



Methodological Review

Fall prevention intervention technologies: A conceptual framework and survey of the state of the art

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ABSTRACT

In recent years, an ever increasing range of technology-based applications have been developed with the goal of assisting in the delivery of more effective and efficient fall prevention interventions. Whilst there have been a number of studies that have surveyed technologies for a particular sub-domain of fall prevention, there is no existing research which surveys the full spectrum of falls prevention interventions and characterises the range of technologies that have augmented this landscape. This study presents a conceptual framework and survey of the state of the art of technology-based fall prevention systems which is derived from a systematic template analysis of studies presented in contemporary research literature. The framework proposes four broad categories of fall prevention intervention system: Pre-fall prevention; Post-fall prevention; Fall injury prevention; Cross-fall prevention. Other categories include, Application type, Technology deployment platform, Information sources, Deployment environment, User interface type, and Collaborative function. After presenting the conceptual framework, a detailed survey of the state of the art is presented as a function of the proposed framework. A number of research challenges emerge as a result of surveying the research literature, which include a need for: new systems that focus on overcoming extrinsic falls risk factors; systems that support the environmental risk assessment process; systems that enable patients and practitioners to develop more collaborative relationships and engage in shared decision making during falls risk assessment and prevention activities. In response to these challenges, recommendations and future research directions are proposed to overcome each respective challenge.

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1. Introduction

Falls prevention within the home environment has been a topic of research for over 30 years [1] and is recognised as an important health issue within the United Kingdom (UK), Europe, North America and Australia [2]. The frequency of falls increases with age, often as a result of physical, functional, and cognitive impairments which are likely to emerge as a result of advanced ageing [3]. Consequently, it is estimated that 30% of older adults aged 65 and over fall at least once a year [4]. One in five falls result in bone fractures and the need for specialist medical attention [5]. Fall related fractures may cause disabilities and in some extreme cases premature death among older adults, which has a significant impact on

demand for health and social care services resulting in a cost of £1.8 billion per year to the National Health Service (NHS) in the UK [6].

Falls prevention activities are carried out across a range of health disciplines including occupational therapy, physiotherapy, general practice, nursing, geriatric, gerontology health and social care [7–9]. There is evidence in the falls prevention research literature which suggests that in excess of 50% of potential falls relating to older adults are avoided as a result of ongoing falls prevention interventions [10]. There is a range of clinically established prevention interventions that target fall related risk factors [1]. A number of recent meta analyses, and systematic reviews considered a comprehensive range of falls prevention intervention studies for preventing falls in community-dwelling older people [11–15]. Fig. 1 presents a diagrammatic summary of the key categories of intervention that are considered in these reviews and serves as a high-level overview of the key areas in which falls prevention research has been undertaken in recent years.

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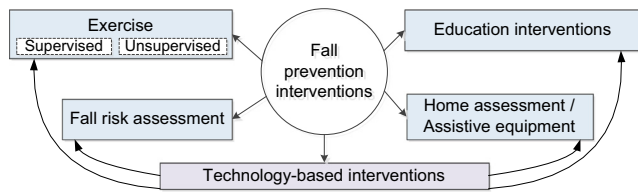


Fig. 1. Overview of falls prevention interventions.

In recent years, one popular approach to falls prevention has been to explore ways of targeting the restoration of muscle strength and balance for prevention of fall risks [16,17]. Exercise interventions are becoming an increasingly popular approach to falls prevention and there is an extensive body of evidence suggesting that these interventions can be effective in reducing falls and the risk of falling [18]. There are many issues, however, with regards to adherence and acceptance of the range of existing *exercise* interventions. *Supervised* one-to-one interventions with the patient and the practitioner are resource intensive in terms of cost and time, whilst supervised group exercise interventions require older adults to be able to travel to the location of exercise classes. Furthermore, there are many issues with regards to adherence and acceptance of existing *unsupervised* home-based exercise interventions, partly due to the lack of interactivity and personalisation that the paper-based exercise interventions typically use in these settings [19]. As such, 3D technology and games are increasingly being seen as a potential means of improving adherence by providing patients with more tailored and interactive exercise programs to engage with [20,21].

Fall risk assessment is an approach used to assess a number of risk factors, specifically mobility issues and physiological factors that include muscle strength and balance, stability, posture and gait reaction time. There are many tests (e.g. Berg balance scale, Timed Up and Go, Turn 180° test) that have been developed to screen older people for fall risks in the community or in a clinical setting [22]. These tests are widely known with research evidence that supports their effective use in predicting fall risks to uncover issues that may lead to falls. Older adults who are exposed to fall risks such as gait and balance abnormalities, admitted into hospital for medical attention as a result of falling are at high risk of falling. Consequently, they are offered a multifactorial fall risk assessment that is administered by clinicians in a clinical setting, or within a specialist fall service. Such assessments are a part of multifactorial risk assessment or a singular assessment. It is crucial that older adults who are at high risk of falling are identified using the fall risk assessment tests so that targeted falls prevention interventions can be prescribed. Conducting such assessments has included high cost equipment in specialist fall services. However, 3D technology and games have shown promise as a low cost solution to augment traditional fall risk assessments and to account for low adherence rates of self-assessment of fall risks done at home [23].

Education interventions are developed to increase knowledge about falls prevention and educate patients regarding their risk of falling and falls prevention strategies based on the available evidence-based literature. This type of intervention, as a single component, is often part of a multifactorial falls prevention programme, which leads to positive outcomes such as behavioural change, decreased fear of falling and increased mobility. Education interventions typically take the form of fact sheets with evidence-based materials. These inform their readers about the preventive measures to reduce falls, or checklist to help to identify fall hazards in the home and to take preventive measures such as change of behavioural patterns. In addition, patients are also offered information regarding where they can seek help and assistance in case of a

fall to avoid long lie syndrome. As such, there is little research evidence of education interventions as a single component intervention that reduces the risk and rate of falls [11].

Home assessments are carried out and *assistive equipment* is prescribed to reduce falls within the home environment. Typically, home assessments involve clinicians visiting the older adult's home to assess the suitability of the home environment in relation to the mobility of the patient. Clinicians then propose adaptations, often via the installation of assistive equipment, in order to facilitate independent living and to mitigate any potential fall risks, which could arise during performing activities of daily living (ADLs). Accordingly, reviews in the falls literature have revealed that home assessments and adaptations as a single intervention do not, in general, significantly reduce the risk of falling. They do, however, have some positive effect for those who are at higher risk of falling [8,11]. Furthermore, identifying environmental risks and adapting the living environment accordingly may reduce fall risks among older adults significantly [24]. By definition, assistive equipment are systems or specialist devices prescribed by clinicians, that provide functional support to older adults to help with mobility, which would otherwise been proven difficult to do and maximises independent living and reduces falls. Assistive equipment includes grab rails, walking frames, hoists, raised toilet seats, stair rails, raised chairs and beds within the patient's home [25–30]. Notwithstanding the benefits of the assistive equipment provision, there are issues which often persist with the use of equipment as it is not always adopted successfully. Consequently, research evidence indicates that more than 50% of home modifications and equipment are rejected [31–33]. As a result, there has been an increase in functional decline, leaving older adults vulnerable to the risk of falling. Equipment abandonment is often associated with a number of factors such as lack of knowledge about the equipment's use, involving the users in the decision making process, their attitude towards the equipment, and a lack of fit of the equipment between service users and their environment [32,34–36].

