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REVIEW

Performance of digital technologies in assessing fall risks among older adults with cognitive impairment: a systematic review

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Abstract Older adults with cognitive impairment (CI) are twice as likely to fall compared to the general older adult population. Traditional fall risk assessments may not be suitable for older adults with CI due to their reliance on attention and recall. Hence, there is an interest in using objective technology-based fall risk assessment tools to assess falls within this population. This systematic review aims to evaluate the features and performance of technology-based fall risk assessment tools for older adults with CI. A systematic search was conducted across several databases such as PubMed and IEEE Xplore, resulting in the inclusion of 22 studies. Most studies focused on participants with dementia. The technologies included sensors, mobile applications, motion capture, and virtual reality. Fall risk assessments were conducted in the community, laboratory, and institutional settings; with studies incorporating continuous monitoring of older adults in everyday environments. Studies used a combination of technology-based inputs of gait parameters, socio-demographic indicators, and clinical assessments. However, many missed the opportunity to include cognitive performance inputs as predictors to fall risk. The findings of this review support the use of technology-based fall risk assessment tools for older adults with CI. Further advancements incorporating cognitive measures and additional longitudinal studies are needed to improve the effectiveness and clinical applications of these assessment tools. Additional work is also required to compare the

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performance of existing methods for fall risk assessment, technology-based fall risk assessments, and the combination of these approaches.

Keywords Falls risk assessment · Fall prediction · Cognitive impairment · Older adults · Digital technologies

Introduction

One in four older adults above the age of 65 fall every year [1], and the prevalence of falls increases to 40% among older adults above 80 years old [2]. Falls among older adults result in adverse consequences such as injuries, prolonged hospitalisation, and reduced quality of life [3–5]. Such falls occur twice as frequently among older adults with cognitive impairment (CI) [6]. The factors predisposing older adults with CI include poor decision-making, executive function, attention, and processing speed [7, 8]. Furthermore, older adults with CI typically experience higher rates of physical decline resulting in poor postural control, muscle weakness, and impaired gait [9–11], compared to older adults without CI [12]. In recent years, multi-component fall prevention programmes have demonstrated some efficacy in addressing the concurrent decline in cognitive and physical function to prevent falls in this vulnerable population [13–15].

Multicomponent fall prevention programmes can be individualised for older adults by accurately assessing their unique risk factors and assigning specific intervention components to them. As cognitive impairment is a known risk factor of falls [6], by this standard, all older adults will be categorised as high risk for falls. As such, having a comprehensive understanding of the specific risk of falls will be important in designing interventions for this understudied population. Conventional fall risk assessments in the clinical setting are usually done through short questionnaires such as the STEADI Comprehensive Fall Assessment (CFA) [16, 17], and/or clinician-rated functional performance tests such as the short physical performance battery (SPPB) [18]. However, these traditional tools may not accurately assess the risk of falls in cognitively impaired older adults as they rely on older adults' attention, recall, and decision-making [19]. As such, there is increasing interest in using objective and easy-to-use technologies that are less reliant on patients' cognitive ability [20–22]. Fall risk prediction technologies may also be more economical compared to current methods [23] and have broad potential for applications in both clinical and non-clinical settings [21]. However, many studies evaluating the predictive validity of these technologies typically exclude older adults with CI due to the complex nature of assessing fall risk in this population [21, 24]. Hence there is a gap in knowledge on fall risk prediction in this underserved population. We found one recently published systematic review discussing the use of risk prediction technologies for falls among older adults with and without CI. However, it only included four studies with older adults with CI [25]. In addition, their focus was only on sensors, disregarding other viable technologies that demonstrate potential in accurately assessing fall risk.

Therefore, the objective of this systematic review was (1) to understand the performance of current technologies used in fall risk assessments in older adults with CI, (2) to characterise the features of these technologies, and (3) to discuss their relevance to be used as potential fall risk assessment tools.

Methods

Protocol

The preferred reporting item for systematic review and meta-analysis (PRISMA) guidelines were utilised to prepare and report this systematic review. This review was registered in PROSPERO (CRD42022316702).

Search strategy and eligibility criteria

A literature search was performed for using PubMed, IEEE Xplore, Embase, Cochrane, Web of Science, Scopus, and JSTOR databases. Searches were performed with specific keywords and medical subject headings (MeSH) terms, in combination with Boolean terms to scan all fields for PubMed and IEEE Xplore, as these databases are very comprehensive and most relevant to the research question. Subsequently, searches for other databases were conducted to scan relevant titles and abstracts only. Articles were searched using the combination of these keywords: (fall prediction OR fall risk assessment*)

AND (digital technology* or sensors* OR mobile health OR devices) AND (dementia* OR cognitive impairment* OR neurological disease). These search terms were validated by reviewing the retrieval of representative articles. No filters were applied at this stage to enable the searches to be as inclusive as possible. Secondary literature such as reports, conference articles, and dissertations were also conducted using Google Scholar and ProQuest databases. Reference lists of included studies were also scanned for relevant secondary literature. Two authors (VK, WXL) independently screened and assessed the eligibility and suitability of the papers. We only included articles relating to falls as outcomes in this systematic review. The full search strategy can be found in the Appendix Table 6. The first comprehensive search was conducted on 27 July 2022, and an update was conducted on 20 July 2023.

Studies were included if:

1. They utilised digital health technologies for assessing fall risks in older adults such as mobile applications, health information and technology, wearable sensors, mixed-reality games, and devices with Internet of Things (IoT) capabilities.
2. They involved older adults 60 years and above with cognitive impairments.
3. They identified fall risk (high or low fall risk/faller or non-faller) based on retrospective, prospective, and/or clinical assessments of falls.
4. They presented an evaluation of the technology for fall risk assessments through effect measures or performance characteristics such as sensitivity and specificity.

Studies were excluded if they fulfilled any of the following exclusion criteria:

1. They involved digital health technologies only for fall prevention, monitoring, and detection.
2. They involved devices or medical devices that do not utilise digital capabilities.

Studies included were not restricted to any specific setting as available literature for older adults with CI is at a nascent stage. As such, this systematic review included studies performed in clinical, community, and institutionalised settings such as nursing homes. Furthermore, studies that focused on the larger population but involved participants with CI were included as well. This ensured that the systematic review was comprehensive and accounted for any available information relating to this underserved population. In addition, the systematic review was also open to all study designs including in silico studies. There was no restriction on the geographical location of the study and time intervals. However, due to language restrictions, only studies with English texts were included in this systematic review. Additional measures have been taken to search for English texts should the manuscripts be published in another language, before excluding them.

Study selection

After the literature search and removal of duplicates, two authors (VK, WXL) independently screened the titles and abstracts of all articles retrieved. Abstracts were screened based on the eligibility and inclusion criteria mentioned above. Disagreements between the two authors were resolved through a consultation with a third author (DM or AC). Once abstracts and titles were reviewed, full-text articles were further screened to ensure that all articles retained still fit the eligibility criteria. Similarly, disagreements between the two authors were resolved through consulting with a third author (DM or AC). The systematic review management was performed using Rayyan (http://rayyan.qcri.org) [26], where final decisions were made and detailed reasons for disagreements and conclusions were documented.

Data extraction and synthesis

Data extraction was performed independently by two authors (VK, WXL) and systematically recorded using a standardised data extraction sheet in Microsoft Excel. The collected data was cross-checked to ensure completeness of data extraction by a third author (KZT). First, information such as first author's name, publication date, study setting, study design and participant characteristics (such as number, age, CI status, and screening scores), neurological disease type, and fall outcomes were extracted. We then collected information regarding the technologies; this included types of technology utilised for fall risk assessment, location of which technologies were placed, and duration of technology. Information

regarding fall risk assessments was extracted, they include a broad category of fall predictors, specific fall predictors, functional tests being conducted for assessment of fall risk, and total follow-up time. Lastly, the performance of these technologies was also captured, such as the models used for the classification of fall risk, effect sizes, and receiving operating characteristics (ROCs) such as the area under the curve (AUC), sensitivities, and specificities. The receiving operating characteristic curve is a plot describing the performance of the test. It is created by plotting the sensitivity over 1-specificity [27]. The AUC under the ROC aggregates the performance of the classifier across the range of classification thresholds. AUC is hence a summary of the overall performance of the test, where AUC values from 0.8 to 0.9, 0.7 to 0.8, and 0.6 to 0.7 indicate good, fair, and poor discriminant values respectively [28, 29]. Sensitivity is defined as the true positive rate and specificity is the true negative rate [27]. A narrative data synthesis was conducted for this study due to the heterogeneity of studies in this emergent field.

