Falls are unintentional: Studying simulations is a waste of faking time

Emma Stack[1,2]

Abstract

Researchers tend to agree that falls are, by definition, unintentional and that sensor algorithms (the processes that allows a computer program to identify a fall among data from sensors) perform poorly when attempting to detect falls 'in the wild' (a phrase some scientists use to mean 'in reality'). Algorithm development has been reliant on simulation, i.e. asking actors to throw themselves intentionally to the ground. This is unusual (no one studies faked coughs or headaches) and uninformative (no one can intend the unintentional). Researchers would increase their chances of detecting 'real' falls in 'the real world' by studying the behaviour of fallers, however, vulnerable, before, during and after the event: the literature on the circumstances of falling is more informative than any number of faked approximations. A complimentary knowledge base (in falls, sensors and/or signals) enables multidisciplinary teams of clinicians, engineers and computer scientists to tackle fall detection and aim for fall prevention. Throughout this paper, I discuss differences between falls, 'intentional falling' and simulations, and the balance between simulation and reality in falls research, finally suggesting ways in which researchers can access examples of falls without resorting to fakery.

Keywords

Age in place, assessment physiotherapy, posture analysis, rehabilitation, remote sensing, sensor design, sensors/sensor applications

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Introduction

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Falls are unintentional, by definition

Clark et al.[1] defined a fall as

> an event that results in a person coming to rest unintentionally on the ground or other lower level, not as a

[1]Faculty of Health Sciences, University of Southampton, Southampton, UK
[2]SPHERE EPSRC Interdisciplinary Research Collaboration, Universities of Bristol, Reading and Southampton, UK

Corresponding author:
Emma Stack, University of Southampton, Mailpoint 886, E Level, Southampton SO16 6YD, UK.
Email: els1n09@soton.ac.uk

result of a major intrinsic event or overwhelming hazard

In defining falling, researchers tend to focus on the event, while elderly people and health-care providers tend to focus on the antecedents and consequences.[2] Interpretations differed widely when 477 community-dwelling elderly people and 31 community-based health-care providers defined a fall, so researchers and clinicians should always define what they mean by 'falling'. Clearly, at that time, falls researchers did not always do so: only 46/90 papers reviewed in 2006[3] included a definition of falling; two of the most frequently cited were by the Kellogg group[4]

unintentionally coming to the ground or some lower level and other than as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure

and the FICSIT collaboration[5]

unintentionally coming to rest on the ground, floor or other lower level

The above definitions illustrate the consensus that falls are *unintentional, inadvertent, involuntary, or accidental events*, after which the individual comes to rest at *a lower level*. Despite this consensus amongst clinical researchers, a 2013 review on body-worn sensors[6] found that papers on *fall detection* still frequently 'lacked an established definition'. Definitions such as '*any abnormal movement with respect to ADL*'[7] omit the key feature of falling, i.e. finding oneself heading unexpectedly down to the ground and allow researchers inappropriately to label 'experimental', 'active' or 'intentional' actions as 'falls'.

Some[8] describe simulations performed by volunteers as 'experimental falls', some[9] as 'falls'. The use of 'perform' in the sentence '*eight healthy adult subjects were arranged to perform...two kinds* (of) *fall activities* (*active and passive*)'[10] means neither activity was falling.

Researchers have developed algorithms capable of discriminating simulations they deemed 'intentional falls' from other activities.[11–13] As participants had thrown themselves to the ground, no algorithm actually detected *falls* (despite the papers' titles). Clinically, people who present in such circumstances differ from people who have fallen. Researchers found that 144 people who had thrown themselves from a height *intentionally* tended to be older and to have descended from a greater height than 8992 people who presented at hospital having *fallen* from a height; a greater proportion were female and they were more likely die before reaching hospital or during treatment than the fallers.[14] For various reasons, some hospital inpatients intentionally drop (or throw themselves) to the floor. Defining their planned actions (neither sudden nor unintentional) is a challenge when monitoring falls in hospital: Staggs et al.[15] suggested categorising situations in which 'a patient aged 5 years or older falls on purpose' as 'intentional fall events', a term that researchers studying simulations could adopt.

Researchers need not add adjectives to the word fall, if they define falling appropriately. 'Accidental', 'Real', 'Real-world' and 'Unintentional' falls are simply falls. In the current paper, I call any events that meet Clark et al.'s definition[1] 'falls' and any intentional descents to the floor 'simulations'.