Technology-based interventions have been deployed in a wide range of falls prevention contexts and include diagnosing and treating fall risks [37–39], increasing adherence to interventions [40–42], detecting falls and alerting clinicians in case of falls [43–45]. Technology is also seen as having the potential to play a key role in enabling older adults to self-assess, which is in line with the personalisation agenda within the UK, giving older adults the opportunity to perform self-assessments for assistive equipment provision [46–50]. With an increasing pressure and demand on the NHS and with limited spending budgets, partly due to an unprecedented increase of life expectancy resulting in an ageing population [51], there is a need to find new ways of providing care to enable patients to provide effective self-care and further steps towards recognising patients as experts of their own care by giving them the chance to provide their own care [52]. Innovations in technology are seen as key to reducing costs and lessening the burden on the healthcare system, whilst also improving the quality and effectiveness of care provided [48], thus enabling patients to engage in the effectiveness of self-care to improve clinical outcomes. Encouraging the adoption of technology, however, has been a primary area of focus, particularly among the older population. There are contributing factors that include usability for the older adult cohort [53], exploring older users' perceptions and beliefs [54], intuitive interactions [55], and multisensory feedback [56], which play a central role in motivating older adults to engage in clinical interventions. These should be catered for if technological interventions are to be adopted by older adults. Therefore, deploying usable and effective information and communication technologies (ICT) in areas of assisted healthcare, specifically falls prevention, within the home has the potential to enable older

adults to maintain their independence and engage in unsupervised interventions, remotely monitored by clinicians. There is, however, an urgent need to explore the extent to which technology has been developed for the falls prevention domain and to identify the areas in which work is still required to respond positively to the broad range of challenges presented by this domain. Technology-based interventions have been identified as having valuable potential in the applied sub-domains highlighted in Fig. 1; *exercise, fall risk, education and home assessment*. However, relatively little research has surveyed the extent to which technology has actually been applied to each of the sub-domains and the provision of collaborative care, specifically the emerging patient–practitioner paradigm within the context of falls prevention. Furthermore, little research has covered the extent to which opportunities to support fall interventions have been explored respectively and the extent to which patients are being enabled to deliver effective self-care to improve clinical outcomes.

A number of systematic reviews have been carried out in the falls prevention domain, some of these include: (1) general reviews [15,57], (2) exercise interventions [13,58], (3) fall risk assessment [59,60] and technology-based interventions [61]. Although a number of technology-based systematic reviews have been presented in the literature to date, such reviews tend to focus mainly on specific sub-domains of a much broader context of technology-based interventions. To the best of our knowledge, there is no existing research which surveys and categorises across the full falls prevention intervention landscape, the types of existing technology-based fall prevention systems, their key collaboration functions, the technologies they exploit, and the specific types of falls prevention interventions they support. Furthermore, there is little existing research which, as a result of taking this holistic view, identifies the areas of clinical practice, which appear to be well catered and identifies areas which require more attention.

In light of the need to better understand the state of the art of the falls prevention technology landscape, this paper provides a comprehensive review and a conceptual falls prevention technology framework, which was developed as a result of carrying out a survey of the range of fall technology systems presented in the literature. Section 2 outlines the research methods used to conduct the literature survey. Section 3 presents the conceptual framework and its component parts are explained. Through presenting the

conceptual model, Sections 7 survey the falls technology systems such as that of pre-fall, post-fall, fall injury and cross fall prevention systems found in the literature to date, respectively. Section 8 discusses challenges of existing falls technology systems and recommends future research directions based on the gaps that exist based on the survey of the state of the art in falls prevention technology research. Conclusions are drawn in Section 9.

2. Research method

This section provides a detailed explanation of the methods employed for this study. The steps taken to develop the conceptual framework and carry out the survey of the state of the art are presented in Fig. 2 and are described in more detail throughout this section.

2.1. Literature search strategy

Initially, a number of survey papers were sourced to gain background knowledge of the research area. Part of the search strategy used for finding existing research was derived from reading previous survey papers such as [15,58,63–65]. This provided candidate search terms, keywords specific to the falls technology domain. The literature search strategy was a two-phase process. In Phase 1, *electronic search and manual search* was performed using electronic databases (IEEE Xplore, ACM, Pubmed, Web of Science, BioMed Central and ScienceDirect) to scan for papers that contain the search terms derived from the falls technology survey papers that had already been considered. For each paper, a manual scan of the title and abstract was conducted, and then the paper was included if it was considered relevant (the inclusion criteria is specified in the next section). In Phase 2, each paper's *reference list*, found from the electronic search, was manually scanned in order to identify other potentially relevant studies. Thus, the *snowballing technique* [66] was used in phase two to pursue additional papers from *citation counts* and the list of references in each paper, essentially performing forward and backward searches. All searches conducted are based on a full screening of the studies, which were published between January 2010 and December 2014. The following search strings were used in the electronic databases:

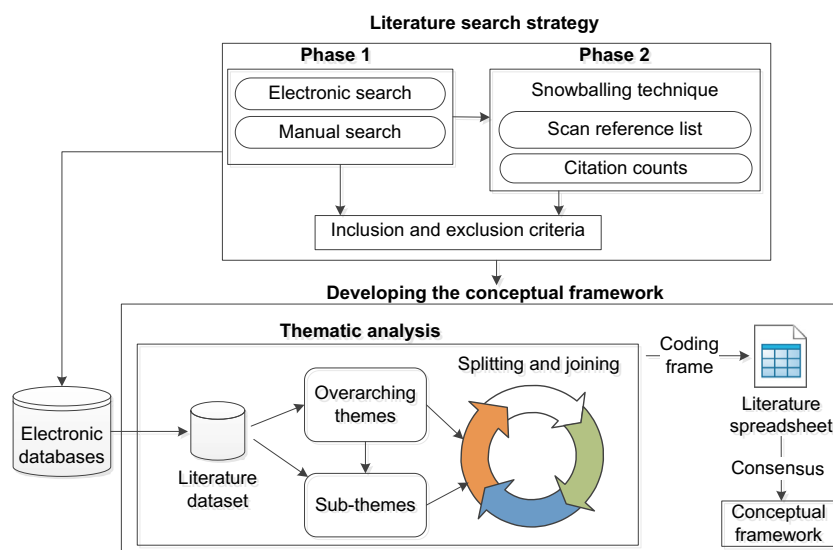


Fig. 2. Literature survey research protocol adapted from Afzal et al. [62]. The *literature search strategy* includes resources and the necessary steps used to survey the evidence and criteria for including studies. The *developing the conceptual framework* consists of the method and protocol used to construct the conceptual framework from the literature dataset.

- Falls prevention technology AND older adults OR elderly.
- Falls systems AND patients OR older adults OR elderly.
- Falls management AND patients OR older adults.
- Falls prevention assistive technology AND patients OR older adults.
- Falls prevention approaches AND patients OR older adults.

Search terms that were used in this review were purposely kept general to avoid potential bias in identifying a candidate dataset of studies which represents the state of the art. To enhance the search, Boolean operators were used so that synonyms of search terms were included when carrying out automated searches. Preliminary searches were conducted to identify search terms from existing reviews and to combine those search terms that derived from the reviews. Fig. 3 presents the list of electronic databases used, the number of studies retrieved from the searches carried out using search terms with for each respective electronic database, the duplicate papers removed, and the total number of papers that were deemed relevant.

