Cohort before-aftera Case seriesb	I= 8 weeks C= 32 (16) weeks	AI radar sensor vs no sensors	n= 1410 I=199 (164) C=690 (357) I^T=363 C^T=1047	n.r.	n.r.	Rate admissions with falls[a] Rate admissions with fall injuries [a] Staff experience-report[b]
Gervasi 2025 Italy	Cohort Parallel Stratified groups	I= 3 months C= 3 months	AI video camera vs no video monitoring	n=362 (580 observation units = OU) I=228 OU C=352 OU	75.3 y	58.6%	Falls/ 1000 person days
Jones 2021 USA	Cohort before-after	I= 2 months C = 5 months	Computer analysed depth camera vs no camera monitoring	n=372 I=151 C=221	n.r.	44.3%	Falls/1000 admissions Fall injuries/1000 admissions
Potter 2017 USA	Cohort before-after [a] Case series[b]	Baseline =12 months Phase 1 = 6 months Phase 2 = 10 months	Computer analysed depth camera vs no camera monitoring	n.r.	n.r.	n.r.	Falls/1000 patient days [a] Fall injuries/1000 patien days [a] Staff response - interview [b]
Wright 2022 United Kingdom	Cohort before-after [a] Case series[b]	I= 22 months C =12 months	Computer analysed video camera vs no video monitoring	n.r.	n.r.	n.r.	Falls/1000 bed days [a] Staff response – survey [b] Staff workload – survey [b]

Project: AI-based motion monitoring

Appendix 2. Characteristics of included studies

a)

Author year country	Study design	Length of follow-up	Study groups; intervention vs control	Patients (n)	Mean age (years)	Male (%)	Outcome variables
Kramer 2020 USA *Workshop paper with results from 4 otherwise unpublished studies*	A. Cohort before-after	I= 24 months C= 12 months	Computer analysed depth camera vs no camera monitoring	n= n.r. I>700	n.r.	n.r.	Falls/1000 patient days
	B. Cohort before-after	I= 12 months C= 12 months	Computer analysed depth camera vs no camera monitoring	n.r.	n.r.	n.r.	Number falls/year
	C. Cohort before-after	n.r.	Computer analysed depth camera vs no camera monitoring	n= approx.. 650	n.r.	n.r.	Rate decreased in unassisted falls
	D. Cohort before-after	n.r.	Computer analysed depth camera vs no camera monitoring	I=2473 C>7500	n.r.	n.r.	Rate decreased in unassisted falls
Coahran 2018 Canada	Case series	12 weeks	Computer analysed near IR camera	n= 6	n.r.	66.7%	Falls/device nights Sens, spec, ppv &npv Staff experience-Interview
Eichenbrenner 2024 Switzerland *abstract*	Case series	n.r.	AI radar sensor	n= 119	84.08	61%	Number of falls Sens, spec, ppv &npv
Hasemann 2024 Switzerland *abstract*	Case series	10 months	AI radar sensor	n=119	84.08	61%	Number of falls
Ryser 2024 Switzerland *abstract*	Case series	2 years	AI radar sensor	n=24	n.r.	n.r.	Staff experience–scoring Likert scale
Health Economy							
Nyttokalkyl för Fallprevention Innovationsprojekt Fallprevention 2024a, b Sweden	Cohort before-after	I= 8 weeks C= 32 (16) weeks	AI radar sensor vs no sensors	n= 1410 I=199 (164) C=690 (357) I^T=363 C^T=1047	n.r.	n.r.	Health economy

a) Outcome in study with mixed study design originating from cohort (before-after). b) Outcome in study with mixed study design originating from * case series. I = intervention group. C=control group. $^{T)}$ = total. N.r.= not reported.