The circumstances of falling: The reality

The circumstances of falling have attracted considerable interest among researchers. While an individual's risk factors for falling (such as age and function) are constant, no one falls constantly: the interaction between their behaviour and their environment triggers an individual to lose their balance where and when they do. To prevent falls and their consequences, clinicians need to understand how and why someone has fallen previously. They may do this by taking a 'fall history' to elucidate the circumstances surrounding a fall, which will encompass:

Before balance loss	Loss of balance	After balance loss
1. Faller's location 2. Fall-related activity i.e. what the faller was doing or attempting	3. Suspected cause i.e. why the faller fell *there and then*	4. Landing (direction; contact) 5. Injuries sustained 6. Help needed (to get up, and/or healthcare)

In reality, these elements happen together: fallers may be engaged in a task when, without warning, they are unable to stop themselves hitting the unforgiving ground. Actors awaiting instructions to simulate 'falling' onto a laboratory crash mat are going to behave very differently in actively making movements and striving for positions that fallers do their best to avoid. Fallers' own accounts often emphasise a bewildering lack of control that is impossible to fake:

Trying to open the back car door, my balance went and I was on the floor[16]
I turned with my body but my legs wouldn't move[17]
Tripped walking to car; (landed) face downwards, in sprawl; fractured nose, damaged hand[17]

Healthy, active adults. Even among healthy, active adults, a proportion fall, sustaining injury (including, hip fractures: the most serious injuries predominantly sustained through falling). One quarter of 431 'relatively healthy' elderly Norwegians interviewed had fallen in the previous six months; 55/104 fallers (53%) were injured and 15 fallers (14%) sustained fractures (including seven hips) during their last fall.[18] Half of 96 'healthy, active' elderly Australian women tracked for a year (using falls diaries and monthly phone calls) fell; 44/47 fallers (94%) were injured and nine fallers (19%) sustained fractures (including two hips).[19] In both studies, most falls were *outdoors* (often in the street), most during walking, and most attributed to external causes (rather than impaired function), commonly tripping (followed by steps and slipping).

A longitudinal study on aging[20] illustrates how the frequency and circumstances of falling change. Researchers analysed the two-year fall histories of 292 young (20–45 years), 616 middle-aged (46–65 years) and 589 older people, 94% of who rated their health as good or excellent. With age, the proportion falling rose from 19% to 21%, then 35%, and the proportion falling at home rose from 1% to 4%, then 10%. Young people tended to fall walking, running or during sport; middle-aged people walking, during sport or on steps and older people walking, on steps or during transfers. With age, the proportion injured falling rose from 13% (commonly wrists/hands, knees and ankles) to 15% (commonly knees), then 25% (commonly head and knees), and the proportion sustaining fractures rose from 1% to 2%, then 5%. Fall detection sensors are, however, more likely to contribute to managing the risks associated with falling among less healthy populations than these.

Vulnerable populations. Some groups fall more frequently than do healthy, active adults – and under different circumstances. Two-thirds of 1172 falls (67%) by 328 older adults at high risk of falling happened *at home*.[21] The most common fall-related activity was walking (27%, followed by standing up, steps, reaching, turning and bending), caused by '*loss of balance*' (32%), tripping (29%) and slipping. Falling forward was common (42%), followed by sideways, backwards into sitting and backwards into lying.

The more fallers differ from the volunteers faking falling, the less realistic the simulations. People with cognitive impairments are particularly vulnerable: some expose themselves to risks and cannot manage the consequences. Common 'behavioural factors' in falls by people with intellectual disabilities[22] include distraction (e.g. forgetting a step), rushing (individuals 'losing balance through their own momentum') and unsafe behaviours (e.g. leaning on inappropriate support, performing tasks when unwell and carelessness with or avoidance of mobility aids). Wandering, delirium and symptoms of urinary tract infection are commonly associated with falls among people with dementia.[23] Two-thirds of 229 falls occurred inpatients' own rooms on a psychogeriatric ward in Sweden. Falls when standing or walking (46%) and from the bed or chair (42%) were common but people had fallen sitting down, toileting, in conflict with others and climbing over bed rails. Of 276 falls by Japanese nursing homes residents with dementia,[24] most occurred in people's bedrooms: one-third (32%) caused minor injuries (frequently to the head) and nine (3%) caused fractures.