Assessment of methodological quality

Three authors (VK, WXL, KZT) conducted a formal methodological quality assessment of each article included in this systematic review using the Newcastle–Ottawa Scale (NOS) for case–control and cohort studies [30]. An adapted NOS was used to perform the quality assessment for cross-sectional studies [31]. The quality assessment evaluated three key domains: selection of study participants, comparability of participants, and assessment of outcomes. The selection of study participants was awarded a maximum of four stars (case–control, cohort) or three stars (cross-sectional). Comparability was awarded a maximum of two stars and assessment of outcomes was awarded a maximum of three (case–control, cohort) or two stars (cross-sectional). The total number of stars awarded were presented in Table 3, with a greater number of stars indicating higher methodological quality.

Results

One thousand one hundred thirty studies were identified from the database search, grey literature search, and manual search. After removing duplicates, 848 studies were screened by title and abstract, and 67 full-text articles were reviewed based on the eligibility and inclusion criteria. Some reasons for exclusions after screening by title and abstract included the following: irrelevant title (most articles identified were not within the scope of the research question); inappropriate intervention (the intervention was not a health digital technology); inappropriate outcome (the outcome was not on falls or fall risk); and inappropriate population (the population was not on older adults with cognitive impairment).

A total of 21 studies were included in this systematic review. An updated search was conducted on 20 July 2023 where one more article was added, bringing the total to 22 studies included in this systematic review (Fig. 1).

Study and participant characteristics

Studies included were published from 2007 to 2022. Nine studies were cohort studies, eight were cross-sectional studies and three were case–control studies. Two studies were primarily in silico studies, utilising multiple datasets and machine learning methodologies. Four studies were conducted in the community, six studies were conducted in institutions such as nursing homes and five studies were conducted in laboratories. Five studies observed participants in multiple settings—four studies were conducted in both laboratory and community settings, while one study observed participants in both the community setting and in assisted living institutions.

A total of 3595 participants were included in this systematic review. The mean age among the older adults with CI ranged between 61.6 and 81.7 years old. Two studies examining older adults with cerebellar ataxia (CA) were also included [32, 33]. As CA has an earlier onset, these two studies had younger participants with the youngest participant being 53 years old. The Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MOCA) were the most used screening tests for CI among older adults. Nine studies utilised the MMSE to screen participants while five studies used the MOCA for screening. The scores ranged between 9.3 to 29.2 and 9 to 26 for each test, respectively. Six studies did not conduct an initial screening of CI using standardized tests but involved older adults with neurological disorders, such as dementia, where

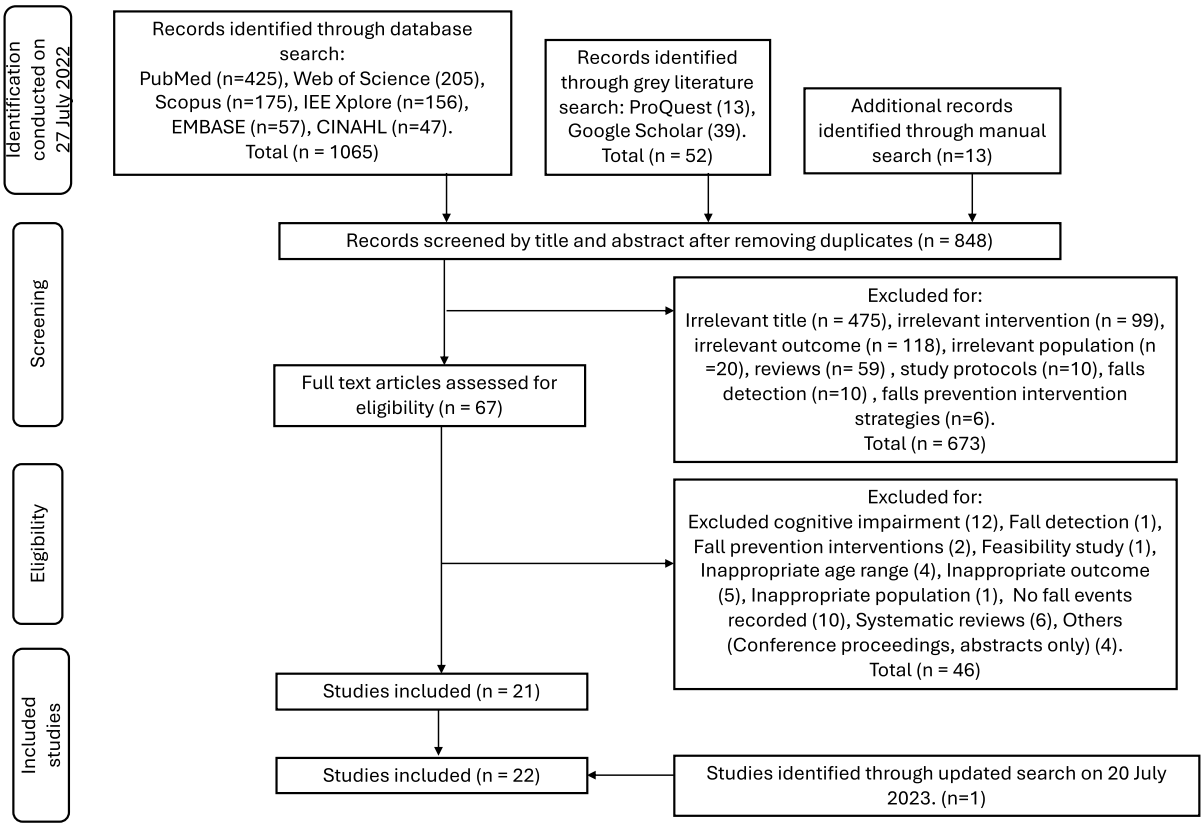

Fig. 1 PRISMA flowchart of literature search

deteriorating cognition is part of the diagnostic criteria. These studies recorded and retrieved participants' diagnoses from institutional records. In addition, one study identified participants with dementia and conducted additional screeners such as the severe impairment battery (SIB) to record the status of cognitive impairment [34]. One study utilised the fall risk score and identified participants with cognitive disorders through self-reporting [35]. Overall, studies included participants with cognitive disorders and neurological disorders, associated with cognitive impairment including dementia, Parkinson's disease, Alzheimer's disease, Alzheimer-type dementia, cerebellar ataxia, and multiple sclerosis. Most studies involved participants with mild CI, while a few looked into individuals with moderate-severe CI.

All studies examined falls as their final outcome. Eighteen studies looked at either prospective or retrospective falls, though did not differentiate between different types of falls (i.e. non-injurious falls, injurious falls, or recurrent falls). Five studies distinguished between different types of falls as they were interested in one or more such falls. For example, Fiems et al. were interested in examining recurrent fallers, defined as participants who had fallen two or more times in the past 6 months. In addition, two other studies were interested in the frequency and severity of falls [33, 36]. Nine studies determined outcomes based on retrospective fall history, eleven studies determined outcomes based on prospective falls, and two studies did so based on both retrospective and prospective assessments of falls. At the same time, thirteen studies classified the risk of falls into fallers and non-fallers, while nine studies classified older adults based on the strength of association with fall outcomes. Participant, study characteristics, and fall outcomes can be found in Table 1.

