

Supplementary Table S1. Characteristics of all Tier 1 studies included in the action-trigger decision-support synthesis (n = 38)

ID	Citation	Year	Country/ Region	Setting/ Ward type	Population	Study design type	Monitoring inputs/sens ors	AI/model (as reported)	Target event(s)	Trigger type	Recipient/d estination	Workflow integration elements	Main reported endpoints	Notes
T1-1	Danial M, Chow CT, Lim MH, Ayop NA, Looi I, Ch'ng ASH. AI-based patient monitoring for fall prevention in stroke patients: a pilot study at a Malaysian acute stroke unit. J Neuroeng Rehabil. 2025;22(1):216. doi:10.1186/s12984-025-01706-9	2025	Malaysia	Acute stroke unit, inpatient ward	30 stroke inpatients	Real-world clinical implementation/evaluation	Optical sensor video; alert panel; control panel	AI-based motion sensing; uniform recognition/staff recognition	Bed-exit attempts ; falls	Alert	Observation counter/ward staff	Real-time alerts; blurred images for privacy; staff recognition; response-time logging	Alerts; false alarms; response time; fall incidence	Strong Tier 1 inpatient pilot
T1-2	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	2025	Italy	Medicine and oncology wards, inpatient hospital	362 hospitalized patients	Real-world clinical implementation/evaluation	In-room video monitoring	AI-based computer vision system	Bed exit; risky situations; falls	Alert	Nurses via monitored system/mobile devices	Continuous ward monitoring; staff workflow implied	Fall incidence; IRR estimates	Strong clinical outcome study; workflow detail thinner

	intelligence. Front Digit Health. 2025;7:1548209. doi:10.3389/fdgth.2025.1548209													
T1-3	Lee JS, Jun JH, Kim DH, Oh SJ. Implementation of a Patient Risk Behavior Monitoring System Using Real-Time Sensor Data and AI. IEEE Access. 2025;13:177907-177918. doi:10.1109/ACCESS.2025.3617960	2025	South Korea	Psychiatric inpatient wards	Psychiatric inpatients/ward context	Real-world clinical implementation/evaluation	CCTV; mmWave radar; wearable devices; location sensors	VideoMAE; LSTM-AutoEncoder; multimodal fusion	Risk behaviors, including falls	Alert	Medical staff	Immediate alerts; multimodal integration; privacy-conscious monitoring	Technical integration metrics; risk detection performance	Falls included but not sole target
T1-4	Lin CL, Ho YH, Lin FY, Sung PS, Huang CY. Fall-Risk Monitoring in Diverse Terrains Using Dual-Task Learning and Wearable Sensing System. IEEE J Biomed Health Inform. 2025;29(6):4059-4070.	2025	Taiwan	Hospital-linked older adult validation	Young volunteers and hospital's older adults	Methodological validation study	Terrain sensors + IMU wearable sensing	Modified CNN-LSTM/dual-task learning	Fall-risk level; pre-impact fall monitoring	Alert	Not clearly reported	Monitoring concept explicit; terrain-aware risk monitoring	Monitoring accuracy; prediction accuracy; lead time	Hospital older adult validation noted

	doi:10.1109/JBHI.2025.3536030													
T1-5	Chang YS, Lin GY. Real-time Fall Detection and Reporting System Using the AlphaPose Model of Artificial Intelligence. Sens Mater. 2025;37(4):1639-1656. doi:10.18494/SAM5419	2025	Taiwan	Hospital care/healthcare monitoring context	Elderly individuals/patients	Methodological validation study	Web camera	AlphaPose + ST-GCN	Falls	Notification	Healthcare providers or family members via communication software	Immediate alerts after detection	Training accuracy; reporting/notification functionality	Reporting system explicit; setting not deeply characterized
T1-6	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;13:60403-60423. doi:10.1109/ACCESS.2025.3558004	2025	Taiwan	Hospital-linked bedside monitoring with clinical validation	Elderly patients; clinical human trials	Validation study with clinical component	RGB sensor; edge device	OpenPose -light; skeleton recognition; edge AI	Bed exit; bedside fall warning	Warning	Nurse station and mobile interface	Real-time edge processing; staged posture recognition	Accuracy; clinical validation performance	Strong bedside early-warning paper
T1-7	Rathod U, Chakrabarty S, Sarda D, Mavuri M, Kumbhare D, Hoang S, Quinones C, Wilson J, Atwogbol T. Real-time	2025	Not clearly reported	Patient safety monitoring context	Not clearly reported	Proof-of-concept/simulation-	Video-based patient monitoring	Deep learning system	Falls/patient safety events	Alert	Not clearly reported	Real-time system concept explicit	Detection/system performance	Needs full-text confirmation of setting/wo