Fallers with physical impairments also fall in circumstances difficult to simulate. Some people with impaired mobility use walking aids (sticks or frames) to reduce pain during weight bearing, improve balance control or to compensate for generalised frailty. However, the risk of falling associated with walking aids (through tripping over them or them impeding balance control) that frequently hospitalises a 'highly vulnerable population' may be under-recognised.[25] For example:

> I can't get out of the habit of rushing and the next minute, I only took two steps and got my foot caught in the trolley, hit the ground and cracked my jaw[16]

Data on people aged 65 and older treated in US emergency departments often implicates walking aids in falls. In one study, 60% of 3932 injuries identified occurred at home and 16% in nursing homes.[25] Frequently, tripping while walking led to falling but in some cases, the aid caught an obstacle and the user fell. Some people with Parkinson's slow down and shorten their stride when using a walking aid for the first time,[26] immediate gait changes that 'may predispose individuals . . . to instability and falls'.

People with a neurological condition: For example, Parkinson's. The differing circumstances in which people with Parkinson's and stroke fall show that some features show a tendency toward disease specificity. Stack and Ashburn[27] interviewed 55 people with Parkinson's (mean age 72) a mean four years after their diagnoses, most of whom (47, 85%) had fallen and/or nearly fallen in the previous year. Using similar questions, Hyndman et al.[28] interviewed 21 people with stroke (mean age 69), half of whom (a mean 51 months post-stroke) had fallen once in the previous year, half of whom (mean 22 months post-stroke) had fallen repeatedly. In both studies, falls happened most frequently at home, notably in bedrooms, living rooms and gardens but the fall-related activities and suspected causes differed. People with Parkinson's fell turning,

reaching or carrying, largely after tripping, whereas people with stroke fell walking, turning or transferring to or from sitting, largely after losing their balance, inattention or dragging their feet. The former commonly fell forwards ('*I feel I'm going forwards and I stagger forwards*'); the latter commonly fell sideways (with 12 falls (24%) causing minor injury and three (6%) causing clavicle, pelvis, rib and thumb fractures). A later study[17] echoed these findings: among 124 people with Parkinson's, 80% of 639 falls had happened at home (in bedrooms, living rooms, kitchens or gardens). Over half (55%) followed:

- Tripping when ambulant: 13%
- Freezing, festination and retropulsion (standing or ambulant): 11%
- Balance lost:
  - Bending or reaching from standing: 9%
  - During transfers: 8%
  - When walking: 7%
  - When washing or dressing: 7%

Stack and Roberts[29] focused on the circumstances surrounding the minority of falls among people with Parkinson's happening *away from home*. The 249 falls that 136 people (median age 72; median years since diagnosis eight) described frequently followed trips, inattention or freezing, or happened when they were attempting to turn or hurry. Most falls (58%) were forwards; one quarter (26%) caused minor injuries; 3% caused fractures or dislocations. The circumstances of falling differed with fall frequency. The 19 (14%) who fell only once commonly fell walking (e.g. missing their footing) or when transferring to or from sitting. Repeat fallers felt 'shaken' and sought medical advice after falling. The 31 most frequent fallers (at least monthly: a median 18 falls *at home* and six elsewhere) commonly fell backward, in shops and after a collapse.

You cannot fake any of this. Researchers need to consider tailoring fall detection to specific people and events, as it is unlikely any single algorithm could detect the whole spectrum of falls: researchers trying to detect 'fainting' events,[30] conceded that other events such as tripping and slipping would appear very different.

Falls happen for different reasons, with different outcomes, in different settings. Fallers from vulnerable groups have physical and cognitive impairments no actor could fake: for example, a faller with Parkinson's fell (when frozen) while their *'feet felt as if they were glued to the ground'*.[27] At the other end of the spectrum, people fall during strenuous activities: 50 community-dwelling people (aged 60 or older) fell 91 times (hurrying (31%), inattentive, slipping or tripping) when walking on level or uneven ground (24%

each), hurrying to complete work, gardening or carrying something heavy or bulky.[31] Throwing oneself to the ground from a stationary start would poorly simulate these falls, let alone the loss of leg sensation that preceded three, or the 13 injurious landings that necessitated intervention. To summarise, an actor cannot fake:

The faller (Age; Function)	Before balance loss (Environment; Activity)	Loss of balance (Sensation; Control)	After balance loss (Landing; Injury)
|	|	|	|
People with and without physical and/ or cognitive impairments move (e.g. turn) differently	Few falls are from stable, stationary positions; none occur on command, under controlled conditions	Active and passive movement differs; e.g. you cannot fake collapse, freezing or inattention	Injuries arise from unwanted impact; control throughout (to guarantee a safe landing) is not falling

Some argue that automatic fall-detection has had limited success 'in the wild' because focusing on accelerations overlooks *potential changes* in the faller's orientation[7] or because elderly people *fall more slowly* than the simulations studied.[32] Observing falls would confirm that fallers often change orientation, crashing to the ground. Falls can be fatal, confusing, embarrassing and painful:

> Not sure (what happened); turned quickly opening kitchen door and lost balance; (landed) heavily on side, banged head; cut head, arm and shoulder[17]
> The pavement went like that, and then you had a step, and then you had the front door with a very high threshold and although I had a handle on the door, as I said, my hands were full so I just went flying[16]

Investigating falls (and fallers) like these would eliminate some of the need for speculation and allow researchers to design and test sensors and algorithms appropriately.