Technological features used in fall risk assessments

A variety of technologies such as wearable sensors equipped with inertial measurement units (tri-axial accelerometers, gyroscopes, and magnetometers),

Table 1 Participant and study characteristics

Author, year	Study setting	Number of participants (mean age)	Cognitive screening scores (median, SD), disease type	Fall outcomes	Outcome time perspective
Gago F. M. et al., 2014	Laboratory	36 (C: 72.31 ± 7.08; AD-F: 77.64 ± 4.80; AD-NF: 73.56 ± 8.72)	MOCA (AD-F: 10.09 ± 4.42; AD-NF: 12.22 ± 6.63) AD	• Faller status (fallers defined as those with at least one fall[a] in the previous 6 months)	Retrospective
Gago M F et al., 2016	Laboratory	39 (19 HC: 71 (51–78), 11 AD-F: 76 (66–82), 9 AD-NF: 75 (61–82))	MOCA: AD-F: 9 (5–9); AD-NF: 12 (7–17) AD	• Number of fallers (at least one fall[a] in the past 12 months)	Retrospective
Greene R. B. et al., 2021	Laboratory	1057 (TD: 72.2 ± 10.9, PD1: 67.3 ± 7.1, PD2: 64.9 ± 7.3)	TD set: Excluded MMSE < 18; PD1: excluded MMSE < 22 PD2: no exclusions PD	• Falls rate: mean number of falls[a] per patient over study window	Retrospective
Najafi B. et al., 2007	Laboratory	11 (79 ± 6)	Fall risk score (3/11 participants with discrete cognitive disorders)	• Falls[a] in the preceding year	Retrospective
Rehman R et al., 2020	Laboratory	384 (F: 65.0 ± 12.7; NF: 61.6 ± 12.2)	Various neurological disorders	• Faller status (fallers defined as those with at least one fall[a] in the past 2 years)	Retrospective
S Del Din et al., 2017	Community	270 (F: 73.33 ± 6.78; NF: 69.05 ± 7.67)	MMSE: F: 28.04 (1.72), NF: 28.87 (1.6), PD	• Number of fallers (at least one fall[a] in the past 6 months)	Retrospective
Rispens M. S. et al., 2015	Community	114 (78.4 ± 7.8)	MMSE: 27.6 ± 2.1 Some participants with Mild cognitive impairment	• Number of falls[a] in the 12 months preceding measurements	Retrospective
Schwenk M. et al., 2014	Community	77 (81.8 ± 6.3)	MMSE 22.1 ± 3.2 Dementia	• Faller status: fallers (fallers defined as those with at least 1 fall[a] in the 3-month follow-up period)	Prospective
Fiems L C et al., 2019	Community	68 (RF: 69.5 (69.5–76.5), NRF: 69.5 (60–74))	Idiopathic PD patients (Hoehn and Yahr level I-III)	• Faller status: recurrent fallers (fallers defined as those with 2 or more falls in the last 6 months)	Prospective

Table 1 (continued)

Author, year	Study setting	Number of participants (mean age)	Cognitive screening scores (median, SD), disease type	Fall outcomes	Time perspective
Schniepp R et al., 2021	Laboratory and community	396 (53 ± 18)	MOCA: 26 ± 9 Various neurological disorders	• Fall status: • Fallers[a] • Fall frequency: No falls, occasional falls, frequent falls (2 falls) • Fall severity: number of non-injurious and injurious falls	Prospective and retrospective
Srulijes K et al., 2019	Laboratory and community	14 PD: 71.2 ± 6.1 12 PSP: 65.9 ± 5.9, 31 C: 70.7 ± 4.0	MOCA: PD: 26.9 (3.4), PSP: 22.1 (3.9) PD, PSP	• Absolute number of falls[a] per person years (py) • Falls[a] per exposure to individual physical activity	Prospective
T Illuz et al., 2014	Laboratory and community	40 (62.2 ± 10.0)	MMSE: 29.18 ± 1.21 PD	• Faller status: • Recurrent faller (fallers defined as those with at least two falls in the past 6 months)	Retrospective
Zhou YH et al., 2020	Laboratory and community	384 (F: 65 ± 12.7; NF: 61.6 ± 12.2)	19% PD, 9% MS, 6% dementia	• Number of fallers (at least one fall[a] in the past 2 years)	Retrospective
K S. van Schooten et al., 2015	Community and assisted living	169 (75.4 ± 6.8)	MMSE: 27.7 ± 2.2	• Number of falls[a] (1)	Prospective and retrospective
Schniepp R et al., 2022	Institution	93 (C: 49 ± 14, CA: 57 ± 18)	MOCA (24 ± 6) CA	• Fall status: • Fallers[a] • Fall frequency: No falls, occasional falls, frequent falls (2 falls) • Fall severity: number of non-injurious and injurious falls	Prospective
Marquesa R. N. et al., 2018	Institution	23 (F: 80.34 ± 5.3, NF: 77.54 ± 8.4)	MMSE: F (12.8 ± 1.09); NF (20.6 ± 1.94) Mild-severe cognitive impairment	• Faller status: fallers (defined as monthly fall[a] history in 6-month follow-up period)	Prospective
Kearns D. W. et al., 2012	Institution	69 (76.9 ± 11.9)	MMSE: 18.3 ± 7.2 (F: 16.8 ± 3.08, NF: 19.00 ± 2.34) Mild-moderate cognitive impairment	• Faller status: fallers (defined as at least one validated fall – fell while ambulating during the monitoring interval, and had tracking data 7 days prior)	Prospective

Table 1 (continued)

Hauer K. et al., 2020	Institution	102 (82.82 ± 6.19)	MMSE 22 (20.75–24) Dementia	• Faller status: in-hospital fallers • (fallers defined as having one or more falls[a] during 3-week ward-based rehabilitation) • Additional fall risk factors: previous fall, previous fallers (defined as people who had at least one injurious fall or at least two non-injurious falls in the last 12 months)	Prospective
M Gietzelt et al., 2014	Nursing home	40 (76.0 ± 8.3)	MMSE: 9.3 ± 8.0 Dementia	• Short-term (2 months), mid-term (4 months) and long-term (8 months) falls[a]	Prospective
C S. Sterke et al., 2012	Institution	57 (81.7 ± 7.0)	Alzheimer type dementia, moderate-severe dementia	• Fall status: fallers[a] in 3 months	Prospective
Ng K-D et al., 2020	Institution	31 (F: 78.4 ± 8.9, NF: 75.5 ± 8.6)	AD	• Number of falls[a] experienced in 2 weeks	Prospective
Adeli V et al., 2023	Institution	108 (All: 76.4 ± 7.9; F: 77.0 ± 8.5; NF: 75.9 ± 7.3)	SIB: (All: 28.6 ± 14.1; F: 26.4 ± 13.1; NF: 30.10 ± 14.7) Dementia	• Number of falls[a] • Fallers status: recurrent fallers (defined as participants who fell more than once during the 4-week follow-up period)	Prospective

F faller, *NF* non-faller, *C* control, *AD-F* Alzheimer's disease-fallers, *AD-NF* Alzheimer's disease-non-fallers, *RF* recurrent fallers, *NRF*: non-recurrent fallers, *PD* Parkinsons' disease, *PSP* progressive supranuclear palsy, *MS* multiple sclerosis, *CA* cerebellar ataxia, *TD* training dataset, *PD1* Parkinson's disease dataset 1, *PD1* Parkinson's disease dataset 2, *MMSE* Mini-Mental State Examination, *MOCA* Montreal Cognitive Assessment, *SIB* severe impairment battery

[a] Authors did not differentiate type of fall (i.e. non-injurious fall, injurious fall, recurrent fall)

pressure-sensitive mats, and foot switches were used to collect movement data. Eighteen studies used one type of technology, while four others combined different technologies to collect information; these include infrared cameras for video and motion capture [35, 37], mobile applications [38], and virtual reality [39].

All studies involved sensors or wearable sensors in some form. They included commercially available technologies such as ActivPAL, DynaPort MoveMonitor, GAITRite, Inline FootSwitches, Hasomed RehaWatch, and Shimmer, while others utilised wearable sensors developed in-house. Participants used between one to five wearable sensors. These sensors were mostly worn on the chest, trunk, lower back, thighs, shin below the knee, and the foot. For pressure-sensitive mats such as GAITRite, these mats were placed on the ground for participants to walk across. Pressure-sensitive mats, footswitch sensors and most wearable sensors were used for walking tests and free-living mobility tests. Other wearable sensors such as the QTUG sensors were used for specific tasks, including timed up and go, the Romberg test and sway test.