	patient safety system using deep learning. Biomed Sci Instrum. 2025;61(2):394-405. doi:10.34107/UDUK9890394					oriented study								rkflow detail
T1-8	Kalaiaarasi P, Naveen K, Kumar MVA, Adhitya V, Lavanya K. A Real-Time Vision-based Fall Detection System using YOLOv10 and Deep Learning for Ensuring Elderly and Patient Safety. Proc ICESC 2025. doi:10.1109/ICESC6514.2025.11212604	2025	Not clearly reported	General patient safety context	Elderly people and patients	Proof-of-concept/conference/simulation-oriented study	Vision-based sensing	YOLOv10	Falls	Alert	Not clearly reported	Real-time fall detection concept	Detection accuracy/system performance	Conference paper
T1-9	Karson S, Gilys D, Skvyrski D, Cook N, Gromov M, Saniie J. RiskWatch: Wearable Fall Detection and Healthcare Accountability Device. IEEE International	2025	Not clearly reported	Wearable healthcare device context	Not clearly reported	Proof-of-concept/conference/simulation-oriented study	Wearable sensors	Device-based fall detection system	Falls	Alert	Not clearly reported	Accountability/alerting concept	System/device performance	Conference paper

	Conference on Electro Information Technology. 2025. doi:10.1109/eIT64391.2025.11103628													
T1-10	Abdelfattah S, Ali F, Kalleti SG, Baza M, Badr MM. Real-Time Vision-Based Risk of Fall Detection Using YOLOv8. ICETM 2025. doi:10.1109/ICETM63734.2025.11051889	2025	Not clearly reported	General healthcare/patient safety context	Not clearly reported	Proof-of-concept/conference/simulation-oriented study	Vision-based sensing	YOLOv8	Risk of fall/falls	Alert	Not clearly reported	Real-time detection concept	Detection performance	Conference paper
T1-11	Pham CT, Visvanathan R, Strong M, Wilson ECF, Lange K, Dollard J, Ranasinghe D, Hill K, Wilson A, Karnon J. Cost-Effectiveness and Value of Information Analysis of an Ambient Intelligent Geriatric Management (AmbIGeM) System Compared to Usual Care to Prevent Falls in Older	2023	Australia	Geriatric Evaluation and Management Unit wards, inpatient hospital	Older inpatients	Economic evaluation using trial data	Wearable sensors	AI-enabled alerting system	Falls; injurious falls	Alert	Hospital staff	Staff-trigger alerts before fall; hospital deployment	Costs; cost-effectiveness; value of information; injurious falls	Strong economic paper

	People in Hospitals. Appl Health Econ Health Policy. 2023;21(2):315-325. doi:10.1007/s40258-022-00773-6													
T1-12	Mayer J, Jose R, Bekbolatova M, Coletti C, Devine T, Toma M. Enhancing patient safety through integrated sensor technology and machine learning for bed-based patient movement detection in inpatient care. Artif Intell Health. 2024;1(2):132-143. doi:10.36922/aih.2790	2024	Not clearly reported	Inpatient care	Not clearly reported	Methodological validation study	Bed-based sensor technology	Machine learning	Bed-based patient movement	Alert	Not clearly reported	Integrated monitoring in inpatient care	Detection/performance metrics	Inpatient care explicit
T1-13	Mendes NKN, Pinheiro FVS, Oliveira VT, Francisco Laurindo C, Gomes RL, Andrade RMC. FallReportAPI: Integration of Digital Health Systems for Fall	2024	Not clearly reported	Hospital systems	Not clearly reported	Proof-of-concept/conference/simulation-oriented	Digital health system integration	API-based integration/AI-enabled fall detection context	Falls	Notification	Hospital systems	Notification/integration explicit	System integration focus	No DOI in supplied source