The inclusion and exclusion criteria were used to identify appropriate studies, which proposed technology-based systems/

applications that aimed to: aid in fall risk assessment and/or prevention activities, respond to falls, or aid in reducing the risk of falling with or without the support of clinicians. Incomplete studies and studies written in another language other than English were excluded. To ensure that the literature dataset reflected recent developments in the field whilst remaining manageable, all studies that appeared in the period 2010–2014 were included, any studies that were outside this time period were excluded from the sample. Studies that did not involve the use of technology for falls prevention activity were also excluded from the corpus. Each study reference list was scanned for additional studies that met the inclusion criteria.

2.2. Developing the conceptual framework

The conceptual framework was derived from surveying and analysing the literature dataset identified from deploying the literature search strategy presented in Fig. 2. A thematic analysis of the literature dataset was then performed in order to review and categorise the studies that were included in the literature sample. Thematic analysis is a qualitative analysis method for searching,

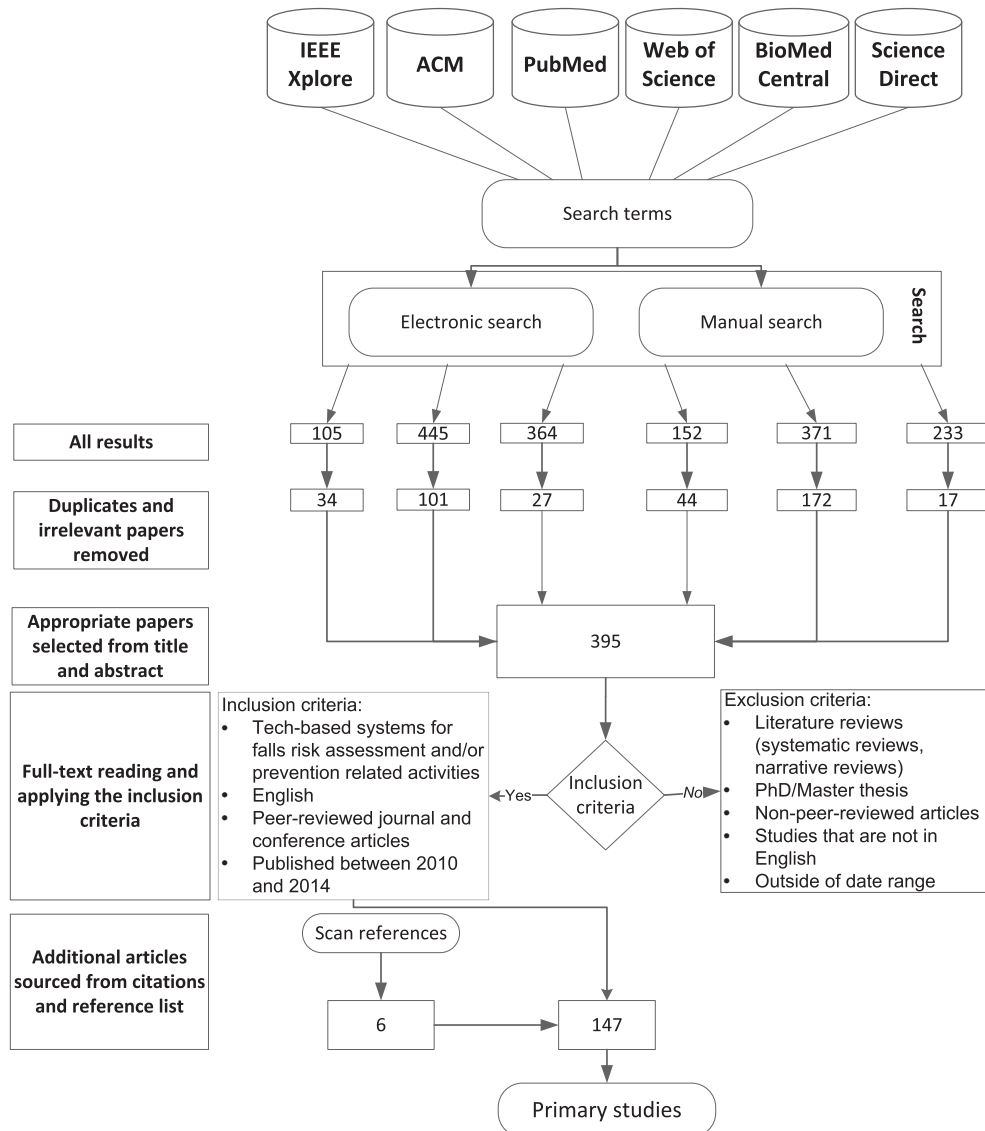


Fig. 3. Literature search strategy. Including the search strategy used to search through the falls prevention technology literature, inclusion criteria set to include relevant studies, and results obtained from the search.

analysing and representing the overarching themes and sub-themes that emerge from textual datasets [67]. Consequently, the themes and sub-themes and their observed interrelated structure which emerged as a consequence of carrying out a thematic analysis on the literature dataset were articulated via the incremental development of a conceptual framework that represents the state of the art of the falls prevention technology landscape. The following steps were taken to analyse the literature dataset and develop the conceptual framework. Initially, all falls prevention technology studies were added into a spreadsheet (used as a data management tool for primary studies that met the inclusion criteria), making up the dataset. After studies were added, the individual studies listed in the dataset were initially examined and *overarching themes* that emerged from the dataset were recorded in the *literature spreadsheet*, which served as a coding frame for carrying out the thematic analysis. Each theme was

allocated to the appropriate code name and extracts of text from the studies that fit each concept were identified. The dataset was examined iteratively, to further develop themes and sub-themes. This was achieved via a process of *splitting and joining* together of themes and associated text that was related to themes and sub-themes. At this point, a list of themes and sub-themes were used to classify each study in the dataset within the coding frame. Several iterations of this reflective process were carried out until the themes and sub-themes reflected the representative literature dataset. Any inconsistencies were rectified, arriving at a *consensus* pool of themes and sub-themes that formed the conceptual framework in Fig. 4. The resulting conceptual framework represents the falls prevention technology landscape according to the literature dataset which was analysed. A detailed description of the conceptual framework and its component parts (themes and sub-themes) is now provided in the next section.