Ten studies included continuous monitoring of older adults in community or institution settings with the use of wearable sensors such as DynaPort, ActivPAL, or Ubisense sensors between 3 days to a year. Most of these studies began with a baseline assessment in a laboratory setting before observations were conducted in the community using wearable sensors. In addition to sensors, one study involved participants being assessed in a laboratory using technologies that utilised virtual reality [39]; while two other studies conducted in institutions used cameras for motion capture analyses [34, 37]. Technologies and their performances are presented in Table 2.

Commercially available technologies such as GAITRite, DynaPort MoveMonitor, and RehaWatch sensors can provide validated gait parameters [40–42], whereas QTUG sensor provides both validated time up and go parameters and fall risk scores [43]. Hence, these technologies are easily accessible and require minimal effort to provide quantitative assessment and implement in clinical settings.

Predictors of fall risk

Most of the included studies predicted falls using gait characteristics. Gait characteristics included stride length, stride time, and stance time. Fall risk predictors used in other studies included real-life missteps, postural stability, mobility, and physical activity. While a variety of different indicators were used to predict falls, most studies only assessed indicators in one specific domain, i.e. gait, postural control, mobility, or physical activity. Six studies [33, 34, 36, 39, 44–46] included indicators from different domains for fall prediction. For example, in a study by Del Din et al. [44], ambulatory bouts and gait characteristics were quantified to identify distinctions between fallers and non-fallers. The study also established PD-specific correlations of walking features with these predictors. Additionally, they segmented free-living gait characteristics into two groups: short bout duration (describing pace, rhythm, variability, asymmetry and postural control, and long bout duration (i.e. volume, pattern of ambulatory bouts) [44]. Similarly, in a prospective study by Schwenk et al. [47], the longest walking, standing, sitting, and lying bout durations were captured.

Most studies used other predictors of falls such as demographic and clinical measurements. Geriatric assessments were performed for sixteen studies, which included screening tests for cognition, i.e. the MMSE, MOCA, and SIB; measurements of physical condition, i.e. SPPB, Performance Oriented Mobility Assessment (POMA) and the 5-chair stand. Other fall-related measurements collected include fall history, St. Thomas Risk Assessment Tool in Falling elderly inpatients (STRATIFY), Falls Efficacy Scale (FES) and the Activities-specific Balance Confidence Scale (ABC). Other clinical information such as medical history and polypharmacy were collected as well. In addition, one study conducted comprehensive clinical examinations to predict falls using brain imaging via computer tomography and cerebrospinal fluid diagnostics [36]. Predictors of fall risk were presented in Table 2.

Functional tests performed during fall risk assessment

Functional tests administered during data collection included walking at various speeds, ambulatory activities, dual-tasking activities, and balance measurements such as the Roberg test. Validated tools commonly used in fall risk assessment such as Timed-up and Go (TUG) and Sit-to-stand/

Table 2 Features of technology and data collected

Author (Year)	Technology type	Technology location	Duration of technological assessment	Measures of predictors	Other information collected
Gago F. M. et al. (2014)	Wearable IMU-based sensor	Trunk (COM), both legs (middle of ankle-knee distance), and both thighs (middle of knee-iliac crest distance)	In-lab measurement (6 different standing Romberg positions)	COM displacements, velocity, positions, and angles	Demographic, clinical, and anthropometric data
Gago M F et al. (2016)	Werable IMU-based sensor, sensing sensor and virtual reality headset (Oculus Rift VR headset) device)	VR: head Sensor: COM	In-lab measurements (approx. standing for 10 min, in VR environment)	**Signal-based gait parameters**, COM sway area and path	MOCA
Greene R. B. et al. (2021)	Wearable IMU-based sensor (QTUG sensors)	Each shin below the knee	In-lab measurements (Timed Up and Go)	**Temporal gait parameters**, **spatial gait parameters**, gait asymmetry, **gait variability**, TUG test time	MDS-UPDRS III, age, BMI, TUG
Najafi B. et al. (2007)	Werable IMU-based sensor, validated using motion capture system (VICON)	Left acromion, sternum	In-lab measurements (sit to stand and stand to sit, 3 times each activity)	Stand-sit and sit-stand parameters (mean and standard deviation of transition duration, number of successful transition)	
Rehman R et al. (2020)	Wearable IMU-based sensor (Rehawatch®)	Lower back (L4-L5), both ankles (superior to the malleoli)	In-lab measurements (20 m walk)	**Temporal gait parameters**, **spatial gait parameters**, gait asymmetry	-
S Del Din et al. (2017)	Wearable IMU-based sensor (Axivity AX3)	Lower back	Off-lab mobility measurement (continuously over 1 week)	**Temporal gait parameters**, **spatial gait parameters**, gait asymmetry, **gait variability**, walking time	Age, sex, Hoehn and Yahr scale, MDS-UPDRS III
Rispens M. S. et al. (2015)	Wearable IMU-based sensor (DynaPort MoveMonitor)	Lumbar spine	Off-lab mobility measurement (2 separate weeks)	**Temporal gait parameters**, **spatial gait parameters**, **signal-based gait parameters**, **gait variability**, gait asymmetry, gait smoothness, local dynamic stability	-
Schwenk M. et al. (2014)	Wearable IMU-based sensor (Physilog system)	Chest	Off-lab mobility measurement (24 h)	Walking, standing, lying and sitting time	POMA, TUG, 5-chair stand

Table 2 (continued)

Author (Year)	Technology type	Technology location	Duration of technological assessment	Measures of predictors	Other information collected
Fiems L C et al. (2019)	Mobile phone (using Sway Balance mobile application utilising triaxial acceletrometer within iPod Touch/iPhone)	Chest	In-lab measurements (4 balance condition, 30 s each, specifically during ON state of PD medications)	Sway (using an overall "stability score")	Age, sex, PD duration, medications, fall history, MDS-UPDRS motor examination, Mini-BESTest, ABC Scale
Schniepp R et al. (2021)	Pressure senstive mat (GAITRite), wearable IMU-based sensor (ActivPAL)	Mat: walk across the mat Sensor: thigh of dominant leg	In-lab measurements (10.7 m walk on pressure-sensitive mat, four times) and off-lab mobility measurement (continuously 14 days)	**Temporal gait parameters**, **spatial gait parameters**, gait asymmetry, **gait variability**, ambulatory, sedentary and sleeping behaviour	Ambulatory status, medication, fall history via Hopkins falls grading scale, FES-I, ABC, MOCA, TUG, FGA, standardised neuro-otological testing and additional diagnostic procedures
Srulijes K et al. (2019)	Wearable IMU-based sensor (ActivPAL)	Anterior aspect of the thigh	Off-lab mobility measurement (continuously 1 week)	Walking time, number of Sit-to-stand transfer	Age, sex, age of disease onset, disease duration, BMI, UMSARS, DGI, MOCA, TMT, FES-I
T Illuz et al. (2014)	Wearable IMU-based sensor (DynaPort Hybrid)	Lower back (L4-L5)	In-lab measurements (2 min walk, single and dual-tasking) and Off-lab mobility measurement assessment (continuously over 3 days)	Number of mis-steps	Dynamic Gait Index, Berg Balance Scale, Timed Up and Go test, Four Square Step Test, MMSE
Zhou YH et al. (2020)	Wearable IMU-based sensor	Lower back and both ankles	In-lab measurements (20 m walk, single and dual-tasking)	**Temporal gait parameters**, **spatial gait parameters**, **gait variability**, ankle dorsiflexion and plantar flexion	-
K S. van Schooten et al. (2015)	Wearable IMU-based sensor (DynaPort MoveMonitor)	Trunk L5	Off-lab mobility measurement (continuously over 8 days)	**Temporal gait parameters, spatial gait parameters, gait variability, signal-based gait parameters**	LASA fall-risk profile, MMSE, TMT-A, TMT-B, FES-I, GDS, hand grip strength

Table 2 (continued)