	Detection in Hospital Systems. CEUR Workshop Proceedings. 2024;3795:316-331.					study								
T1-14	Sofer T, Dabran I, Ginzburg E, Levi E, Ron T. Smart Healthcare Bed for Prevention of Hospital Inpatient Falls. COMCAS 2024. doi:10.1109/COMCAS58210.2024.10666175	2024	Israel	Hospital inpatient collaboration	High-risk inpatients/te st participants	Proof-of-concept/conference/simulation-oriented study	Smart bed; force/bed sensing	CNN-based prediction	Imminent fall-related behavior	Alert	Nurse station interface	Smart bed warning concept	Prediction success/warning concept	Bed-centered Tier 1 study
T1-15	Guedes AFS, Friedrich DN, Bock FM, Isidoro DF, Casagrande LF, Brasil RM. New Electronic Health Telemetry Device (Stakecare) applied in the Monitoring and Controlling Falls of Individuals. Proc SPIE. 2024;12948:129480H. doi:10.1117/12.3005982	2024	Not clearly reported	Monitoring context not clearly specified	Not clearly reported	Proof-of-concept/conference/simulation-oriented study	Telemetry device	AI-enabled/telemetry-based monitoring	Falls	Alert	Not clearly reported	Monitoring/controlling concept	Device/system performance	Broad setting; workflow detail limited
T1-16	Wei H, Chew E, Bentley BL, Pinney J, Lee PL. A	2024	Not clearly	Robot-assisted	Not clearly reported	Proof-of-	Humanoid robot	AI-enabled	Falls	Alert	Not clearly reported	Robot-enabled detection	Detection/system	Broad setting

	Novel Fall Detection System Using the AI-Enabled EUREKA Humanoid Robot. Lect Notes Netw Syst. 2024;845:491-501. doi:10.1007/978-981-99-8498-5_41		reported	monitoring context		concept/conference/simulation-oriented study	sensing	robot-based detection				concept	performance	
T1-17	Dhakshak P, Veigas AB, Anudeep K, Pradyumna GR, Hegde RB. Third Eye - A Compact Wearable Device and Dedicated Android App for Disabled Senior Citizens and Patients. ICEECT 2024. doi:10.1109/ICEECT61758.2024.10738942	2024	Not clearly reported	Wearable/mobile safety context	Disabled senior citizens and patients	Proof-of-concept/conference/simulation-oriented study	Wearable device + Android app	Device/app-based system	Falls/patient safety events	Alert	Android app/caregivers not clearly specified	App-based alerting concept	Device/app functionality	Conference paper
T1-18	Kondo N, Fujita D, Kobashi S, Fujita T. Prediction of Bed-Leaving Behaviors Using Edge AI to Prevent Medical Accidents. Proc IEEE	2023	Japan	Medical accident prevention context	Not clearly reported	Proof-of-concept/conference/simulation-oriented	Edge AI monitoring	Edge AI	Bed-leaving behavior	Alert	Not clearly reported	Preventive trigger concept	Prediction/detection performance	Bed-leaving trigger explicit

	SMC 2023. doi:10.1109/SMC53992 .2023.10394042					study								
T1-19	Mishra S, Ngangbam B, Raj S, Pradhan NR. CURA: Real Time Artificial Intelligence and IoT based Fall Detection Systems for patients suffering from Dementia. EAI Endorsed Trans Perv Health Technol. 2023;9(1). doi:10.4108/eetpht.9.3967	2023	Not clearly reported	Dementia patient monitoring context	Patients with dementia	Proof-of-concept/conference/simulation-oriented study	IoT-based sensing	AI + IoT	Falls	Alert	Not clearly reported	Real-time detection system concept	System performance	Broad care setting
T1-20	Limbaga NJP, Mallari KLT, Yeung NRO, Oppus CM. A Mixed Cloud-and-Embedded-based Approach with Machine Learning Towards the Development of a Fall Monitoring System. ECTI DAMT and	2023	Not clearly reported	Fall monitoring context	Not clearly reported	Proof-of-concept/conference/simulation-oriented study	Cloud + embedded sensing	Machine learning	Falls	Notification	Not clearly reported	Notification concept	System development/performance	Conference paper