Project: AI-based motion monitoring
Appendix 3.
Excluded articles

Author, year	Reason for exclusion
Ahmed 2024	Wrong study design, non-systematic review.
Asbjörn 2017	Wrong population, no patients, only technical focus.
Azizan 2024	Wrong study design, bibliometric review. No focus on relevant PICO.
Caponi 2023	Wrong population, technical evaluation, no patients.
Chang 2025	Wrong population, no patients, technical focus.
Chen 2025	Wrong population, no patients, development and testing of technique.
Chwyl 2017	Wrong population, no patients, technical focus.
Daley 2021	Wrong intervention, video monitoring without AI.
de Frutos 2024	Wrong population, no patients, technical focus.
Doan 2022	Wrong population, no patients, technical focus.
Feld-Glazman 2019	Wrong intervention, video monitoring without AI.
Haider 2019	Wrong population, no patients, technical focus.
Hogan Quigley 2022	Wrong intervention, video monitoring without AI.
Kim 2025	Wrong population, no patients, technical focus.
Lin 2022	Wrong population, only experimental patient involvement.
Mao 2023	Wrong population, no patients, technical focus.
Mecocci 2016	Wrong population, no patients, technical focus.
Mennella 2025	Wrong population, no patients, technical focus.
Morawski 2021	Wrong population, no patients, technical focus.
Morris 2022	Wrong intervention. Systematic review with different fall prevention initiatives, no AI-based prevention.
Oliu 2025	Wrong population, no patients, technical focus.
Pham 2023	Wrong intervention, wearable sensor placed over sternum.
Rafferty 2016	Wrong population, no patients, technical focus.
Rantz 2014	Wrong population, staff and leadership, no patient data.
Santos 2020	Wrong population, no patients, technical focus.
Sonnby 2024	Systematic review including study with only wrong intervention.
Sosa 2024	Wrong intervention, video monitoring without AI.
Tay 2023	Wrong intervention. Systematic review with different fall prevention initiatives, no AI-based prevention.
Walzer 2025a, Nurses' perspectives	Wrong intervention, sensor in mattress.
Walzer 2025b, Experiences with	Wrong intervention, sensor in mattress.
Werthen-Brabants 2022	Wrong population, no patients, technical focus.
Yadav 2024	Wrong population, no patients, technical focus.
Yamauchi 2023	Wrong population, no patients, technical focus.
Yoon 2024	Wrong population, no patients, technical focus.

Project: AI-based motion monitoring

* + No or minor problems
? Some problems
\- Major problems

Appendix 4.1
Outcome variable: Fall during hospital admission

Author year country	Study design	Number of patients n=	Withdrawals - dropouts	Results		Comments	Directness *	Study limitations *	Precision *
				Intervention	Control				
Slutrapport Innovationsprojekt Fallprevention 2023 Sweden	Cohort before-after	<u>SÄS (SU)</u> n= 1410 I=199 (164) C=690 (357) I^T=363 C^T=1047		<u>SÄS</u> n=4 (2.0%) admissions with falls (95% CI 1.4 - 6.7 p=0.0184) <u>SU</u> n= 6 (3.7%) admissions with falls (95% CI 2.9 - 11.6 p=0.0065) <u>Total</u> n= 10 (2.8%) admissions with falls (p=n.r.)	<u>SÄS</u> n= 42 (6.1%) admissions with falls <u>SU</u> n= 39 (10.9%) admissions with falls <u>Total</u> n= <u>81 (7.7%) admissions with falls</u>	Study periods differ by several years – may affect indication for admission.	+	?/-	+
Gervasi 2025 Italy	Cohort Parallell groups	n=362 (580 observation units = OU) I=228 OU C=352 OU		Accidental falls n= 5 Incidence rate 2.84/1000 person days (95% CI 0.92-6.63) Incidence rate ratio 0.43 (95% CI 0.12-1.24, p=0.0926)	Accidental falls n=15 Incidence rate 6.65/1000 person days (95% CI 3.72-10.96)	Weighting by stratify score. OU = statistical units based on time with VS whereas stratify score change during admission and thus need for VS.	+	?	+
Jones 2021 USA	Cohort before-after	n=372 I=151 C=221		5.53 total falls/1000 admissions (p=0.136)	8.83 total falls/1000 admissions	Difference between participating hospitals whether AVMS were used to monitor or to intervene.	?	?	?
Potter 2017 USA	Cohort before-after	n= n.r. I= n.r. C= n.r.		<u>Evaluation unit Phase 1</u> 4.83[1] falls/1000 patient days Incidence rate ratio 0.58[2] <u>Comparison unit Phase 1</u> 2.97[1] falls/1000 patient days Incidence rate ratio 0.77[2] <u>Comparison unit Phase 2</u> 4.69[1] falls/1000 patient days Incidence rate ratio 0.67[2]	<u>Evaluation unit Baseline</u> 4.78[1] falls/1000 patient days <u>Comparison unit Baseline</u> 4.38[1] falls/1000 patient days <u>Comparison unit Baseline</u> 4.38[1] falls/1000 patient days	Results extracted from table 1[1]. Incidence rate ratio calculated from extracted numbers[2]. Phase 2 only 14.3% of patient population with high fall risk.	?	-	?
Wright 2022 United Kingdom	Cohort before-after	n= n.r. I= n.r. C= n.r.		6.65[3] falls/1000 bed days 48% reduction in rate of nighttime falls (p<0.01)	11.72[3] falls/1000 bed days	Monitoring only during nighttime. Results extracted from Figure 33. (March 2018 excluded due to period includes both I & C)	+	?/-	-
Kramer 2020 USA *Workshop paper with results from 4 otherwise unpublished studies*	A. Cohort before-after B. Cohort before-after	n=n.r. I>700 n.r.		3.05[4] falls/1000 patient days 54% reduction in rate of unassisted falls Total: 11 falls per 12 months (decrease 52.2%)	4.1[5] falls/1000 pat days Total: 23 falls per 12 months	Stated observation period = 6500 patient days. Results extracted from figure 2; 2018 & 2019[4]. Results extracted from figure 2; 2017[5].	?	-	-