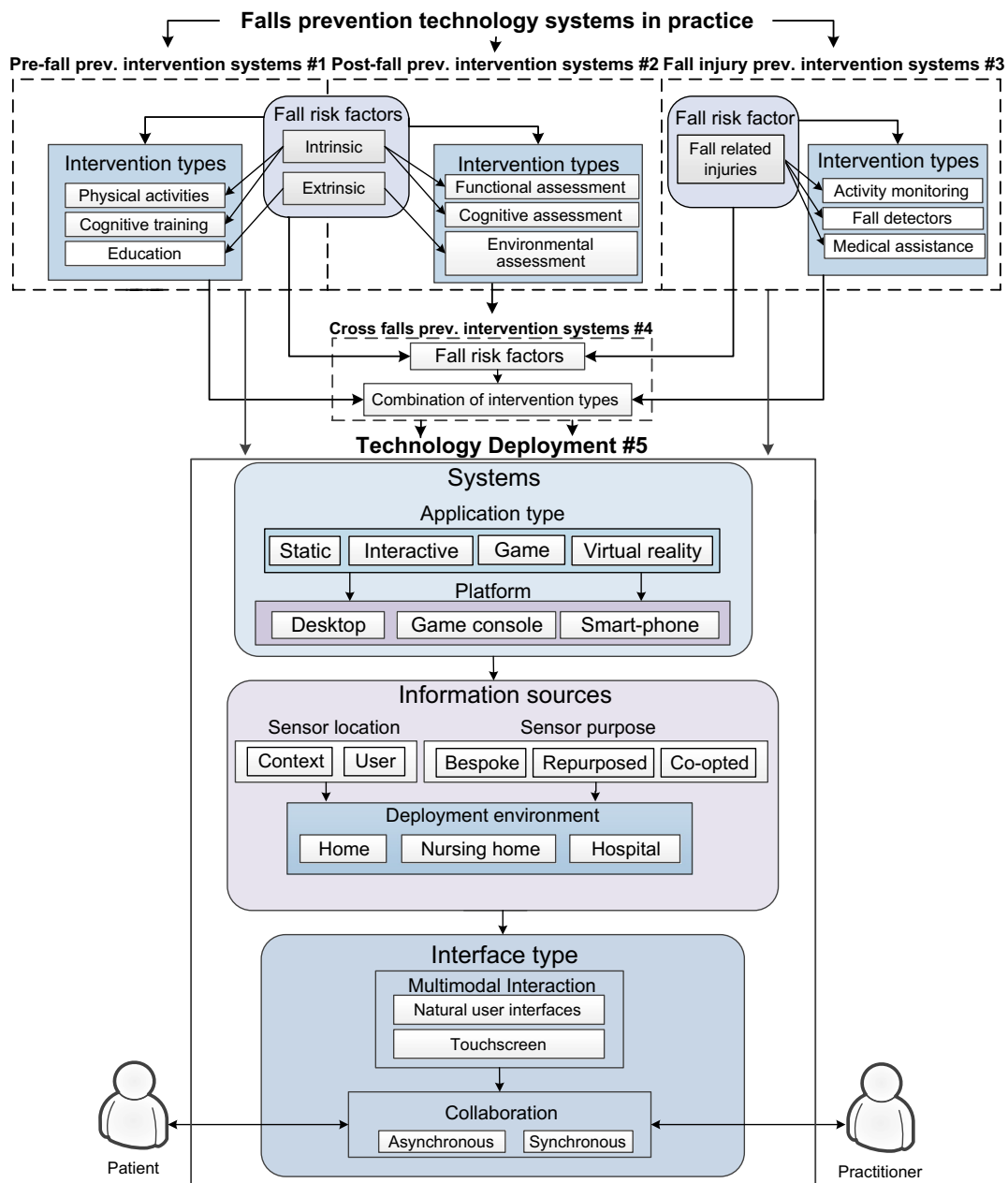


Fig. 4. Conceptual model of falls prevention technology.

3. A conceptual framework of falls prevention technology

The conceptual framework of the state of the art for falls prevention technology is presented in Fig. 4. The model is divided between *falls prevention technology systems in practice* (illustrated in the top part of the figure), which looks at the various falls prevention interventions in practice. The second part of the model considers *technology deployment*, which presents the range of falls technology systems proposed in the literature, the information sources they exploit, the types of user interface which they present and their respective collaborative functions.

3.1. Falls prevention technology systems in practice

There are a wide range of falls prevention interventions and associated systems, which aim to overcome falls and the risk of falling. *Pre-falls prevention intervention systems* (Pre-FPIs) are technology applications that focus on supporting patients who have not yet experienced a fall, but may be considered to be at risk of falling (see Fig. 4, point #1). They take a pro-active approach via the development of applications, which support the delivery of targeted physical activities, exercises and *education* programmes that increase awareness of fall risks and help develop strategies to identify and overcome environmental fall hazards and the complications that may arise after having a fall. *Cognitive training* programmes are also deployed to encourage older adults to engage in activities that stimulate their cognition, hence slowing down the onset of age-related cognitive decline. Cognitive decline occurs as a natural part of the ageing process and can impact on functional ability and therefore lead to increased risk of falls [68–70]. *Fall risk factors* that Pre-FPIs aim to overcome, include *intrinsic risk factors* that relate to natural ageing changes that affect older adults' physical ability, vision, balance, muscle strength and changes to their cognition. Lack of mobility could also result in loss of muscle strength and balance impairments, leading to functional decline and resulting in a fall [71]. *Extrinsic risk factors* include factors that are external to older adults' physical health, functional ability and cognition. These include, for example, environmental hazards that are apparent within older adults' home environment [72] such as poor lighting, wet floor surfaces, loose rugs, slippery handrails, and seating, toileting and bathing furniture, which is not optimally set up or fitted with suitable assistive equipment for an individual's mobility needs or to carry out ADLs safely.

Post-fall prevention intervention systems (Post-FPIs) are applications of technology which focus on individuals who have already experienced a fall and aim to help assess and deliver interventions to reduce the future risk of repeated falling episodes (see Fig. 4, point #2). The strategies employed by Pre-FPI and Post-FPI often share similarities, i.e. applications that support the delivery of exercise and education programmes with a view to overcoming shared *intrinsic* and *extrinsic* fall risk factors. However, the cohort and motivation for delivery of these interventions may be somewhat different in that Pre-FPI takes a pro-active approach and Post-FPI supports the delivery of more re-active interventions. Thus, much of Post-FPIs initially involve fulfilling a diagnostic assessment function, whereby the cause of the fall, which triggered the post fall intervention, is identified along with other intrinsic and extrinsic fall risks. There are a range of *intervention types* that are used to carry out *functional assessment* and *cognitive assessment* of post-fall patients to assess intrinsic risk factors. Functional assessment involves screening the patients' physical movement for risk factors. As such, this includes older adults performing intentional physical activities in order for a range of assessment tests to be performed to gather fall risk behaviour data, which helps to determine the type of risk and the appropriate preventive

measure to take. *Cognitive assessment* includes tests performed to assess cognitive abilities and reduce the progression of cognitive impairments, which typically lead to falls. Delivering this particular intervention provides opportunities for clinicians to determine which preventive interventions are most appropriate to be carried out thereafter and thus, address the intrinsic risk factors identified as a result of the assessment. *Environmental assessment* involves systems developed to assess extrinsic risks that impact on older adults' ability to function independently within their living environment. This type of assessment aims to remove environmental hazards that obscure older adults' ability to perform ADLs and recommend equipment to aid mobility and reduce fall risks in the home.

Fall injury prevention intervention systems (FIPIs) focus attention on patients who are likely and expected to experience falls in the future (see Fig. 4, point #3). Primarily, the aim of many such systems is to detect falls when they occur and to prevent/minimise the injuries that may occur after the event of falling. FIPIs, therefore, often aim to detect falls in order to prevent *fall related injuries* rather than address the risks that lead to falls. There are three main *intervention types* used to tackle these risks. *Activity monitoring* monitors patient movements obtrusively or unobtrusively whilst they perform ADLs and attempts to identify abnormalities, otherwise not apparent. *Fall detectors*, attempt to distinguish fall events from everyday activity signatures, so as to detect fall events when they occur. *Medical assistance* involves the provision of support provided by clinicians after a fall.

Cross fall prevention intervention systems (CFPIs) are technology applications which attempt to support and deliver a combination of pre-fall, post-fall and fall injury prevention interventions (see Fig. 4, point #4).

CFPIs propose technology applications which attempt to deliver system functionality across two or more groups of intervention types i.e. Pre-FPI, Post-FPI and FIPI. An example of a CFPIs that includes Post-FPIs and FIPIs is that of Shi et al. [73] who develop a smart-phone application which assesses fall risks using traditional clinical tests and detects falls after they have occurred in order to prevent fall-related injuries. Another example which combines intervention types of Pre-FPIs and Post-FPIs is that of Silva et al. [37] who assess older adults for intrinsic risks and provide an exercise regime of dancing as a type of physical intervention to enhance the uptake and adherence to exercising more often in the older adult population, particularly those who are prone to falls, in an attempt to and reduce those intrinsic risks such as functional decline and a decline in muscle strength.