	NCON 2023. doi:10.1109/ECTIDAM TNCON57770.2023.10 139738													
T1-21	Mohammad Z, Anwary AR, Mridha MF, Shovon MSH, Vassallo M. An Enhanced Ensemble Deep Neural Network Approach for Elderly Fall Detection System Based on Wearable Sensors. Sensors. 2023;23(10):4774. doi:10.3390/s23104774	2023	Bangladesh/UK collaboration	Wearable monitoring concept	Elderly individuals	Methodological validation study	Wearable accelerometer and gyroscope sensors	Ensemble deep neural network; CNN + RNN	Pre-fall; fall; non-fall	Notification	Remote notification concept	Safeguard and notification concept explicit	Classification accuracy	Hardware implementation not demonstrated
T1-22	Krishna K, Vamsi K V, Reddy K, Thyagarajan KK. A patient-specific single sensor IoT-based wearable fall prediction and detection system using machine learning. AIP Conf Proc. 2022;2519:050025. doi:10.1063/5.0111774	2022	Not clearly reported	Wearable fall monitoring context	Not clearly reported	Proof-of-concept/conference/simulation-oriented study	Single-sensor wearable IoT device	Machine learning	Fall prediction and detection	Alert	Not clearly reported	Alerting concept present	Prediction/detection performance	Conference paper
T1-	Pornpreedawan P,	2022	Thailand	Bed-fall	Not clearly	Method	Pressure and	Sensor-	Bed-	Notification	Caregiver/st	Notification	System	Strong

23	Puengsiricharoen K, Tantissatirapong S, Taweerutchana R, Sueaseenak D. A Bed-Fall Notification System Using Pressure and Ultrasonic Sensors. Curr Appl Sci Technol. 2022;22(3). doi:10.55003/cast.2022.03.22.011			monitoring context	reported	ological validation study	ultrasonic sensors	based rule/ML-supported system	fall/bed-exit related events	tion	aff notification concept	explicit	performan ce	notificatio n paper
T1-24	Yeh C, Lee AW, Dy HKK, Li KC. Internet-of-Things Management of Medical Chairs and Wheelchairs. IoTBDS Proceedings. 2022:183-188. doi:10.5220/0011059600003194	2022	Not clearly reported	Medical chair and wheelchair management context	Not clearly reported	Proof-of-concept/conference/simulation-oriented study	IoT-connected chairs/wheel chairs	IoT management system	Chair-related risk events/safety management	Alert	Not clearly reported	Alerting concept should be verified from full text	System management/performance	Borderline Tier 1; verify workflow-facing trigger wording
T1-25	Ribeiro O, Gomes L, Vale Z. IoT-Based Human Fall Detection System. Electronics. 2022;11(4):592. doi:10.3390/electronics	2022	Portugal	Home-centered primary framing; hospitals	Not clearly reported	Methodological validation study	IoT devices; edge-fog-cloud architecture	ANN + wavelet/hybrid models	Falls	Alert	Not clearly reported	Near-real-time help/alert concept	Accuracy; false negatives	Retained in your T1 list, but hospital specificity should be

	11040592			mentioned as possible deployment										framed carefully
T1-26	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(1):7436. doi:10.1038/s41598-022-08240-x	2022	Belgium	Hospital multi-room monitoring example	Not clearly reported	Methodological validation study	Radar sensing	Split BiRNN/RNN-based activity recognition	Falls/troublesome activities	Notification	Staff	Fast notifications from on-premise device	Recognition performance; notification concept	Hospital example explicit in abstract
T1-27	Koçak H, Çetin G. A Deep Learning-Based IoT Implementation for Detection of Patients' Falls in Hospitals. Lect Notes Data Eng Commun Technol. 2021;76:465-483. doi:10.1007/978-3-030-79357-9_46	2021	Not clearly reported	Hospitals	Patients	Proof-of-concept/ book chapter	IoT-based sensing	Deep learning	Falls	Alert	Not clearly reported	Hospital alerting concept	Detection performance	Hospital setting explicit in title
T1-	Takatou K, Shinomiya	2021	Not	Elderly	Elderly	Proof-	Passive	Cloud-	Falls	Alert	Not clearly	Cloud alerting	Detection	Setting