Simulated falls

Actors are nothing like fallers. Simulators have tended to be much younger (typically in their 20 s and 30 s), healthier and higher functioning than most fallers. While the gulf between fallers and actors is probably why algorithms trained on simulations function poorly 'in the wild', it is also noteworthy that the sample sizes have been very small: the 16 sample sizes below ranged from 1 to 21 (median n = 10). Even if the

participants had been elderly people with impairments *falling in reality*, so few would not represent the wide spectrum of fallers.

Authors	Simulators	(ages in years)
Kangas et al.[8]	20 Middle-aged	(mean 48)
Also compared 5 'real-life accidental falls' (3 older people, median age 91)		
Kangas et al.[12]	3 Healthy volunteers	(median 42)
Leone et al.[33]	13 Professional stuntmen	(30 to 40)
Lim et al.[13]	6 Healthy volunteers	(20 to 50)
Su et al.[9]	3 Professional stunt actors	(mean 32)
Medrano et al.[7]	10 Young and middle aged volunteers	(20 to 42; mean 31)
Wu and Xue[34]	10 Young adults	(19 to 43)
Gjoreski et al.[35]	11 Young, healthy	(24 to 33)
Aziz et al.[36]	10 Healthy students	(22 to 32)
Yuwono et al.[37]	8 Healthy volunteers	(19 to 28)
Bourke et al.[38]	10 Healthy, young	(mean 24)
Klenk et al.[39]	18 Healthy students	(mean 24)
Also compared 5 'real-world backward falls' (4 women, mean age 69, with supranuclear palsy)		
Nyan et al.[30]	21 Young, healthy	(mean 23)
Liang et al.[10]	8 Healthy adults	(not stated)
Li and Stankovic[32]	3 Graduate students	(not stated)
Lindemann et al.[11]	1 Young, healthy gymnast	(not stated)

Simulations (active movements with cushioned landings) are nothing like falls. Elderly people's falls differ from younger people's simulations in the acceleration signals[8] and acceleration and jerk[39] generated. Researchers acknowledge that the 'movement of younger subjects is bound to differ from that of the elderly population'[30] but persist in asking simulators to fake falling in different ways and in different directions (e.g. stand beside a mattress, 'relax' and 'fall to the sides, back, and front' to simulate fainting[30]) – but *intentional descent is not falling*. Drawing on the literature to identify 'common types of fall'[7] does not make a simulation a fall, and no amount of acting skill or 'training' by an 'expert' makes a performance realistic:

- A geriatrician instructed stuntmen to simulate 'realistic falls'[33]
- Nurses 'trained' simulators[10]
- Volunteers took advice from a *'medical expert in order to mimic elderly'*[35]
- Simulators had to '*mimic realistic falling*', supervised by physical education professional[38]
- Simulators were asked to '*fall back as if you were a frail old person*'[39]
- Researchers sought '*expert opinion*' to identify falls for simulation[11]

Actors moving intentionally (in control of their movements) are not going to land like a faller, particularly on to a crash mat installed to meet ethical requirements.[7,11,30,33,37–38]

Ethics: Research and publishing. Of course, researchers must prioritise participant safety during studies. Some justify their choice of younger simulators by arguing that asking elderly people to simulate falling is inappropriate,[7] unfeasibly 'risky'[35] or 'ethically questionable'.[40] Most cite the risk of injury, either when landing a simulation[30,34] or by landing on a behind-the-ear logger 'during an unintentional fall'.[11] However, if we know that simulations and falls differ (so studying one reveals little about the other), is it appropriate to ask anyone to take risks for minimal scientific advance, at best? Whether it is appropriate to attach a logger that could cause injury if fallen upon to a faller's head is debatable.