Author (Year)	Technology type	Technology location	Duration of technological assessment	Measures of predictors	Other information collected
Schniepp R et al. (2022)	Pressure sensitive mat (GAITRite), wearable IMU-based sensor (ActivPAL)	Mat: walk across the mat Sensor: thigh of dominant leg	Off-lab mobility measurement (6.7 m walk on pressure-sensitive mat, 3 different gait speed, 4 repetition each), in-lab measurements (continuously 14 days)	**Temporal gait parameters**, **spatial gait parameters**, base of support, **gait variability**, gait asymmetry, phase synchronization index	Ambulatory status, functional status, medication, fall history via HFGS, FES-I, ABC, MOCA, Each participant underwent a complete neurological and physical examination including the assessment of functional mobility by the Timed up and Go Test (TUG) and the Functional Gait Assessment Score (FGA)
Marquesa R. N. et al. (2018)	Footswitch sensors (Inline FootSwitches)	Hallux and calcaneus of the foot	In-lab measurements (10 m walkway, 50 gait cycles)	**Temporal gait parameters**, **gait variability**	MMSE, SPPB
Kearns D. W. et al. (2012)	Location tracking system (Ubisense ultra-wideband real-time location system)	Ubisense compact tag (carried with the person)	In-institution mobility measurement (one year, in care facilities)	Fractal D (path tortuosity)	SGB, TUG, medication records, clinical diagnosis of dementia, activities of daily living ADL
Hauer K. et al. (2020)	Pressure sensitive mat (GAITRite), wearable IMU-based sensor (DynaPort® Hybrid)	Mat: walk across the mat Sensor: lower back at the height of the second lumbar vertebra	In-lab measurements (4.8 m walk, 30 s balance test, chair stand test)	**Temporal gait parameters**, **spatial gait parameters**, COM sway area, sway path and displacements	STRATIFY, fall history, FES-I, MMSE, POMA, Cognitive subdomains examinations: CERAD
M Gietzelt et al. (2014)	Wearable IMU-based sensor (SHIMMER platform)	-	In-lab measurements (20 m and 60 m walk, 5 repetitions, every 2 months)	**Temporal gait parameters, spatial gait parameters, signal-based gait parameters**	MMSE, Barthel index, TUG, Tinetti test, STRATIFY, height, weight
C S. Sterke et al. (2012)	Pressure sensitive mat (GAITRite1-732 system)	Walk across the mat	In-lab measurements (8 m walk, 5 repetitions, every 3 months)	**Temporal gait parameters, spatial gait parameters, gait variability**	-
Ng K-D et al. (2020)	Motion capture system (Microsoft Kinect v2 sensor)	Sensor mounted in a hallway and captured gait as patients walked naturally	In-institution mobility measurement (tracking care facility patients every time they walk through the hallway)	**Temporal gait parameters, spatial gait parameters, gait variability**, margin of stability	POMA

Table 2 (continued)

Author (Year)	Technology type	Technology location	Duration of technological assessment	Measures of predictors	Other information collected
Adeli V et al. (2023)	Motion capture system (Microsoft Kinect)	Sensor mounted in a hallway and captured gait as patients walked naturally	In-institution mobility measurements	Cadence, estimated margin of stability, estimated parkinsonism score – quantified via the MDS-UPDRS part III gait score	Demographic and clinical data (STRATIFY, POMA, POMA-gait, POMA-balance)

Temporal gait parameters: stride time, swing time, stance time, single support time, double support time, heel-to-heel base support, percentage of stance and swing phase step frequency, or cadence

Spatial gait parameters: gait speed, stride length, circumduction of gait or step width

Signal-based gait parameters: variance of signal, time–frequency distribution, amplitude of dominant frequency or width of dominant frequency

Gait variability: Coefficient of variation (CV) for temporal or spatial gait parameters

COM: Centre of Mass (55% of a person's height above the ground)

stand-to-sit (STS) were used in two studies [35, 45]. Eleven studies assessed walking at varying speeds. A unique study by Gago et al. [39] evaluated participants' compensatory postural adjustments to a virtual reality fall. The volume of ambulatory, sedentary, and sleeping bouts was often collected when monitoring daily mobility using wearable sensors. Other micro gait characteristics often collected were pace characteristics such as step length, and step velocity; rhythm characteristics such as stance time, and swing time; postural control characteristics such as step width and variability including step length variability [48]. The functional tests administered along with technology-derived data collected were presented in Table 3.

Performance of technology-derived data in classifying fall risk for older adults with CI

Majority of the studies employed regression analysis such as multivariable logistic regression and elastic net regression analysis to classify older adults with CI into 'faller' or 'non-faller'. Five studies applied machine learning models (i.e. principal component analysis, stepwise discriminant analysis, and decision trees), while three studies utilised various non-parametric statistical tests to test differences between groups. Of seventeen studies which evaluated model performance, nine studies used a combination of data collected from technologies, demographic, and clinical data in their models to assess fall risk; while the remaining eight only used gait and/or balance parameters in models. Model details and performance are presented in Table 4.

Most studies that evaluated model performance demonstrated reasonably high sensitivity and specificity in classifying fallers and predicting future falls (including severity and frequency of falls). From models that evaluated the AUC under the ROC curve [34, 38, 46, 49, 50], the AUC of such models had a range from 0.65 to 0.8. In a study conducted in community settings [47], models including sensor-captured ambulatory data and questionnaire data obtained the highest AUC of 0.82, with a sensitivity of 70% and specificity of 80.9%. In comparison to studies conducted in institutional settings [51], technologies that captured accelerometry data obtained the highest AUC of 0.80, with a sensitivity of 78.2% and specificity of 71.2%. Finally, in laboratory settings, Schniepp R et al. developed a prediction model

Table 3 Functional tests administered mapped to specific gait parameters collected

	Free-living/monitoring of daily mobility	Walking at comfortable speed	Walking at maximum speed or slow speed	Dual tasking	Chair stand test/Timed-up and Go/Sit-to-stand	Balance assessments
Volume of walking	2017 (S Del Din et al.), 2021 (Schniepp R et al.), 2019 (Srulijes K et al.), 2014 (Schwenk M. et al.)				2021 (Greene R. B. et al.)	
Volume of sedentary/ sleeping bouts	2021 (Schniepp R et al.), 2014 (Schwenk M. et al.)					
Pace						
Stride velocity		2020 (Zhou YH et al.), 2020 (Rehman R et al.)		2020 (Zhou YH et al.)	2021 (Greene R. B. et al.)	
Stride length	2015 (K S. van Schooten et al.)	2012 (C S. Sterke et al.), 2020 (Zhou YH et al.), 2020 (Rehman R et al.), 2022 (Schniepp R et al.)	2022 (Schniepp R et al.), 2020 (Hauer K. et al.), 2021 (Schniepp R et al.)	2020 (Zhou YH et al.)	2020 (Hauer K. et al.), 2021 (Greene R. B. et al.)	
Stride time	2015 (Rispens M. S. et al.)	2012 (C S. Sterke et al.), 2020 (Rehman R et al.), 2022 (Schniepp R et al.), 2020 (Hauer K. et al.),2014 (M Gietzelt et al.), 2020 (Zhou YH et al.)	2022 (Schniepp R et al.), 2021 (Schniepp R et al.)	2020 (Zhou YH et al.)	2021 (Greene R. B. et al.)	
Gait velocity	2015 (Rispens M. S. et al.)	2022 (Schniepp R et al.)	2022 (Schniepp R et al.), 2020 (Hauer K. et al.), 2021 (Schniepp R et al.)		2020 (Hauer K. et al.)	
Stance time	2017 (S Del Din et al.)	2020 (Zhou YH et al.), 2020 (Rehman R et al.)		2020 (Zhou YH et al.)	2021 (Greene R. B. et al.)	
Swing time	2017 (S Del Din et al.)	2020 (Rehman R et al.), 2020 (Hauer K. et al.)			2021 (Greene R. B. et al.)	
Cadence	2023 (Adeli V et al.)	2012 (C S. Sterke et al.), 2020 (Ng K-D et al.)	2020 (Hauer K. et al.)		2020 (Hauer K. et al.), 2021 (Greene R. B. et al.)	
Step time	2017 (S Del Din et al.)	2020 (Ng K-D et al.)				
Postural control						
COM Sway area		2016 (Gago M F et al.) **(VR)**			2020 (Hauer K. et al.)	
Sway path		2016 (Gago M F et al.) **(VR)**			2020 (Hauer K. et al.)	