28	N. A cloud-based fall detection system for elderly care with passive RFID sensor tags. LifeTech 2021:261-265. doi:10.1109/LifeTech52111.2021.9391901		clearly reported	care context	individuals	of-concept/conference/simulation-oriented study	RFID sensor tags	based detection system			reported	concept	system performance	broad
T1-29	Kim TH, Choi A, Heo HM, Kim K, Lee K, Mun JH. Machine Learning-Based Pre-Impact Fall Detection Model to Discriminate Various Types of Fall. J Biomech Eng. 2019;141(8):081010. doi:10.1115/1.4043449	2019	South Korea	Experimental/application-oriented	Healthy participants	Methodological validation study	Inertial measurement unit near iliac crest	Machine learning classifiers	Pre-impact falls; fall types	Alert	Alarm service concept	Pre-impact alerting discussed	Classification accuracy	Application-oriented rather than ward deployment
T1-30	Torti E, Fontanella A, Musci M, Blago N, Paud, Leporati F, Piastra M. Embedding Recurrent Neural Networks in Wearable Systems for Real-Time Fall Detection. Microprocess Microsyst.	2019	Italy	Wearable remote monitoring context	Vulnerable people/elderly framing	Methodological validation study	Wearable tri-axial accelerometers	Recurrent neural network	Falls	Notification	Remote monitoring system	Wireless remote notifications explicit	Runtime feasibility; embedded performance	Strong wearable notification concept

	2019;71:102895. doi:10.1016/j.micpro.2019.102895													
T1-31	Torti E, Musci M, Guareschi F, Leporati F, Piastra M. Deep recurrent neural networks for edge monitoring of personal risk and warning situations. Sci Program. 2019;2019:9135196. doi:10.1155/2019/9135196	2019	Italy	Wearable edge monitoring context	Vulnerable people/elderly framing	Methodological validation study	Wearable 3D accelerometer signals	Deep recurrent neural networks	Falls/warning situations	Alert	Remote alerting system	Edge monitoring and remote alerts explicit	Classification/system performance	Warning situations explicit
T1-32	Ajerla D, Mahfuz S, Zulkernine FH. A real-time patient monitoring framework for fall detection. Wirel Commun Mob Comput. 2019;2019:9507938. doi:10.1155/2019/9507938	2019	Canada	Clinics/retirement homes/smart-city healthcare context	Older adults/patient monitoring framing	Methodological validation study	Wearable devices + edge device	LSTM-based model; Apache Flink streaming	Falls	Alarm	Appropriate authorities	Alarm to appropriate authorities explicit	Accuracy; system framework	Strong framework paper
T1-33	Torres RLS, Shi Q, van den Hengel A, Ranasinghe DC. A	2017	Australia	Hospitals and nursing	Healthy older adults and	Methodological validation	Batteryless wearable sensors	Hierarchical CRF model	Alarming states: out-of-	Alarm	Clinical staff/alarm intervention	Real-time alarm-state prediction	Alarm performance metrics	Strong alarming-state paper

	hierarchical model for recognizing alarming states in a batteryless sensor alarm intervention for preventing falls in older people. Pervasive Mob Comput. 2017;40:1-16. doi:10.1016/j.pmcj.2017.04.002			homes mention ed; hospital patient data included	hospitalized older patients	n study			bed/out-of-chair		concept			
T1-34	Wickramasinghe A, Ranasinghe D, Fumeaux C, Hill K, Visvanathan R. Sequence Learning with Passive RFID Sensors for Real-Time Bed-Egress Recognition in Older People. IEEE J Biomed Health Inform. 2017;21(4):917-929. doi:10.1109/JBHI.2016.2576285	2017	Australia	Hospital-like room deployment	Older adults	Methodological validation study	Passive RFID sensors	Sequence learning/structured prediction	Bed egress	Alert	Caregiver alarm concept	Real-time bed-egress recognition	Precision; recall; delays	Strong bed-egress Tier 1 paper
T1-35	Torres RL, Visvanathan R, Hoskins S, van den Hengel A, Ranasinghe DC. Effectiveness of a	2016	Australia	Clinical-like room deployment	14 healthy older volunteers	Methodological validation study	Batteryless wireless wearable sensor	Weighted CRF-based activity	Bed exits; chair exits	Alert	Caregiver alerting concept	Real-time alert generation concept	Recall; precision; F-score; delay	Volunteer/preclinical validation