3.2. Technology deployment

The *systems* presented in the falls prevention domain host a range of application types and are deployed on a range of hardware platforms (see Fig. 4, point #5). *Application type* refers to the range of applications which are presented to support fall interventions. *Interactive* applications allow the user to interact with the application in some manner, whereas *static* offers no form of interaction between the user and the system. For example, most fall prevention injury applications are static as their main purpose is to collect data and alert when a fall has occurred. *Games* are *interactive* applications that make up another group of falls prevention systems which are typically played by patients with the goal of educating and increasing awareness of fall risks, or to engage the user in exercise and physical activity which is designed to improve mobility and hence reduce the risk of falling. *Virtual reality* (VR) applications present simulated 3D *interactive* environments that allow the user to navigate through these environments and receive feedback in real-time based on multimodal user input. Physical activity interventions are also often augmented by VR applications to engage

users in physical activity and fall related physical exercise. With regards to the *platforms* that falls prevention technology systems are deployed upon; *game consoles* are self-contained platforms in which specific game applications are utilised by falls prevention systems so as to deliver falls prevention related games. For intervention types such as physical activities, the game consoles and sensor devices such as Nintendo Wii and Microsoft Kinect are often used [74–77]. *Desktop computers* are another common platform that systems are often deployed on. In recent years, *smart-phones* have shown promise as an ideal candidate for the deployment of falls prevention applications partly due to advanced processing capability, integrated sensors and communication facilities that such devices now host. A *tablet* is a mobile touchscreen platform, which includes inertia measurement units, sensors (accelerometer, gyroscope, GPS), camera and touchscreen display (requiring touch gestures to interact), replacing the traditional devices such as a keyboard and mouse.

Information sources relate to the range of inputs that systems use to sense the users and the living environments they monitor in order to provide falls prevention system functions. *Sensor location* specifies where the sensors are located, either often as wearable sensors on the *user* or within the *context* of the environment in which the falls prevention system is being used. With regards to context, this may be for example in the form of sensors (camera-based and floor sensors) installed in the living environment which feed information back to the system about the user's interactions with that environment. *Sensor purpose* considers the sensors used by falls prevention systems as belonging to one of three discrete groups: *bespoke*, *repurposed* and *co-opted*. *Bespoke sensors* are developed specifically for falls prevention systems, which often gather physiological data from users. For example, Uzor et al. [41] propose a small sensor which included a big switch to turn the power on and off, light emitting diode (LED) light to show power on and a velcro strap case to enable users to attach the sensor to their body to interact with the falls prevention exercise games. *Repurposed sensors* are sensors, which were originally developed for a different function, but have since been adapted for use within the falls prevention context. For example, Kayama et al. [76] utilise the Microsoft Kinect which was originally developed for gaming, however, due to the natural gesture-based interaction paradigm this technology supports, the Kinect is repurposed to provide the platform for an application that promotes the uptake of a gesture-sensitive falls prevention exercise game. *Co-opted sensors* are typically built into popular devices. For example, the accelerometer and gyroscope that is often built into self-contained smart-phones. These may be used to obtain movement data in order to perform falls prevention interventions, as with the study of Ferreira et al. [78], which exploit the smart-phone platform with the built-in sensors available (e.g. the gyroscope, accelerometer and magnetic sensors) to detect movement by attaching the smart-phone to the user's body. *Deployment environment* reflects the range of living environments in which fall prevention technologies are typically designed to be deployed as specified in the surveyed literature sample. There are three key deployment environments which fall prevention systems are designed to be deployed within: the patient's own *home* living environment; the *hospital* environment, typically for hospitalised patients; and within the *nursing home* environment which may also take the form of an assisted living/sheltered housing environment, whereby residential care is provided to older adults considered to be at risk of falling.

Interface type refers to the form of user interface that each respective falls prevention system provides to its users. *Multimodal interaction* considers the mechanisms that enable users to interact with fall prevention systems, whether the user is the patient or the practitioner. A common interface type used in fall prevention sys-

tems is *natural user interfaces*, which provide patients with a naturalistic way of interacting with fall prevention systems. This typically requires users' natural movements to be monitored and to serve as inputs, gathered via wearable or environmental sensors that are used to control fall prevention systems. This serves as an intuitive way of interacting with the system, particularly when considering that fall prevention systems typically strive to allow users to engage in an unrestricted manner and monitor the user's natural movements within their respective living environments. *Non-interactive interface* is an invisible interface, which relies on intermediary sensor devices to source data from older users and to save that data to a centralised system, with no feedback provided or interaction with the end-users. The other common interface used by fall prevention systems is a *touchscreen interface*, which enables users to interact with fall prevention systems deployed on smart-phones by providing touch gestures to touch an object on the screen. This interface is an evolution of the peripheral devices such as a keyboard and mouse that were used to interact with objects on the screen. Although touchscreens are inherently used for fall prevention systems as they are deployed on smart-phones, they are not part of sourcing of physiological data from users, but rather a means to operate low level tasks.

Users of the fall prevention systems consist of *patients* and *practitioners* interacting with the systems. Patients who use fall prevention systems tend to be older adults, i.e. people over the age of 65 years who experience advanced age changes, age related health decline, and age related declines in physical and functional abilities. *Practitioners* are professionals (e.g. occupational therapists, physiotherapists, nurses, carers, social workers, general practitioners, accident and emergency staff) who deliver care to older adults in the hospital or community. *Collaboration* represents the means by which practitioners work in partnership with patients to deliver an intervention. *Asynchronous collaboration* relates to activities that are performed in real-time, however, the response to these activities do not occur in the time in which they occurred. For example, in case where an older adults' movement data is gathered through the use of fall injury prevention interventions and if a fall event is detected an alert is sent to health care clinicians informing them of a fall. In this particular scenario, there is a time lag between the time of the fall event and the health response to a fall. On the other hand, *synchronous* refers to when users' movement data is gathered in real-time and the response of the movement data is also given in real-time in the form of visual feedback or biofeedback depending on the fall prevention systems that the patient is engaging with. For example, Reed-Jones et al. [79] utilise the Wii to improve balance and mobility in older people. The Wii Fit game was used in conjunction with the Wii balance board, which served as an input device to source movement data from older users to provide real-time visual feedback during game play in order to engage users and to better achieve precise body control as part of the exercise training.

In the following sections, the conceptual framework of falls prevention technology presented in this section is used to survey the systems that have been proposed in the literature. Section 4 reviews pre-falls prevention intervention systems; Section 5 reviews post-falls prevention intervention systems; Section 6 reviews falls injury prevention intervention systems; and Section 7 reviews cross-prevention intervention systems. Table 1 provides a list of abbreviations and terms used throughout the review sections.

4. Pre-fall prevention intervention systems

Pre-fall prevention intervention systems (pre-FPIs) focus on supporting the prevention of falls by targeting risk factors, which if

Table 1
List of abbreviations for terms in the framework.