Table 3 (continued)

	Free-living/monitoring of daily mobility	Walking at comfortable speed	Walking at maximum speed or slow speed	Dual tasking	Chair stand test/Timed-up and Go/Sit-to-stand	Balance assessments
A-P, M-L Displacement					2020 (Hauer K. et al.)	2019 (Fiems L C et al.), 2014 (Gago F. M. et al.)
Variability						
Stride length variability		2022 (Schniepp R et al.)	2022 (Schniepp R et al.), 2021 (Schniepp R et al.)			
Stance time variability	2017 (S Del Din et al.)	2020 (Hauer K. et al.)			2021 (Greene R. B. et al.)	
Swing time variability	2017 (S Del Din et al.)				2021 (Greene R. B. et al.)	
Stride time variability	2015 (Rispens M. S. et al.)	2012 (C S. Sterke et al.), 2022 (Schniepp R et al.), 2020 (Hauer K. et al.), 2021 (Schniepp R et al.)				
Asymmetry						
Swing time	2017 (S Del Din et al.)	2020 (Zhou YH et al.)		2020 (Zhou YH et al.)	2021 (Greene R. B. et al.)	
Stance time	2017 (S Del Din et al.)				2021 (Greene R. B. et al.)	
Cycle						
Swing phase percentage		2020 (Rehman R et al.), 2022 (Schniepp R et al.)	2022 (Schniepp R et al.), 2021 (Schniepp R et al.)			
Gait cycle spatial and temporal variability		2020 (Zhou YH et al.)		2020 (Zhou YH et al.)		
Support						
Double support phase		2012 (C S. Sterke et al.), 2022 (Schniepp R et al.)	2022 (Schniepp R et al.), 2021 (Schniepp R et al.)		2021 (Greene R. B. et al.)	
Base support		2012 (C S. Sterke et al.), 2022 (Schniepp R et al.)	2022 (Schniepp R et al.), 2021 (Schniepp R et al.)		2021 (Greene R. B. et al.)	
Single support phase		2020 (Zhou YH et al.), 2020 (Rehman R et al.)		2020 (Zhou YH et al.)	2021 (Greene R. B. et al.)	

Table 4 Model performance

Author, year	Fall classification	Final variables used in predictions	Models	AUC	Sensitivity	Specificity	Effect size
M Gietzelt et al., 2014	Faller/non-faller	Only gait/balance characteristics	Machine learning (Decision Tree Induction Method C4.5)	0.8	78.2%	71.2%	-
T Iluz et al., 2014	Faller/non-faller	Only gait/balance characteristics	Event/trial logistic regression		93.1% *hit ratio*[1]	98.6%	OR, 1.84 (95% CI, 1.15–2.93)
Zhou YH et al., 2020	Faller/non-faller	Only gait/balance characteristics	Machine learning (partial least square discriminant analysis)	0.77	ST-F, 60% ST-NF, 84%	ST-F, 72% ST-NF, 76%	-
Rehman R et al., 2020	Faller/non-faller	Only gait/balance characteristics	Machine learning (linear discriminant analysis, logistic regression, naïve Bayes, support vector machine, K-nearest neighbour, random forest)	-	99%	98%	-
Greene R. B. et al., 2021	Faller/non-faller	Only gait/balance characteristics	Elastic net regression with Poisson distribution				Mean RMSE, 0.42; correlation coefficient, 0.30)
Schwenk M. et al., 2014	Faller/non-faller	Gait/balance characteristics, retrospective fall history, clinical assessments including MMSE	Logistic regression	0.77 (95% CI, 2.71–21.96)	71.5%	75.5%	OR, 7.71 (95% CI, 2.71–21.96
Marquesa R. N. et al., 2018	Faller/non-faller	Only gait/balance characteristics	Machine learning (stepwise discriminant analysis)		50%	100%	
Adeli V et al., 2023	Faller/non-faller	Gait/balance characteristics and clinical assessments	Machine learning[2]	0.76	72.8%	73.2%	-
Schniepp R et al., 2021	(1) status (faller vs. non-faller), (2) frequency (occasional vs. frequent falls), and (3) severity (benign vs. injurious fall) of patients	Gait/balance characteristics, clinical assessments, and socio-demographic	Logistic regression	-	(1) 62% (2) 86% (3) 71%	(1) 90% (2) 95% (3) 71%	-
Schniepp R et al., 2022	(1) status (faller vs. non-faller), (2) frequency (occasional vs. frequent falls), and (3) severity (benign vs. injurious fall) of patients	Gait/balance characteristics, retrospective fall history, and clinical assessments including MOCA	Logistic regression	-	(1) 70% (2) 77% (3) 75%	(2) 86% (2) 86% (3) 89%	-

Table 4 (continued)

Author, year	Fall classification	Final variables used in predictions	Models	AUC	Sensitivity	Specificity	Effect size
Rispens M. S. et al., 2015	Prediction of falls (strength of association with falls)	Only gait/balance characteristics	Negative binomial regression and logistic regression				B(P), 0.27 (0.02), ICC, 0.81 B(P), 0.48 (0.02)
K S. van Schooten et al., 2015	Prediction of falls (strength of association with falls)	Gait/balance characteristics, retrospective fall history, socio-demographic and clinical assessments including TMT	Logistic regression	0.82 (95% CI, 0.75–0.89)	70%	80.9%	-
C S. Sterke et al., 2012	Prediction of falls (strength of association with falls)	Gait/balance characteristics, retrospective fall history, and socio-demographic	Logistic regression	0.67 (95% CI, 0.59–0.75)	86%	52%	-
Fiems L C et al., 2019	Prediction of falls (strength of association with falls)	Gait/balance characteristics, retrospective fall history, clinical assessments, and socio-demographic	Logistic regression	0.65 (95% CI, 0.51–0.80)	65%	65%	OR, 0.91
Ng K-D et al., 2020	Prediction of falls (strength of association with falls)	Only gait/balance characteristics	Poisson regression				Cadence (regression coefficient:0.64) average eMOS (regression coefficient, − 11.5)
Kearns D. W. et al., 2012	Prediction of falls (strength of association with falls)	Gait/balance characteristics, retrospective fall history, and clinical assessments	Logistic regression	-	-	-	Fractal D (OR:2.55, 95% CI,1.15–5.63); history of fall (OR,7.36, 95% CI,1.76–30.78)
Hauer K. et al., 2020	Prediction of falls (strength of association with falls)	Gait/balance characteristics, retrospective fall history, clinical assessments including cognitive assessments and socio-demographic	Logistic regression	0.75 (95% CI, 0.61–0.88)	-	-	

The best-performing models with the best predictive values of digital health screening tools for fall status and fall risk are presented in this table. Five articles were not represented in this table as no available information regarding model performance was available

MMSE Mini-Mental State Examination, *MOCA* Montreal Cognitive Assessment, *TMT* Trail Making Test. 95% CI, 95% confidence intervals, *B (P)* effect sizes normalized to the characteristic's standard deviation and *P* value, *OR* odds ratios, *ST-F* short term faller, *ST-NF* short-term non-faller, *eMOS* estimated margin of stability

[1]Hit Ratio: represents the number of detected missteps divided by the total number of missteps

distinguishing between occasional versus frequent fallers with a sensitivity of 86% and specificity of 95% [36].

When comparing different classifiers, the best predictive model was found in a machine learning (ML) model using gait outcomes to classify fall risk in older adult neurological patients from a neurology ward [52]. Six ML models were developed, of which the best model, a random forest classifier trained on data pre-processed by the path signature method, demonstrated an accuracy of 98.6%, sensitivity of 99% and specificity of 98% [52]. In a fall risk prediction model based on 3 longitudinal gait features, medication intake and baseline STRATIFY scores, the machine learning model achieved 73.2% specificity and 72.8% sensitivity, with an area under the receiving operating characteristic curve of 76.2% [34]. While traditional models may not seem as accurate as ML models, the effect sizes indicate that such statistical methods were acceptable. In a study conducted by Iluz et al. [53], recording of missteps was collected via free-living monitoring using wearable sensors for three days. An algorithm was then developed to identify missteps. Missteps, also known as near falls, have been related to fall risk among older adults [54, 55]. This model found that fallers have a 1.84 (95% CI, 1.15 – 2.93) times higher odds of having a misstep during the observation period, relative to a non-faller.