	batteryless and wireless wearable sensor system for identifying bed and chair exits in healthy older people. Sensors. 2016;16(4):546. doi:10.3390/s16040546			ent				predictor/ ML classifier						
T1-36	Torres RLS, Visvanathan R, Abbott D, Hill KD, Ranasinghe DC. A battery-less and wireless wearable sensor system for identifying bed and chair exits in a pilot trial in hospitalized older people. PLoS One. 2017;12(10):e0185670. doi:10.1371/journal.pone.0185670	2017	Australia	Geriatric Evaluation and Management Unit ward	26 hospitalized older adults	Pilot feasibility study	Batteryless wearable sensor system	ML-based activity classifier and exit recognition	Bed exits; chair exits	Alert	Care staff/alarm intervention concept	Supervised pilot in hospital rooms	Recall; precision; F-score; acceptability	Strong inpatient pilot
T1-37	Danielsen A, Torresen J. Recognizing Bedside Events Using Thermal and Ultrasonic Readings. Sensors. 2017;17(6):1342. doi:10.3390/s17061342	2017	Norway	Bedside monitoring relevant to hospitals and	Not clearly reported	Methodological validation study	Ceiling-mounted thermal array + ultrasonic sensor	Classification approaches/AI-based bedside event	Bedside falls; bed entry; bed exit	Alert	Not clearly reported	Floating image rule/filter approach	Accuracy for bedside falls and bed entry/exit	In your list written as “Asbjorn D, Jim T”; canonical citation normalize

				care facilities				recognition						d
T1-38	Giri A, Hasib A, Islam M, Tazim MF, Rahman MDS, Khadgi M, Akib ASMAS. Real-Time Human Fall Detection Using YOLOv5 on Raspberry Pi: An Edge AI Solution for Smart Healthcare and Safety Monitoring. Lect Notes Netw Syst. 2026;1597 LNNS:493-507. doi:10.1007/978-3-032-02831-0_40	2026	Not clearly reported	Smart healthcare and safety monitoring context	Not clearly reported	Proof-of-concept/conference/simulation-oriented study	Camera + Raspberry Pi edge device	YOLOv5	Falls	Alert	Not clearly reported	Real-time edge AI detection concept	Detection/system performance	Conference paper; inpatient specificity should not be overstated

Note: This table presents the full Tier 1 study set included in the action-trigger synthesis. Terminology for AI methods, trigger types, and workflow-related elements was retained as closely as possible to the original reports reviewed by the authors. When a contextual or workflow element was not explicitly reported in the source article, it was not inferred. Studies were retained in Tier 1 when the full text provided minimum evidence of a workflow-facing alert, alarm, warning, or notification relevant to inpatient fall prevention, even when reporting depth for ward context or downstream workflow elements was limited.

Supplementary Table S2. Characteristics of Tier 2 studies used to characterize evidence gaps in workflow-facing decision support (n = 20)

Supplementary Table S2 summarizes the Tier 2 studies retained to characterize evidence gaps in workflow-facing decision support. These studies reported fall prediction, classification, recognition, or detection approaches relevant to falls or fall-proximal risk, but did not provide sufficient information to confirm an explicit action-trigger pathway intended for inpatient clinical workflow.

ID	Citation	Year	Setting/context	Inputs/sensing	Main analytic aim	Why classified as Tier 2	Key missing workflow elements	Notes
----	----------	------	-----------------	----------------	-------------------	--------------------------	-------------------------------	-------

T2-1	Xue W, Duan A, Zhao Y, Zuo H, Isleem HF. AI-enabled multimodal monitoring for enhanced safety and functional recovery in elderly and post-stroke care: A mixed-methods study. Digit Health. 2025;11:20552076251384834. doi:10.1177/20552076251384834	2025	Elderly and post-stroke safety monitoring; inpatient relevance plausible, but workflow context not clearly specified	Multimodal monitoring	Safety surveillance/monitoring	Monitoring reported, but workflow-facing action-trigger pathway not sufficiently described	recipient; alert channel; routing; downstream action	Retained for gap mapping
T2-2	Marchal N, Popescu M, Robinson EL, Wolpert R, Song X. Classifying Adverse Events from SOAP Notes and Sensor Features in a Clinical Trial of Older Adults. medRxiv [Preprint]. 2025:2025.08.20.25334088. doi:10.1101/2025.08.20.25334088	2025	Clinical trial/older adults; inpatient applicability unclear	SOAP notes + sensor features	Adverse event classification	Classification study without explicit fall-prevention trigger workflow	trigger; recipient; intended action	Retained for gap mapping
T2-3	González-Castro A, Benítez-Andrades JA, González-González R, Prada-García C, Leirós-Rodríguez R. Predicting fall risk in older adults: A machine learning comparison of accelerometric and non-accelerometric factors. Digit Health. 2025;11:20552076251331752. doi:10.1177/20552076251331752	2025	Older adults; setting unclear	Accelerometric and non-accelerometric factors	Fall-risk prediction	Prediction only; no explicit workflow-facing trigger described	alert generation; recipient; routing; downstream action	Risk prediction study
T2-4	Zhou Y, Zhang D, Ji Y, Bu S, Hu X, Zhao C, Lv Z, Li L. Wearable sensors and machine learning fusion-based fall risk prediction in covert cerebral small vessel disease. Front Neurosci.	2025	Neurological population; setting unclear	Wearable sensors + machine learning	Fall-risk prediction	Prediction only; no explicit workflow-facing trigger described	trigger; channel; intended preventive use	Risk prediction study