Abbreviation	Meaning
Async	Asynchronous
Bal	Balance impairments
Bs	Bespoke sensor
Co	Co-opted
Cog	Cognitive impairments
C	Context
DC	Desktop Computer
Eh	Environmental hazards
Fun	Functional ability deficit(s)
G	Game
GC	Game Console
He	Home environment
Hs	Hospital
Nii	Non-interactive interface
NUI	Natural User Interface
Rp	Repurposed sensors
S	Static
Sm	Smart-phone
Sync	Synchronous
Ts	Touch screen
U	User-worn
VR	Virtual Reality

present, are known to be the cause of falls. Table 2 provides a summary of Pre-FPIs considered in this literature survey and which make up the sole focus of this section.

4.1. Fall risk factors

Pre-FPIs target *fall risk factors* that may be considered as a function of two distinct categories: *intrinsic* risk factors [18,19,40–42,75–97,99–109]; and *extrinsic* risk factors [74,98]. With regard to intrinsic risk factors, *functional ability deficits* are the sole focus of a number of studies [74,78,80,83,85,92,107]. In these examples, a range of technologies is used to proactively mitigate observed deficits in functional ability. The study, for example, by Visvanathan et al. [107] monitors the physical activity of patients who are hospitalised and considered to be at a high risk of falling as a result of functional decline. This is achieved via the use of wearable sensors and a sensor network that detects signs of potential risks as a result of physically impaired patients moving around the hospital room without aid. De Morais and Wickstrom [85] develop a serious game based on tai chi, to help improve the stability of those who exhibit balance impairments and impaired mobility. Initially, older adults are given a demonstration of pre-recorded tai chi activities at the start of the game and are then required to mimic those movements during gameplay.

Functional ability deficits and *balance impairments* are the sole focus of many studies [18,19,40–42,75,78,79,81,82,84,86–90,92–95,99,101–106,108], which provide technology-based interventions to enable patients to retain their balance and improve functional abilities in order that physical activities can be performed safely within their normal living environments. For example, Uzor et al. [41] and Williams et al. [42] use 3D visualisation technologies and games to increase adherence rates and engagement with home-based exercises with the aim of improving muscle strength and balance. Another example of this is provided by Hardy et al. [90], who propose an exergame (i.e. exercise game) to reduce balance and gait impairments, thus encouraging older adults to exercise by providing a game that requires movements similar to that of activities found in evidence-based exercise programmes. Although many systems augment evidence-based exercises, some systems encourage users to engage in less structured exercise activities such as dancing. Lange et al. [93], for example, use an off-the-shelf game to help reduce impairments that impact

on older adults' balance by encouraging patients to engage in dancing activities.

The systems presented in [76,77,91,96,97,100] focus on alleviating *functional ability deficits* and *cognitive impairments* (Fun + Cog), which are typically targeted via the use of game applications. As such, cognitive impairments are considered to impact on the patients' functional ability. Some systems attempt to measure the extent to which cognition impacts upon functional ability. For example, Pisan et al. [77] integrate cognitively demanding tasks within a virtual environment, such as solving maths problems in a "simplified stroop test" whilst performing stepping exercises within an immersive virtual environment. The aim is to measure the patient reaction time whilst stepping, in order to uncover the severity of balance impairments whilst multitasking. Hilbe et al. [91] focus on patients in hospitals and nursing homes who are cognitively impaired. Patients are monitored to establish whether they leave their beds and, if so, the clinicians are informed so as to avoid falls in patients who are considered to be at high risk. Kayama et al. [76] and Mirelman et al. [96,97] address the reduction of the dual-task ability, cognition, and balance impairments by executive function and delivering dual-task training as it is believed that such activity improves cognitive function. Dual tasks include users engaging in problem solving tasks and performing tai chi exercises simultaneously within an immersive virtual reality environment. Finally, Schoene et al. [100] propose a game deployed on a game console that includes stepping and balance control tasks to improve reaction time in order to improve physical and cognitive abilities of community-dwelling older adults.

The Pre-FPIs presented in [74,98] both focus on reducing *extrinsic* risk factors, in addition to *intrinsic* risk factors. For example, Bell et al. [74] use a desktop-computer-based game and user-worn sensors to reduce impaired mobility via engaging users in exercise tasks and a gaming narrative which educates the player on environmental fall risk factors such as clutter, placement of furniture, and the dangers of spills on different types of flooring. Otis and Menelas [98] present a smart-phone application which is the only system that focuses solely on reducing extrinsic risk factors. It considers the environmental conditions in which older adults function and notifies them of potential risks. The environment is scanned for slippery surfaces and steep slope by means of a smart shoe with built-in sensors.

4.2. Intervention types

Intervention types used for preventing fall risks in [18,19,41,42,74–108] are typically administered either by practitioners or self-administered by patients. *Physical activities* are intervention types targeted by [18,19,40–42,75,78–95,98,99,101–108], to mitigate these intrinsic risk factors. Studies [18,19,40–42,74–90,92–97,99–108] all explore the value of VR and gaming technologies as a more interactive and engaging platform for patients to engage in exercise activity compared with more traditional approaches. For example, Chao et al. [75] investigate the barriers that lead to a lack of adherence to falls rehabilitation exercises and issues concerning older adults' behaviour towards exercising. Their resulting system included the application of the self-efficacy theory to enhance exercise behaviour to engage older adults in physical activities to increase adherence rates of exercise programmes. The system made use of the Wii which provided both visual and audio feedback based on users performance during the game to encourage users to exercise whilst still using the original idea and purpose of the game to entertain users. Silveira et al. [101] explore the barriers to physical activities such as varying adherence rates to exercise programmes, behaviour towards physical activities and lack of social company whilst exercising. The proposed system is developed to specifically increase exercise

Table 2
Pre-fall prevention interventions.