Project: AI-based motion monitoring

* + No or minor problems ? Some problems - Major problems

Appendix 4.1
Outcome variable: Fall during hospital admission

Author year country	Study design	Number of patients n=	Withdrawals - dropouts	Results: Intervention	Results: Control	Comments	Directness *	Study limitations *	Precision *
	C. Cohort before-after D. Cohort before-after	n= approx.. 65(I=2473 C >7500		I= n.r. 54% decrease in unassisted falls I= n.r. 46% decrease in unassisted falls	C= n.r. C= n.r.				
Coahran 2018 Canada	Case series	n=6 I=6		5 falls/267 device nights					
Eichenbrenner 2024 Switzerland *abstract*	Case series	n=119 I= n.r.		49 falls (33 falls in the surveillance zone)					
Hasemann 2024 Switzerland *abstract*	Case series	n=119 I= n.r. C= n.r.			Incidence rate reported as twice as high				

I = intervention group. C=control group. T) = total. N.r.= not reported. VS = Verso Vision System. AVMS = automated video monitoring system. 1) Results extracted from table 1, Potter, 2017. 2) Incidence rate ratio calculated from extracted numbers, Potter, 2017. 3) Results extracted from figure 3, Wright, 2022. 4) Results extracted from figure 2, 2018 & 2019, Kramer, 2020.

5) Results extracted from figure 2, 2017, Kramer, 2020.

Project: AI-based motion monitoring

* + No or minor problems ? Some problems - Major problems

Appendix 4.1
Outcome variable: Fall injuries during hospital admission

Author year country	Study design	Number of patients n=	Withdrawals - dropouts	Results: Intervention	Results: Control	Comments	Directness *	Study limitations *	Precision *
Slutrapport Innovationsprojekt Fallprevention 2023 Sweden	Cohort before-after	SÄS (SU) n= 1410 I=199 (164) C=690 (357) I^T=363 C^T=1047		SÄS n=2 (1.0%) admissions with fall injuries SU n= 2 (1.2%) admissions with fall injuries Total n= 4 (1.1%) admissions with fall injuries	SÄS n= 12 (1.7%) admissions with fall injuries p= n.r. SU n= 12 (3.4) admissions with fall injuries p= n.r. Total n= 24 (2.3%) admissions with fall injuries	Study periods differ by several years – may affect indication for admission.	+	?/-	+
Jones 2021 USA	Cohort before-after	n=372 I=151 C=221		0.55 fall injuries/1000 admissions	2.52 fall injuries/1000 admissions (p=0.025)	Difference between hospitals whether AVMS were used to monitor or to intervene.	?	?	?
Potter 2017 USA	Cohort before-after	n= n.r. I= n.r. C= n.r.		Evaluation unit Phase 1 0.32[1] falls with injury/1000 patient days Comparison unit Phase 1 0.89[1] falls with injury/1000 patient days Comparison unit Phase 2 0.78[1] falls with injury/1000 patient days	Evaluation unit Baseline 0.55[1] falls with injury/1000 patient days Comparison unit Baseline 1.16[1] falls with injury/1000 patient days Comparison unit Baseline 1.16[1] falls with injury/1000 patient days	Results extracted from table 1[1] Phase 2 only 14.3% with high fall risk	?	-	?

I = intervention group. C=control group. [T)] = total. N.r.= not reported. AVMS = automated video monitoring system. [1)] Results extracted from table 1, Potter, 2017.