	2025;19:1493988. doi:10.3389/fnins.2025.1493988							
T2-5	Steenerson KK, Griswold B, Keating DP 3rd, Srour M, Burwinkel JR, Isanhart E, Ma Y, Fabry DA, Bhowmik AK, Jackler RK, Fitzgerald MB. Use of Hearing Aids Embedded with Inertial Sensors and Artificial Intelligence to Identify Patients at Risk for Falling. Otol Neurotol. 2025;46(2):121-127. doi:10.1097/MAO.0000000000004386	2025	Clinical population; setting unclear	Hearing aids with inertial sensors	Identification of patients at risk for falling	Risk identification without workflow-facing trigger	recipient; routing; action pathway	Clinical risk-identification study
T2-6	Ming A, Schubert T, Marr V, Höttsch J, Stober S, Mertens PR. Video game-based application for fall risk assessment: a proof-of-concept cohort study. EClinicalMedicine. 2024;78:102947. doi:10.1016/j.eclinm.2024.102947	2024	Proof-of-concept cohort study; setting unclear	Game-based motion assessment	Fall-risk assessment	Assessment only; no alert/alarm pathway described	trigger; recipient; alert channel	Proof-of-concept assessment
T2-7	Maiores J, Rezola-Pardo C, García G, Sanz B, Graña M. Older Adult Fall Risk Prediction with Deep Learning and Timed Up and Go (TUG) Test Data. Bioengineering (Basel). 2024;11(10):1000. doi:10.3390/bioengineering11101000	2024	Older adults; setting unclear	TUG test data + deep learning	Fall-risk prediction	Prediction only; no workflow-facing action-trigger pathway described	alert generation; recipient; downstream action	Functional-test-based prediction
T2-8	Bayad I, Mahfouz S, Samrouth K, Mourad-Chehade F, Amoud H. Adaptive Fall Detection Using WiFi CSI for Unseen Environments and New Individuals. IEEE MeMeA. 2025.	2025	Setting unclear	WiFi CSI sensing	Fall detection	Detection-focused study without sufficient	recipient; alert destination; escalation logic	Technical detection study

	doi:10.1109/MeMeA65319.2025.11068083					workflow detail		
T2-9	Guerrón-Paredes N, Guerrero-Rodríguez L, Guerrero-Navarro D. Fall Detection with Neural Networks. Lect Notes Netw Syst. 2024;1067 LNNS:152-164. doi:10.1007/978-3-031-66431-1_10	2024	Setting unclear	Neural-network-based sensing	Fall detection	Detection only; workflow-facing output not described	recipient; alert channel; downstream action	Conference-style technical study
T2-10	Anitha N, Vishnu Vardhan RB, Pradeep R, Nazeem A. A Lightweight Wearable Fall Detection System using Gait Analysis for Elderly. Proc ICWITE 2024. doi:10.1109/ICWITE59797.2024.10502620	2024	Setting unclear	Wearable gait-based sensing	Fall detection	Detection only; workflow integration not described	recipient; routing; downstream action	Wearable detection study
T2-11	Mobsite S, Alaoui N, Boulmalf M, Ghogho M. Activity Classification and Fall Detection Using Monocular Depth and Motion Analysis. IEEE Access. 2024;12:1525-1541. doi:10.1109/ACCESS.2023.3348413	2024	Setting unclear	Monocular depth and motion analysis	Activity classification and fall detection	Detection only; no workflow-facing action pathway	recipient; channel; acknowledgement logic	Technical computer-vision study
T2-12	Sharma S, Singh V, Sarkar D. Machine Vision Enabled Fall Detection System for Specially Abled People in Limited Visibility Environment. ASIANCON 2023. doi:10.1109/ASIANCON58793.2023.10270769	2023	Setting unclear	Machine vision sensing	Fall detection	Detection only; workflow-facing use not sufficiently described	intended recipient; workflow integration; action pathway	Conference paper
T2-13	Shilpa Aarthi M, Juliet S. Intelligent Fall Detection System based on Sensor and Image data for Elderly Monitoring. ICIRCA 2022. doi:10.1109/ICIRCA54612.2022.9985734	2022	Elderly monitoring context; setting unclear	Sensor + image data	Fall detection	Detection only; workflow-facing action not described	alert destination; recipient; downstream action	Technical detection study
T2-14	Amiroh K, Rahmawati D, Wicaksono AY.	2021	Geriatric	Accelerometer +	Fall prediction	Prediction only;	trigger; recipient;	Prediction study