Pre-fall prevention system	Pre-fall prevention interventions											
	Fall risk factors		Intervention types			Systems		Information sources			Interface type	
	Intrinsic	Extrinsic	Physical activities	Cognitive training	Education	Application type	Platform	Sensor location	Sensor purpose	Deployment environment	Multimodal interaction	Collaboration
Bailey and Buckley [80]	Fun		X				DC	U	Bs	He	NUI	Sync
Bainbridge et al. [81]	Fun		X			G	GC	C	Rp		NUI	Sync
Bell et al. [74]	Fun	Eh	X		X	G	GC	U	Bs	Ns	NUI	Sync
Bieryla et al. [82]	Bal		X			VR + G	GC	C	Rp	He	NUI	Sync
Chao et al. [75]	Fun + Bal		X			VR + G	GC	C	Rp	Ns	NUI	Sync
Chou et al. [83]	Fun		X			S	Sm	U + C	Co + Bs		Nii + Ts	Async
de Bruin et al. [84]	Fun + Bal		X			VR + G	GC	C	Rp	He	NUI	Sync
De Morais and Wickstrom [85]	Fun		X			G	DC	U	Bs		NUI	Sync
Doyle et al. [86]	Fun + Bal		X			VR	DC	U	Bs	He	NUI	Sync
Duclos et al. [87]	Bal		X			VR + G	GC	C	Rp		NUI	Sync
Ferreira et al. [78]	Fun + Bal		X			G	Sm	U	Co	He	NUI + Ts	Sync
Geraedts et al. [19]	Fun		X			VR	Sm	U	Bs	He	NUI + Ts	Sync
Gerling et al. [88]	Bal		X			G	GC	C	Rp	He + Ns	NUI	Sync
Griffin et al. [89]	Fun		X			G	GC	C	Rp		NUI	Sync
Hardy et al. [90]	Fun + Bal		X			G	GC	C	Rp	He	NUI	Sync
Hilbe et al. [91]	Fun + Cog					S	DC	C	Bs	Hs + Ns	Nii	Aync
Horta et al. [92]	Fun		X				Sm	U	Co		NUI + Ts	Async
Jorgensen [18]	Fun + Bal		X			VR + G	GC	C	Rp	He	NUI	Sync
Kayama et al. [76]	Fun + Cog		X	X		G	DC	C	Bs		NUI	Sync
Lange et al. [93]	Bal		X			G	DC	C	Bs	He	NUI	Sync
Majumder et al. [94]	Fun		X			S	Sm	U	Co		Nii + Ts	Async
Ferrari et al. [95]	Fun		X			S	DC	U	Bs	Hs	Nii + Ts	Async
Mirelman et al. [96]	Fun + Cog		X	X		VR	DC	C	Bs		NUI	Sync
Mirelman et al. [97]	Fun + Cog		X	X		VR	DC	C	Bs		NUI	Sync
Otis and Menelas [98]		Eh	X			S	Sm	U	Co		Nii	Async
Pisan et al. [77]	Fun + Cog		X	X		G	DC	C	Bs		NUI	Sync
Rajaratnam [99]	Fun + Bal		X			VR + G	GC	C	Rp	He	NUI	Sync
Reed-Jones et al. [79]	Fun + Bal		X			VR + G	GC	C	Rp	He	NUI	Sync
Schoene et al. [100]	Fun + Cog		X	X		G	GC	C	Bs	He	NUI	Sync
Silveira et al. [101]	Fun + Bal		X			G	T		Co	He	Ts	Sync
Singh [102]	Fun + Bal		X			VR + G	GC	C	Rp	He	NUI	Sync
Smith [103]	Fun + Bal		X			VR + G	GC	C	Rp	He	NUI	Sync
Sparrow et al. [104]	Fun + Bal		X			S	DC			He	Nii	sync
Taylor et al. [105]	Bal		X			VR + G	GC	C	Rp	He	NUI	sync
Taylor et al. [40]	Fun		X			G	GC	C	Bs		NUI	Sync
Uzor et al. [41]	Fun + Bal		X			VR + G	DC	U	Bs	He	NUI	Sync
van Diest et al. [106]	Fun + Bal		X			G	DC	C	Rp	He	NUI	Sync
Visvanatha et al. [107]	Fun		X			S	DC	U	Bs	Hs	Nii	Sync
Williams et al. [42]	Fun + Bal		X			G	DC	C	Bs		NUI	Sync
Young [108]	Fun + Bal		X			VR + G	GC	C	Rp		NUI	Sync

adherence rates and behaviour by involving users in social groups to stimulate participation with training regimes and integrating the system into their daily routine. It also provides feedback on in-game performance and remote contact to supervise older adults during their exercise. The systems presented in [76,77,96,97,100] use a combination of both *cognitive training* and *physical activities* intervention types to reduce fall risks. For example, Pisan et al. [77] present a balance training game that uses Microsoft Kinect to enable older adults to interact with the proposed game. The game involves a series of stepping exercises where squares appear randomly on the screen and the user is required to step on the squares as quickly as possible while solving basic arithmetical problems. The results from this study revealed that performance during the stepping exercises decreases when participants engage with physical and cognitive tasks simultaneously, indicating that users could potentially be at high risk of falling when multitasking. Schoene et al. [100] use exergames to address the issue of lack of adherence to exercise programmes in light of improving older adults' balance, stepping ability, cognition and other factors associated with falling. This exergame consists of a dancing gameplay, which provide instructions to perform dance moves using a step pad, with the aim of train balance, reaction and attention. *Education* and *physical activities* are intervention types in [74] which are used to reduce both intrinsic and extrinsic risk factors of falling. Bell et al. [74], for example, investigate the benefits of utilising the Nintendo Wii game console for preventing falls in assisted-living environments. Participants in this study engaged in exercise training with the use of the Wii combined with falls prevention education sessions. The fall prevention education sessions focus particularly on reducing clutter, arrangement of furniture in the living area, positioning of the rug, flooring and spills within the home environment, lighting, and staircase and bathroom safety, presented in the format of checklists.

4.3. Systems

Pre-FPIs take the form of a range of *application types* and are deployed on a range of *platforms*. The application types presented in [83,91,94,95,98,104] are all *static*; they are essentially data collection tools which issue an alert to notify users of potential fall risks as a consequence of abnormal walking/behavioural patterns, which are collected from sensors. For example, Majumder et al. [94] propose a system which includes a feature extraction technique to conduct an analysis of walking patterns collected in real-time to determine whether there is a potential risk of the user falling. This system does not involve any notable form of interaction, as it simply analyses and sends alerts based on the data that is collected from patients. Otis and Menelas [98] develop a prototype of an instrumented shoe with embedded sensors actuators which are positioned in certain parts of the shoe to collect data, categorise the fall risk status of the environment, and then broadcast this in real-time to a smart-phone application. Horta et al. [92] propose a smart-phone-based system using built-in sensors to collect physiological data from older adults to inform them of any abnormal behaviour in their walking pattern. Chou et al. [83] detect the position of patients from that of lying-to-sit and alert the user with a warning that there is a high risk of falling while getting out of bed. Once the transitions of the patients have been detected, a notification is sent to clinicians in order to provide care and prevent bedside falls.

All of the *game* applications presented in [40,42,74,76–78,80,81, 85,88–90,93,100,101] make use of the Wii games console to detect user movements in real-time and enable users to interact with games and control in-game avatars. These studies explore the effects of such an interaction paradigm and evaluate its suitability to the fall and the prevention intervention domain. With regards

to suitability, the Wii game console is a relatively low-cost solution and has the capability to simulate an array of physical activities; hence it has become a popular repurposed platform used in attempting to overcome the issue of uptake of and adherence to falls-related exercise interventions. Bainbridge et al. [81] examine the efficacy of a Wii Fit game for reducing balance impairments among community-dwelling older adults. Although the results in this study suggest that the Wii Fit game program can be an effective intervention for clinicians to prescribe to patients, it also reports that further research is needed to optimise its effectiveness and to better target the types of movement necessary to reduce fall risks. The most common sensor devices used with the Nintendo Wii are colloquially referred to as “Wii-motes”, which are hand-held sensor devices with built-in infrared and accelerometer sensors and are similar in size to a TV remote control. The Wii balance board, with pressure sensors, is often used to monitor and assess patients balance. Williams et al. [42], Bell et al. [74] and Schoene et al. [100] use the Wii balance board with the Wii Fit game to assess its feasibility for improving the balance of older adults who had fallen previously, based on clinically established balance assessment tools such as the Berg Balance Score (BBS), Tinetti Test, Falls Efficacy Scale – International (FES-I), and Timed Up and Go Test (TUG). Pre-FPI systems presented in [19,86,96,97] are VR applications. The use of the Wii balance board device appears to reduce the fall-related risks based on the outcome measures of balance and functional ability, as reported in the studies. However other systems, specifically [18,41,75,79,82,84,87,99,102, 103,105,108], are all interactive *virtual reality* and *game* applications which typically provide the user with a means of interacting with the application by the system responding to the user's physical state, where aspects of the system are manipulated by their movement.