Furthermore, if a team has only studied simulations, is publishing a paper with 'falls' in its title misleading? Quite appropriately, some write about '*Detecting Simulated Falls*'[41] or '*Fall Activity Detection*'[10] while those who studied falls,[8,39] include 'falls' in paper titles. However, 'fall detection' is in the title of every other paper listed above, though the research was all on simulations.[12,13,32,33,35,37] Without having studied falls, authors write about distinguishing falls from daily Activities of Daily Living (ADL)[7,32,38] and claim pre-impact fall detection is feasible.[9,30,34,36]

Simulation in clinical research

Simulation is appropriate in certain situations: it offers some advantages over reality and, sometimes, may be the only possibility. If a *device* is valid (adequately matching reality) and researchers monitor the intended *and unintended* effects of its use, it can simulate symptoms or be subject to significant intentional 'injury' (unlike a volunteer). For example:

How accurately does a simulation glove reflect function?[42] Gloves simulating rheumatoid arthritis in the hands made volunteers (mean age 38) generate less power and complete tasks more slowly – but were not 'a fully accurate match' of patients' (mean age 56) reduced function. With accurately simulated impairment, healthy people could test aids that might exacerbate real stiffness and pain.

The simulation of hallucinations[43] Educators have used simulated hallucinations to increase empathy towards people with schizophrenia, as it would be unacceptable to induce actual hallucinations, but a review indicates they must use them cautiously. Simulated hallucinations do tend to increase empathy *but also* the desire for distance from people experiencing real symptoms.

Simulating the Mechanics of Human Falls[44] A device simulating hip impact with the floor on falling could help test protective garments.

Estimation, simulation, and experimentation[45] A dummy simulated head deceleration and impact following a fall from bed.

Approaches to simulation in falls research

Fall detection. Simulations offer fall detection researchers no advantage over studying actual events: the inadequacy of algorithms stems from simulators and their safe controlled actions differing significantly from fallers and falls, particularly pre-impact. Recent systematic reviews (on fall detection studies since 1998) describe the insufficient evidence-base for commercially available devices[6] and state that creating highly accurate unobtrusive devices, subject to more 'real-world testing', remains a challenge.[46] For example, algorithms developed from simulations generated up to *85 false alarms per day* in one faller's home.[47] The proportion of false alarms among events detected 'in the wild' remains high: In a 10-day study,[10] ceiling mounted radar in an elderly person's living room detected 16 false alarms alongside 13 falls.

Although simulation is not the only way to train sensors to identify fall risk, it has been the *dominant* approach in recent years, generating a body of literature on 'detecting simulated falling'. Papers include processes and terminology with which clinical researchers will be relatively unfamiliar, so I conclude this section with a summary for non-experts.

Sensing devices vary considerably; some are wearable, some are not, and every type has strengths and limitations. Radar can sense motion.[10] Doppler radar uses the Doppler Effect to produce velocity data about an object by bouncing a radio wave off a target (e.g. a falling human) and analysing how the object's motion has altered the frequency of the returned signal. The faller's motion creates frequency change between the signals sent and received by the radar but so do other motions; signal processing is necessary to screen out the 'non-fall activities'[10] such as ADL during which falls commonly occur. Others[33] have captured data using camera-based systems.

Researchers have explored whether accelerometers (e.g. embedded in smartphones[7]) can detect actions that indicate someone is falling. An accelerometer is a device that measures acceleration due to free fall. At rest on a surface, it measures acceleration due to Earth's gravity of $9.81\,\mathrm{m/s^2}$ (or $1\,g$), whereas in free fall (at $9.81\,\mathrm{m/s^2}$) it will measure zero. Others[48] captured data using gyroscope-based wearable devices. Gyroscopes measure angular velocity, the change in rotational angle per unit of time, i.e. degrees per second. Inertial measurement units contain accelerometers (detecting rate of acceleration) and gyroscopes (detecting rotational changes in pitch, roll and yaw): some include a magnetometer, to provide orientation (as in a compass) and to compensate for drift.

To test whether a device can detect an event (a fall or simulation), researchers need to develop an algorithm: a method by which a computer program can distinguish the event from all other surrounding activity, such as ADL. Raw signals from sensors require processing to remove 'noise' before an algorithm is applied. Researchers have developed algorithms using the 'simple threshold method'[11] or more sophisticated 'machine learning methods'.[36–37] In the former, the sensor data indicates a fall if a parameter's value (acceleration, angular velocity or combinations from both) *exceeds a certain threshold*. For example, an algorithm (for an accelerometer behind a volunteer's ear[11]) recognised an 'intentional fall' if acceleration of the head towards the ground exceeded $2\,g$; velocity of all spatial components pre-impact exceeded $0.7\,\mathrm{m/s}$ (at impact head velocity became zero) and acceleration of all spatial components exceeded $6\,g$ (a value never achieved during ADL). In 'machine learning methods',[36,37] with 'potentially better detection rates',[49] various types of event and ADL patterns are trained by a *learning algorithm*, then an event is classified as either an event or ADL by applying it to an *evaluation algorithm*. Algorithms can detect events other than falls. Work on detecting chair rises[50] illustrates a problem common to fall research: better detection rates under controlled conditions (fully attending to a protocol) than in the wild when additional movements introduce complexity and 'larger variance'. Stepping right after rising impeded the algorithm's ability to estimate maximum acceleration and jerk (rate of change in acceleration).