Methodological quality assessment

Most cohort and case–control studies included in this systematic review had acceptable methodological quality while cross-sectional studies performed poorer. Cohort studies and case–control studies achieved a mean score of seven and six respectively (out of nine stars). However, cross-sectional studies achieved a mean score of three out of seven stars. The cross-sectional studies included were not entirely representative of the average target population and comparability between respondents and non-respondent characteristics was not satisfactory. Some articles from all three study designs did not control for age or CI status in statistical analyses, which resulted in a lower evaluation of the category 'comparability'. Quality assessment can be found in Table 5.

Discussion

This discussion section presents the insights gathered from the systematic review in synthesising the performance of technologies for fall risk assessments among older adults with CI. We examined the study design, data collection, the performance of technologies, and test characteristics to highlight the effectiveness of these technologies and their potential practical applications in overcoming the barriers of evaluating fall risk in older persons with CI.

With the exception of two studies [38, 56], all studies included in this systematic review reported that data obtained from technology-based assessments successfully distinguished between faller status or risk of falls among older adults with CI. All studies included participants with at least mild CI, with other studies including participants with wide-ranging neurological disorders with associated cognitive decline. Recording daily life through ambulatory data may be more suitable for individuals with CI as it provides a more realistic understanding of their abilities to manage the dual-task nature of walking in real-life scenarios [32, 33, 44]. It also enabled reliable data collection compared to in-laboratory procedures that rely on their comprehension and decision-making skills [57]. However, adherence to wearing sensors among this population may pose a considerable challenge [58].

All studies examined the outcome of falls through fall history (retrospectively) or future falls (prospectively). However, only five studies distinguished different types of falls while the remaining articles classified falls as one homogenous group. This is an important implication as falls among older adults are known to be generally heterogenous [59], and this heterogeneity may be greater among older adults with CI [60], especially as older adult fallers with cognitive impairment tend to present balance deficits, poor mobility, and slow gait speed [60]. As such, to ensure better assessments of fall risk and subsequent interventions for this population, it may be important to differentiate the outcome of falls in predictive models.

Most studies focused on gait and/or balance indicators but missed the opportunity to include cognitive performance inputs measured through clinical assessments. Four studies included some measures of cognitive performance by including scores from the MMSE, MOCA, or Trail Making Test (TMT) into the models [36, 46, 47, 50]. For example, a study conducted by Hauer et al. [46], integrated cognitive sub-performance inputs to improve the test characteristics of falls prediction in older adults

Table 5 Assessment of methodological quality. Greene R. B. et al., 2021 and Adeli V et al., 2023 were excluded in Table 5 as in-silico studies with multiple data sets of different experimental study designs were used

Cohort studies	Selection (4 stars)	Comparability (2 stars)	Outcome (3 stars)	Total score (9 stars)
M Gietzelt et al., 2014	★★★	★	★★	6
K S. van Schooten et al., 2015	★★★	★★	★★	7
C S. Sterke et al., 2012	★★★	★★	★★	7
Schniepp R et al., 2021	★★★★	★★	★★	8
Schniepp R et al., 2021	★★★★	★★	★★	8
Jearns D. W. et al., 2012	★★★	★★	★★★	8
Schwenk M. et al., 2014	★★★	★★	★	6
Marquesa R. N. et al., 2018	★★★	★★	★★★★	8
Srulijes K et al., 2019	★★	-	★★	4
Case–control studies	**Selection (4 stars)**	**Comparability (2 stars)**	**Outcome (3 stars)**	**Total score (9 stars)**
Gago M F et al., 2016	★★	★★	★	5
Gago M F et al., 2014	★★★	★★	★	6
S Del Din et al., 2017	★★★★	★	★★	7
Cross-sectional studies	**Selection (3 stars)**	**Comparability (2 stars)**	**Outcome (2 stars)**	**Total score (7 stars)**
T Illuz et al., 2014	-	-	-	0
Zhou YH et al., 2020	★★	-	★	3
Fiems L C et al., 2019	★	★★	★	4
Najafi B. et al., 2007	-	-	★	1
Rehman R et al., 2020	★★	-	★	3
Ng K-D et al., 2020	-	-	★★	2
Rispens M. S. et al., 2015	★	-	★	2
Hauer K. et al., 2020	★★	★★	★★	6

with CI [46]. In this study, the combination of both cognitive performance domains such as visuospatial abilities along with balance parameters yield the highest performance (AUC = 0.75) compared to individual models with the cognitive domain (AUC = 0.64) or balance parameter (AUC = 0.74) alone. Future research should be done to include cognitive domains that affect falls and not purely motor domains only to predict fallers among older adults with CI. This may improve the performance of classification models, and accurately describe the underlying physical and cognitive decline among older adults with CI. Executive function is associated with gait dysfunction [61, 62], while complex attention (sustained, divided, and selective attention) and perceptual-motor function (visual perception, visuoconstructional reasoning, and perpetual-motor coordination) have demonstrated associations with fall risk as well [8]. As such, cognitive subdomains that should be assessed in future studies include executive functioning, language semantic memory, episodic memory encoding and recall, visuospatial abilities, and speed of information processing [63]. The neuropsychological deterioration of these subdomains has been shown to occur up to approximately eight years preceding mild CI, prior to neurological disorders such as AD [63]. As such, future research should consider paying greater attention to cognitive subdomains and integrating them into models with gait and balance parameters. However, an important point to note is that older adults with severe cognitive impairments and/or neurological disorders will have various comorbidities that will manifest in the data. It would be important to also control for these systemic comorbidities in the design or analyses of such work for interpretability and applicability of results.

In addition, studies also demonstrated that models that included other predictive parameters such as socio-demographic indicators, clinical assessment, and in-/out- of laboratory mobility assessments demonstrate greater performance than models that only

utilise data collected from technologies [36, 46, 47, 50, 64]. However, fall history remains one of the most important independent predictors of a future fall [36, 38, 47]. While that may be so, fall history is not a modifiable risk factor and findings from this review have shown that parameters derived from technology, along with other clinical and socio-demographic inputs can also be powerful in predicting and classifying future fallers.

As alluded to earlier, wearable sensors for ambulatory monitoring may be suitable for older adults with CI. From the included studies, participants with mild CI may be able to wear sensors for up to a year, though there should be caution about non-compliance with such long observation periods [65–67]. On average, most wearable sensors were worn between a week and a month. Researchers, clinicians, and caregivers must be trained on how to attach the sensors without causing any distractions or disturbances to participants. The wearability of these technologies is considered a significant issue as poor design may cause participants to experience discomfort or irritation, resulting in skin irritation and leading to non-compliance [68]. Hence, it would be important to prioritise user comfort, ease of use and minimising disruption to usual activities to improve compliance and data collected during these fall risk assessments. If done well, these technologies can be a cost-effective and practical way of collecting data in clinical and community settings; and even going a step further such as monitoring the progress of participants in personalised fall intervention programmes.

While traditional methods of classification have satisfactory capabilities in distinguishing fallers, machine learning techniques may be valuable in achieving greater performance. For example, Iluz et al. demonstrated 98.6% specificity in detecting missteps among fallers and non-fallers [53]. However, the interpretation and application of this finding are limited as the nature of missteps in the community may be difficult to detect accurately. With a greater number of non-detected missteps among non-fallers, this may result in a smaller number of false positives, hence greater specificity obtained. Furthermore, while researchers tried reducing this bias by inducing missteps in the laboratory to simulate the collection of community missteps, this was in artificial conditions compared to the community setting. A larger, community-based, study should be conducted to further verify these results. While ML models may demonstrate high accuracies, we should be cautious about interpreting such data as ML models are dependent on factors such as computational power, data quality and availability, expertise, and cost [69, 70]. One limitation of ML models is the need for a large training dataset and/or sample size, which may not be widely available for older adults with CI [51, 56, 64, 71]. This sample size heterogeneity exists as the sample size available for fallers with CI naturally will be smaller compared to fallers within the general population. In addition, in one study, large datasets of various neurological disorders were used but did not account for the degree of CI [52]. Once again, it would be important to include underlying disease-specific impairments such as physical and cognitive sub-performance domains in falls prediction models. This would be helpful to demonstrate the clinical value of falls prediction technologies, and ultimately be helpful for clinicians in identifying unique underlying factors that increase falls within this complex population.