	Intelligent System for Fall Prediction Based on Accelerometer and Gyroscope of Fatal Injury in Geriatric. Jurnal Nasional Teknik Elektro. 2021;10(3):154-159. doi:10.25077/jnte.v10n3.936.2021		context; setting unclear	gyroscope		no alert/alarm workflow described	workflow use	
T2-15	Ranakoti S, Arora S, Chaudhary S, Beetan S, Sandhu AS, Khandnor P, Saini P. Human fall detection system over IMU sensors using triaxial accelerometer. Adv Intell Syst Comput. 2019;798:495-507. doi:10.1007/978-981-13-1132-1_39	2019	Setting unclear	IMU sensors/triaxial accelerometer	Fall detection	Detection only; no workflow-facing trigger pathway described	recipient; alert channel; downstream action	Technical detection study
T2-16	Cao P, Min CH. Fall Prediction in People with Parkinson's Disease. Annu Int Conf IEEE Eng Med Biol Soc. 2022:1502-1505. doi:10.1109/EMBC48229.2022.9872013	2022	Parkinson's disease population; setting unclear	Clinical/movement data	Fall prediction	Prediction only; no explicit alerting pathway described	recipient; action pathway; workflow use	Conference paper
T2-17	Greene BR, McManus K, Ader LGM, Caulfield B. Unsupervised Assessment of Balance and Falls Risk Using a Smartphone and Machine Learning. Sensors (Basel). 2021;21(14):4770. doi:10.3390/s21144770	2021	Setting unclear	Smartphone-based sensing	Balance and falls-risk assessment	Assessment only; no action-trigger pathway described	trigger; recipient; channel	Falls-risk assessment study
T2-18	Roshdibenam V, Jogerst GJ, Butler NR, Baek S. Machine Learning Prediction of Fall Risk in Older Adults Using Timed Up and Go Test Kinematics. Sensors (Basel). 2021;21(10):3481. doi:10.3390/s21103481	2021	Older adults; setting unclear	TUG kinematics	Fall-risk prediction	Prediction only; no workflow-facing trigger described	alert generation; workflow output	Functional-test prediction study
T2-19	Rehman RZU, Zhou Y, Del Din S, Alcock L,	2020	Neurological	Wearables + gait	Classification of fallers	Classification	recipient; alert	Classification

	Hansen C, Guan Y, Hortobágyi T, Maetzler W, Rochester L, Lamothe CJC. Gait Analysis with Wearables Can Accurately Classify Fallers from Non-Fallers: A Step toward Better Management of Neurological Disorders. Sensors (Basel). 2020;20(23):6992. doi:10.3390/s20236992		disorders; setting unclear	analysis	vs non-fallers	only; no workflow-facing action-trigger pathway described	channel; downstream action	study
T2-20	Zhou Y, Zia Ur Rehman R, Hansen C, Maetzler W, Del Din S, Rochester L, Hortobágyi T, Lamothe CJC. Classification of Neurological Patients to Identify Fallers Based on Spatial-Temporal Gait Characteristics Measured by a Wearable Device. Sensors (Basel). 2020;20(15):4098. doi:10.3390/s20154098	2020	Neurological patients; setting unclear	Wearable gait sensing	Identification of fallers	Classification only; no workflow-facing alert pathway described	trigger; recipient; workflow use	Classification study

Note: This table summarizes the Tier 2 studies retained to characterize evidence gaps in workflow-facing decision support. These studies reported fall prediction, classification, recognition, or detection approaches relevant to falls or fall-proximal risk, but did not provide sufficient information to confirm an explicit action-trigger pathway intended for inpatient clinical workflow. When a workflow-facing element was not explicitly reported in the source article, it was not inferred.