Fall assessment. Though actors cannot fake falling, individuals who have fallen or nearly fallen can simulate previous experiences, to a point. Connell and Wolf[51] used reconstruction to investigate 'how personal factors affect safety during routine environmental use'. They asked 15 'relatively healthy' community-dwelling individuals (aged 70–81 years) to describe and re-enact 19 incidents 'to the point they felt comfortable doing so', and identified seven patterns:

- Excessive environmental demands (e.g. trip over an untypically high door threshold)
- Collisions in the dark (e.g. with furniture en route to the bathroom at night)
- Failing to avoid temporary hazards (e.g. tripping over cable that is usually elsewhere)
- Preoccupation with temporary conditions (e.g. backing into forgotten hazard, carrying a box)
- Frictional variations between shoes and floor (e.g. soles prevented intended pivoting)
- Inappropriate environmental use (e.g. washing foot in sink while watching TV in next room)
- Habitual environmental use (e.g. adjusting clothing before sitting on the toilet)

This type of simulation informs researchers and clinicians about the interaction between

environmental conditions and the user's behaviour therein. Understanding the circumstances preceding the loss of balance helps to prevent further similar events. However, the approach stops short of the point at which the individual lost their balance: by definition, one cannot intentionally fall and it would be ethically inappropriate to induce a fall. For example, people fall leaning on support that gives way:[22] researchers could simulate this experimentally using support that participants were unaware was unsound.

Sensors could help researchers, clinicians and fallers understand falls and near-misses ('occasions on which individuals felt that they were going to fall but did not actually do so'[27]) *throughout the whole event*, from before balance loss to after landing. Deploying sensors in research might revolutionise what we know about falls and fallers.

Studying real falls and real fallers

Schwickert et al.[6] highlighted the 'substantial lack of real fall recordings' in 96 articles, proceedings and reports published between 1998 and 2012. Few researchers have published acceleration data on a falls by older people and their sensors have yet to reveal the mechanisms underlying the falls captured.[49] Relying on self-reporting has drawbacks, as '*without witnessing an event or having video to review, clinicians...can only glean what happened from someone's recollection*':[52]

- Fallers have little (if any) warning to act on before balance is lost
- During the rapid descent, attention (if any) is directed towards damage limitation
- Landing may leave little (if any) evidence of the cause or effects of falling
- Insights (if any) are likely to fade over time

Pijnappels et al.[53] recruited 12 young (20–34 years) and 11 older (65–72 years) volunteers to a study on the kinematics and ground reactions forces of the support limb during falls and successful recoveries after tripping. An obstacle suddenly appearing from the floor tripped the volunteers during a proportion of walking trials. Seven of the older group would have hit the floor had not a ceiling-mounted safety harness prevented them. These events are still not falls. Researchers have acknowledged that elderly people's falls *may* differ from simulations, for example, there being a greater decrease in velocity at impact[11] but few have reported sensor data on falls and fewer still have compared data from falls and simulations. We need to observe, record and study real events.

Real falls

Successfully recording a significant number of real falls requires sensors to be on the right people. Researchers have observed one group who fell approximately 17 times per hour.[54] Rather than limit themselves to examining 'periodic gait over a straight, uniform path', they observed and recorded the *spontaneous activity* of 136 study participants in a laboratory and 15 in their homes. They used handheld cameras in both settings, supplemented by fixed cameras in the laboratory. By so doing, the authors, who wanted to understand how infants naturally learn to walk, found that 12- to 19-month olds put in immense practice, averaging 2368 steps and 17 falls an hour.

Successfully recording falls requires sensors to be in the right location for the right length of time. Video cameras successfully recorded 25 falls by 17 elderly residents, in the entrance hall of a care facility, over 15 months.[55] Most occurred during walking (17, 68%); four in standing (16%); two rising (8%) and two in sitting (8%). In all but three cases, images were sufficiently clear to reveal attempted saving reactions, including arm extension (14 cases), stepping (10 cases), change in walking pace (3 cases) and grabbing (2 cases). Researchers[41] have, however, turned to studying simulations after recording only four falls on a stroke unit, despite monitoring 15 inpatients *at high risk of falling* (mean age 67) over 309 patient days (a mean 18 days per participant). Clearly, 18 days was insufficiently long: someone falling every 18 days would fall 20 times per year – and that is very unusual. Unfortunately, the authors did not report on any of the circumstances surrounding the four falls recorded, let alone on the data from the bi-axial accelerometer participants wore. Others have omitted to describe the events they detected, e.g.:

- Eight elderly inpatients at risk of falling (ages 75-plus) wore accelerometers for a mean 21 days (168 days in total) that detected eight 'falling events'[56]
- Doppler radar detected 13 falls in 10 days in an elderly person's living room[10]

Klenk et al.[39] reported on acceleration and jerk during five backward falls by elderly people, selected from 20 falls that they recorded when they monitored 29 patients for 48 h: we urge more researchers to collect and report 'real-world' falls data in this way (though we disagree with the argument that this might help develop 'more realistic simulations'). We do agree that 'real-life acceleration data are needed to study fall mechanisms':[8] Kangas et al. provided data on five falls (after six months testing wireless sensors with 16 residents of Scandinavian elderly care units).

It is possible to record real falls – and the longer the sensors are in the right position and the higher the

participant's risk of falling, the more likely one is to achieve success. Clinicians on the team can identify frequent fallers to recruit; engineers can describe more of the events they capture.

Can we automatically detect 'real' falls? Researchers acknowledge the need to establish whether their algorithms recognise falls as well as simulations: testing 13 fall detection algorithms on a set of 29 falls, the efficacy was much lower in the 'real-world' than when the designers had tested them experimentally.[47] In a recent review of fall detection systems for older people,[46] only 7% of the 57 reports on wearable systems (and none of the 35 reports on non-wearable systems) included monitoring in a 'real-world setting':

- A healthy, active 83-year-old woman (at low risk of falling) monitored for a day did not fall[11]
- Two groups of five elderly people each wore a wearable system 8 h per day for two weeks: during 833 h monitoring, no one fell.[57] Authors concluded development was required as 42 false alarms triggered but only nine transmitted to a caretaker site.
- Ten elderly people each wore a waist-worn accelerometer for 3–7 h at home: during 52 h monitoring, no one fell.[58] Applying different algorithms, the false-positives detected (e.g. bicycling or lying down quickly) ranged between 1 and 45 per day.
- A system detected eight 'falling events' and 30 'alarm release events' when eight elderly inpatients (at risk of falling) were monitored for a mean 21 days each, 168 days in total.[56]

There is clearly not yet a body of literature to support automatic fall detection, partly because most papers are about detecting simulations and partly because researchers who have ventured into 'the wild' have recorded very few falls. Of the studies above, only one[56] detected any falls; another[10] recorded 13 falls (along with 16 false alarms when adjusting a chair's height; standing up quickly and bending to pick up an object). Balancing sensitivity and specificity in the automatic detection of falls is important: failure to detect a fall (by a system with high specificity) is potentially more dangerous and expensive than a false alarm mistaken for a fall (by a highly sensitive system). For this reason, some researchers[59,60] are considering cost-sensitivity analysis rather than accuracy per se, in trying to understood the costs associated with both false alarms and missed alarms.

Real fallers

Being able to detect that someone has fallen, if they need but cannot summon help themselves, is an admirable aim. It is an aim that might well be met using sensors and algorithms when researchers turn their full attention from simulations to falls. In doing so, researchers need to spend more time with people at high risk of falling – and one way to do that is to recruit people who have already fallen repeatedly to participate in studies in their own homes. Regardless of the many challenges (technical and practical) associated with moving outside the laboratory, and ever cognisant of the ethical balance between risk and reward, appropriately skilled multidisciplinary research teams should be able to include fallers in well run studies that address the questions most worth asking. Studying a few relevant participants is arguably better value than studying a greater number of healthy volunteers, stuntmen, students and gymnasts. Clinical researchers identifying, recruiting and supporting people at risk of falling facilitate non-clinical colleagues' work; more of the fall detection literature needs multidisciplinary authorship. Sensors on fallers when they fall could provide novel and highly informative data – over and above simply that someone is on the floor. Perhaps more exciting than the possibility of using sensors to detect a fall after it has happened, is the possibility of using sensors 'in the wild' to detecting a changing *risk* of falling (enabling timely intervention to prevent falls). If researchers found ways of detecting 'near-misses', they could monitor their frequency and alert people at risk of falling to any increase. Every argument for studying falls, not simulations, applies equally to the study of near-misses. Studying faked near-misses would generate no more useful knowledge than studying faked falls but one could argue that it is less ethically problematic to induce genuine near-misses than genuine falls.