Lastly, this systematic review demonstrates how the use of technology-based fall risk assessments is promising in distinguishing fall status or risk of falls. However, there are various steps required to translate these findings into clinical practice. Additional work needs to be done to compare the performance of three potential options: existing methods for fall risk assessment (status quo), technology-based fall risk assessments, and the combination of both traditional and technology-based approaches. In addition, health technology assessments including cost-effectiveness analyses should be conducted to advise decision-makers on the best option based on the options' cost and utilities.

Strengths and limitations

To the best of our knowledge, this is the first systematic review focusing on fall risk assessments using technologies among older adults with CI. While

there has been ample focus on using technologies to detect falls and quantify mobility or designed as digital interventions, using it as a fall risk prediction tool in this subpopulation has been less well-studied. Some recent systematic reviews have begun focusing on fall predictions in general populations but considered only one specific type of technology (i.e. sensors). Our review provided an analysis of the various technologies used, functional tests carried out, and classification models which would be valuable to clinicians or researchers interested in using technology-based fall risk prediction tools for older adults with CI. However, as assessing fall risk in older adults is particularly challenging, it is no surprise that studies evaluating novel fall risk assessment technologies exclude older adults with CI. This makes selection of studies quite limited, as such, we had to include two studies with a slightly younger population and studies that considered the general population with a sub-population of older adults with CI to ensure a comprehensive analysis. In addition, we utilised the adapted NOS Quality Assessment Scale to critique bias for cross-sectional studies. This may not be a well-validated tool compared to others such as the Appraisal tool for Cross Sectional Studies (AXIS). We recognise this limitation; however, as the result analysis and interpretation of this systematic review is primarily based on the methodology and results which have similar components between the adapted NOS and AXIS, we chose to ensure that the risk of bias scores was comparable across different study designs by using the same quality assessment tool.

Lastly, most studies involving technologies mainly focused on gait abnormalities instead of cognitive domains, which limited our ability to synthesise information on the various subdomains of CI that may be a considerable risk factor for older adults with CI. Despite that, we recognise and recommend that the combination of various clinical assessments and sociodemographic characteristics along with technology-derived data would be valuable in predicting fall risk. Moving forward, as this field matures, this review should be updated with a meta-analysis when more high-quality studies become available.

Conclusion

Evidence from this review suggests that digital technologies along with their classifiers demonstrate promising results as screening tools for fall risk among older adults with CI. We found that with the use of wearable sensors, data can be collected through everyday monitoring of participants, which may be more suitable for older adults with CI. To advance this field and promote translation into practice, future work is required to integrate technologies with inputs from cognitive subdomains and conduct additional longitudinal studies with larger cohorts to assess its practical applications in the clinical setting and medical decision-making. In addition, comparative studies assessing the performance and cost-effectiveness of existing approaches, technology-based methods, and/or various combinations of them should be conducted moving forward.

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Data availability Data utilised for this study is available at the Health Services and Systems Signature Research Programme of DUke-NUS Medical School. De-identified data can be made available upon reasonable request.

Declarations

Competing interests The authors declare no competing interests.

Appendix

Table 6 Full search strategy utilised on 27 July 2022, and an update was conducted on 20 July 2023

Database	Search field	Search query
PubMed	All fields	((((accidental falls) OR (fall prediction)) OR (fall risk assessment)) AND (((((((digital technology) OR (device)) OR (health technology)) OR (game)) OR (mobile application)) OR (sensors) OR (wearable sensors) OR (machine learning))) AND ((((dementia) OR (cognitive impairment)) OR (cognitive decline)) OR (parkinson's disease))
IEE Xplore	All fields	((("All Metadata":fall risk assessment OR "All Metadata":fall prediction OR "All Metadata":assess fall OR "All Metadata":accidental falls) AND ("All Metadata": dementia OR "All Metadata": cognitive impairment OR "All Metadata": cognitive decline OR "All Metadata": Parkinson's Disease OR "All Metadata": Alzheimer's Disease)))
SCOPUS	Title and abstract only	(TITLE-ABS-KEY ("cognitive impairment") OR TITLE-ABS-KEY-AUTH ("cognitive decline") OR TITLE-ABS-KEY (neurological AND diseases) OR INDEXTERMS ("cognitive impairment) OR INDEXTERMS(" neurological AND diseases)) AND (TITLE-ABS-KEY (technology) OR TITLE-ABS-KEY (devices) OR TITLE-ABS-KEY (sensors) OR TITLE-ABS-KEY (mobile AND applications) OR INDEXTERMS (technology) OR INDEXTERMS (sensors) OR INDEXTERMS (device) OR TITLE-ABS-KEY (machine AND learning) OR INDEXTERMS (machine AND learning) OR TITLE-ABS-KEY (health AND technology) OR INDEXTERMS (health AND technology)) AND TITLE-ABS-KEY (fall AND risk AND assessment) OR TITLE-ABS-KEY (assess AND falls) OR TITLE-ABS-KEY (fall AND prediction) OR INDEXTERMS (falls) OR INDEXTERMS (fall AND risk AND assessment)
EMBASE	Title and abstract only	('cognitive defect'/exp OR 'cognition disorder' OR 'cognition disorders' OR 'cognitive defect' OR 'cognitive defects' OR 'cognitive deficit' OR 'cognitive disability' OR 'cognitive disorder' OR 'cognitive disorders' OR 'cognitive dysfunction' OR 'cognitive impairment' OR 'delirium, dementia, amnestic, cognitive disorders' OR 'overinclusion' OR 'response interference' OR 'neurologic disease'/exp OR 'nervous disease' OR 'nervous disorder' OR 'nervous system disease' OR 'nervous system diseases' OR 'nervous system disorder' OR 'neural disease' OR 'neurogenic disease' OR 'neurologic complaint' OR 'neurologic disease' OR 'neurologic disorder' OR 'neurologic disturbance' OR 'neurologic dysfunction' OR 'neurologic manifestations' OR 'neurologic sign' OR 'neurologic symptom' OR 'neurologic syndrome' OR 'neurological complaint' OR 'neurological deficiency' OR 'neurological disease' OR 'neurological disorder' OR 'neurological disturbance' OR 'neurological sign' OR 'neurological symptom' OR 'neurological syndrome' OR 'sign, neurologic' OR 'symptom, neurological') AND ('technology'/exp OR technology OR 'digital technology'/exp OR 'digital technology' OR 'sensor'/exp OR sensor OR 'pedar-x' OR 'environmental sensor' OR 'reusable sensor holder' OR 'sensor' OR 'sensor holder, reusable' OR 'sensors') AND ('fall risk assessment'/exp OR 'fall risk assessment' OR 'fall risk assessment tool')
CINAHL	Title and abstract only	((cognitive decline or cognitive impairment or cognitive function) OR (neurological disorders or neurological disease or disability) OR (cognitive decline or dementia or alzheimers or cognitive impairment or memory loss) OR cognitive decline in aging adults OR (cognitive decline" or "cognitive health" or "cognitive function")) AND (S1 AND S2) where S1: (fall assessment or fall assessment tool or fall risk assessment) OR fall assessment tool OR fall prediction OR (fall screenings or fall assessments) and S2: technology OR (devices or technologies or technology) OR sensor OR (mobile applications or apps or mobile apps) OR (virtual reality or vr or augmented reality)
Web of Science	Title and abstract only	((TS = (technology OR devices OR sensors OR wearable technology OR game OR machine learning OR health technology OR mobile applications)) AND TS = (cognitive impairment OR cognitive decline OR neurological diseases OR cognitive impairment in aging adults)) AND TS = (fall risk assessment OR fall screening OR fall prediction OR assess falls)
Grey literature		
Google Scholar	Title and abstract only	fall risk assessment AND cognitive impairment AND (technology OR sensors OR devices OR mobile applications)
ProQuest	Title and abstract only	(fall risk assessment) AND (cognitive decline) AND (technology OR devices OR sensors OR mobile phones)

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