Project: AI-based motion monitoring

* + No or minor problems
? Some problems
- Major problems

Appendix 4.1
Outcome variable: Health economics

Author year country	Study design	Number of patients n=	Withdrawals - dropouts	Results: Intervention	Results: Control	Comments	Directness *	Study limitations *	Precision *
Nyttokalkyl för Fallprevention Innovationsprojekt Fallprevention 2023 Sweden	Cohort before-after	SÄS (SU) n= 1410 I=199 (164) C=690 (357) I^T=363 C^T=1047		SÄS n=4 (2.0%) admissions with falls (95% CI 1.4 - 6.7 p=0.0184) SU n= 6 (3.7%) admissions with falls (95% CI 2.9 - 11.6 p=0.0065) Total n= 10 (2.8%) admissions with falls (p= n.r.)	SÄS n= 42 (6.1%) admissions with falls SU n= 39 (10.9%) admissions with falls Total n= 81 (7.7%) admissions with falls	Study periods differ by several years – may affect indication for admission.	+	?/-	+

I = intervention group. C=control group. $^{T)}$ = total. N.r.= not reported.

Project: AI-based motion monitoring
Appendix 4.1
Outcome variable: Sensitivity, specificity, positive predictive value, negative predictive value for detection of falls

* + No or minor problems
? Some problems
\- Major problems

Author year country	Study design	Number of patients n=	Withdrawals - dropouts	Results		Comments	Directness *	Study limitations *	Precision *
				Intervention	Control				
Coahran 2018 Canada	Case series	n=6 I=6		Sensitivity = 0.8 Specificity = n.r. Positive predictive value = 0.01 Negative predictive value = n.r.					
Eichenbrenner 2024 Switzerland *abstract*	Case series	n=119 I= n.r.		Sensitivity = 0.7 Specificity = 1.0 Positive predictive value = 0.96 Negative predictive value = 1.0					

I = intervention group.

Project: AI-based motion monitoring

*	+	No or minor problems
	?	Some problems
	-	Major problems

Appendix 4.1
Outcome variable: Staff experience

Author year country	Study design	Number of patients n=	Withdrawals - dropouts	Results Intervention	Results Control	Comments	Directness *	Study limitations *	Precision *
Slutrapport Innovationsprojekt Fallprevention. 2023 Sweden	Case series	SÄS (SU) n= 1410 I=199 (164) C=690 (357) I^T=363 C^T=1047		Shortened alert – response time. Usable for other purposes, good nighttime room-control. Poor introduction. False alarms. Wrong alarms. Stress due to alarms.		Survey and interviews 4 weeks into i and after completed intervention N = n.r.			
Coahran 2018 Canada	Case series	n=6 I=6		Nurses are supportive of new technology that contributes to improvements in clinical practice and patient care, particularly when it functions as intended. While early detection is valuable, technology should focus on fall prevention. Fall-alerting mechanisms should be easy to use. The HELPER system has positive features over technologies that currently exist. Technological issues with the system and hospital infrastructure limit current usefulness in practice.		Interview n=9 (11, response rate 81.8%)			
Potter 2017 USA	Case series	n= n.r. I= n.r. C= n.r.		Benefit of alarms (most staff). Quieter environment. Alarm fatigue. Inability to respond to alarm quickly.		Data regarding staff perceptions was gathered through group discussions during planned staff meetings.			
Ryser 2024 *abstract*	Case series	n= n.r.		Usefulness M=0.96 Reliability M=0.45 Usability M=0.95 Privacy M=0.55 Alerts M=1.25		Staff survey with two years interval (unclear whether before and after intervention) n=24 Rating on 4-point Likert scale (very negative = -2, very good = 2)			
Wright 2022 United Kingdom	Case series	n= n.r.		Reduction in falls. Earlier intervention. Staff able to attend and prevent a fall from happening.		Staff survey (n=12)			

I = intervention group. C=control group. $^{T)}$ = total.

Project: AI-based motion monitoring
Appendix 4.1
Outcome variable: Staff workload

* + No or minor problems
? Some problems
\- Major problems

Author year country	Study design	Number of patients n=	Withdrawals - dropouts	Results		Comments	Directness *	Study limitations *	Precision *
				Intervention	Control				
Wright 2022 United Kingdom	Case series	n= n.r.		Help to manage time and prioritise work		Staff survey (n=12)			

N.r.= not reported.