As the pressing issue in healthcare is not simply detecting falls but preventing them, it is appropriate to study and monitor near-misses, aiming to prolong the time to the first fall. Near-misses may be a precursor of future falls.[61,62] Interviews with 586 community-dwelling elderly people revealed that a history of two or more stumbles in the past year predicted falling in the following year.[58] In six-month long 'Fall Diaries', Lindholm et al.[63] asked 141 people with Parkinson's (mean age 68 and years since diagnosis 2) 'Were you close to falling but managed to brace yourself at the last moment (e.g. grab someone, an object or the wall?)' A history of 'near falls' (31% reported 'near falls'; 32% reported falls; 18% reported both) predicted a fall within six months.

Connell and Wolf[51] did not consider a fall a prerequisite for studying environmental and behavioural factors contributing to balance loss or fall avoidance: they included near falls and falls 'to increase the number of incidents available for study'. Of the 452

events Lindholm et al.[63] reported, one-third were falls and two-thirds 'near falls'. In 246 min of video of five people with Parkinson's at high risk of falling moving around their homes, participants appeared at imminent risk of falling 227 times,[52] protecting their balance approximately every 65 s, particularly when:

- Transferring to/from chairs
- Walking (through open spaces and around furniture)
- Turning (in standing and walking)
- Stepping onto, off, or over obstacles/steps
- Performing tasks in standing (e.g. conversing, cooking)

If researchers used more of their resources to study real fallers tackling these types of real activities at home, and less resource studying healthy volunteers throwing themselves to the ground in a laboratory, they would learn where to position sensors optimally to identify potential, impending and actual balance loss. Sipp and Rowley[48] used a gyroscope-based wearable device to measure postural sway during ADL and just before falling. Having observed an interesting signal pattern in postural position data even when a subject appeared stable (well before they took protective action), they went on challenge participant's balance by distracting them while they stood on a balance beam: only 14/40 trials caused the participants to touch a support bar. In the remainder, patterns of postural position data appeared to distinguish six more stable trials from 20 that showed more variation and might constitute the onset of instability. If researchers could do something similar 'in the wild', we would progress towards the goal of automatically detecting an increase of risk of falling when there is still time to do something about it.

Someone's ability to recover their balance is likely to be related to their health, function (and diagnosis) and to diminish over time, so eventually people with a high risk of falling have fewer near-misses and more falls; as a study participant told Stack and Ashburn,[27] 'When I nearly go - I've gone'. As such, algorithms intended to detect near-misses may need to be trained on specific groups of fallers and they will need to be able to detect more subtle features than those that indicate falls to accelerometers (i.e. rapid acceleration to the ground followed by dramatic impact and stillness). The challenge of detecting near-misses is probably greater than that of detecting falls.

Databases. We echo the call for 'a large, shared real fall database';[47] it is still lacking, and many aspects of research (not only sensor-based fall detection) would benefit. Individuals with 'limited insight into their own fall risk', such as those with intellectual disability[22] or those who lose consciousness during or after falling cannot provide a history, and falls frequently occur without witnesses: in one study, two-thirds happened while participants were alone.[31] Even in hospitals and care homes witnesses observe a minority of falls, for example:

- Witnesses observed 14% of falls in care homes[24]
- Witnesses observed 9% of night falls and 26% of day falls on a ward[23]

Consequently, research, clinical practice and facility design will rely on supposition or retrospective self-report until sensors revolutionise our understanding of how and why people fall.

Medrano et al.[7] have made their database of *simulations,* and Doorly and Gilchrist[62] have made their database of 10 *modelled* falls available to other researchers. The latter presented the clinical, physical and mechanical details of falls that caused traumatic brain lesions. They analysed and described non-fatal falls that left people aged from 11 to 87 (median 76) with focal head injuries, and accompanied each case with time profiles of linear and angular velocities, predicted using multibody dynamics modelling simulations. For example, they describe a 76-year-old woman who probably fell backwards from her doorstep, striking her head (over the occipital bone) against a wall and was admitted, confused, to hospital.

While a large database of falls is not yet available, researchers who want to see examples of people falling need look no further than the internet: people have posted plentiful examples of genuine falling, although the fallers are rarely frail or elderly. Although sportspeople and those under the influence of alcohol fall in limited (and unusual) situations, what happens to their bodies after balance is lost, as they try to prevent the fall and on landing is more genuine than any simulation. Several television programs owe their success to the number of falls people have captured on video or camera phones. That such examples often make (sober) viewers wince or look away is evidence (was any needed) of how calamitous a real fall is – and how very unlike a faking simulation.

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ES researched the literature and conceived and wrote the paper.

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