A number of Pre-FPIs [19,78,83,92,94,98,101] are deployed on *smart-phone platforms*. As a result of advancements in smart-phones, they are an ideal technology for tackling an issue like fall prevention, as data can be obtained via built-in sensors. An example of the use of smart-phones is that of Ferreira et al. [78] who propose a smart-phone-based falls prevention system operating based on user movement which was then translated to movements performed for exercises in a serious game application. The main purpose of the study is to increase adherence of older adults exercising within their home. Majumder et al. [94] propose a fall prevention system for identifying abnormal gait patterns in real-time to predict an imminent fall and prevent it from occurring by notifying the user on the likelihood of a fall occurring. This system was deployed on a smart-phone and used the embedded sensors. Horta et al. [92] and Majumder et al. [94] propose a smart-phone-based solution to obtain movement data from older adults in real-time to inform users of abnormal walking pattern behaviour identified by the system, thus helping to avoid the occurrence of falls. This data is also shared with other stakeholders, such as clinicians or carers. The remaining system [101] is deployed on a tablet. Silveira et al. [101] develop a tablet-based exercise intervention system as it provides a touchscreen display rather than keyboard and mouse and is reported to be more intuitive in providing feedback based on in-application performance. The Pre-FPIs presented in [18,40,75,79,81,82,84,86–90,99,100,102, 103,105,108,109] are repurposed *game consoles*. Bell et al. [74] and Lange et al. [93] investigate the utility of the Wii game console for preventing falls, particularly to educate older adults on exercise training and the environmental hazards that often contribute to falls. There are also Pre-FPIs [41,42,74,76,77,80,85,91,93,96,97,104, 106,107] that are deployed on *desktop computers*. This is exemplified in the study conducted by Uzor et al. [41] who develop both a game and VR application for desktop computer platform using bespoke sensors to control the system.

4.4. Information sources

The Pre-FPIs presented in [18,19,40–42,74–108] all use *information sources* to enable the patient and/or practitioner to interact with the systems in some manner. There are, however, differences in the information sources and the way in which information is sourced from the user of the system. *Sensor location* comprises of two distinct categories, namely, are *context* and *user*. *Context* sensors are the main devices used in [18,40,42,75–77,79,81,82,84,87–91,93,96,97,99–106,108] to source information from patients unobtrusively, without the need for users to wear a device to interact with VR or game applications. Kayama et al. [76] utilise Microsoft Kinect as an input device, deployed in the environment, to enable older adults to interact with a game application. Taylor et al. [40] utilise the Nintendo balance board as an input device where the user stands on the board to interact with the game. Hardy et al. [90] and Griffin et al. [89] utilise Nintendo balance board to improve balance by controlling in-game avatar and to move virtual objects in order to achieve the game objective and to physically engage the patient as part of an intervention. Finally, Mirelman et al. [96] and Mirelman et al. [97] use pressure on the treadmill to capture physical movement of older adults performing physical activities. On the other hand, *user-worn* sensors in [19,41,74,78,80,85,92,94,95,98,107] require users to wear them in order to obtain the movement and translate that motion to control the system for clinical use. For example, Uzor et al. [41] built a bespoke sensor device that was used to enable patients to control the game and was considered less intrusive than other devices such as Microsoft Kinect and Wii Remote, and also ideal due to its size to attach it to specific parts of the body to capture the movement. Bailey and Buckley [80] utilise bespoke sensors to collect data from older adults performing ADLs as an attempt to understand the cause of falls.

Sensor purpose refers to the type of sensing devices used to capture data from users and consists of bespoke, repurposed and co-opted sensors. *Bespoke* sensors [19,40–42,74,76,77,80,85,86,91,93,95–97,100] are custom-built sensors developed specifically for fall prevention and deployed within the living environment or worn by older adults. For example, Hilbe et al. [91] propose a “Bed-exit” alarm used to reduce bedside falls. The pressure sensors were designed and integrated on the side rails of the patient’s bed to track their attempt to get out of bed. The side rail is in a certain position so that if pressure is detected from the pressure sensor, with the value exceeding the threshold, an alarm is sent to clinicians (e.g. nurses) in order to prevent a fall from occurring. Williams et al. [42] use the Wii balance board as an input device with the Wii Fit game and balance assessment tools to improve the balance of older adults who are vulnerable to fall risks. Commercially available *repurposed* sensors are used to interact with falls prevention exercise games. For example, Pisan et al. [77] and Kayama et al. [76] utilise Microsoft Kinect with a game developed for older adults at risk of falling. The game measures changes to patients’ functional and cognitive abilities by carrying out physical and cognitive tasks simultaneously, as reduction in multi-tasking is known to be a predictive factor of a risk of falling. In particular, using Kinect is ideal as it is a cost-effective means of obtaining data from patients unobtrusively without the need to wear or to control handheld devices.

Co-opted smart-phone sensors are now enabling applications such as fall prevention, detection and monitoring patients [110,111]. The pre-fall prevention systems presented in [19,78,83,92,94,95,98,101] made use of built-in sensors on smart-phones, which lend themselves well to tracking user movement in order to achieve outcomes of fall interventions. An example of a smart-phone application is that of Horta et al. [92] who use built-in sensors on smart-phones to capture physiological data

from older adults in real-time. Otis and Menelas [98] propose a smartshoe to track the movement of patients and collect information from smart-phone sensors to the developed application. Smart-phones are considered an ideal tool for falls prevention due to their self-containing nature, size, portability and that they can also be used to communicate with other sensors making the applications more wide-reaching. Finally, Chou et al. [83] develop a system to detect the position of patients from lying to sit and alert the user with a warning that there is a high risk of falling while getting out of bed. Once the transitions of the patients have been detected, a notification is sent to alert clinicians in order to provide care and prevent a bedside fall.

4.5. Interface types

Natural user interfaces [18,40–42,74–77,79–82,84–90,93,96,97,99,100,102,103,105,106,108] enable users to interface with systems when performing physical activities during game-play and collect ambulatory/behavioural data from users unobtrusively. Mirelman et al. [96] augment treadmill exercise training with VR technology to improve functional ability and cognitive function, thereby reducing falls. Users perform exercises on the treadmill; those movements are then translated into inputs in a virtual environment which present users with obstacles, as well as other challenges, that they have to overcome. Feedback (visual and auditory) is presented to users based on errors that are made and tasks successfully completed. Systems presented in [19,78] use *touchscreens* and *natural user interfaces*, which are a specialised way of interacting with technology-based interventions to reduce fall risks. Although this type of interaction does not involve nor measure any physiological parameters, it enables touch input in order to operate some systems. It is a required action to interact with some systems. Ferreira et al. [78] propose a falls prevention game that use embedded sensors on smart-phone to enable users to interact with the serious game application via the use of the built-in touchscreen. *Non-interactive interfaces* [91,98,104,107] enable interventions to be administered without an interactive interface to engage users. For example, Sparrow et al. [104] propose an automated home-based exercise programme that provide voice response for real-time guidance whilst older adults performed their exercises. The programme is administered over the telephone with no interactive form of feedback or interface present to guide or engage users in a way that feedback is given of their performance during exercises. The remaining systems [83,94,95] use both non-interactive interface and *touchscreens* for Pre-FPI systems to perform fall prevention activities, such as gathering of data via built-in sensors and to use the platforms touchscreen to initiate the activities or to visualise analysis of the data that prevent fall risks. Chou et al. [83], for example, use sensors integrated into the patient’s bed to detect when an attempt is made to leave the bed without aid. This system does not require any form of interaction, as it is a monitoring tool for clinicians to prevent hospitalised patients from attempting to leave the bed. Once the alarm is triggered, the system on the smart-phone receives the alarm signal and clinicians are notified by a text message alert, which gives details of data received from the bed sensors, such as codes that indicate posture position.

In terms of *collaboration*, the systems presented in [18,19,40–42,74–82,84–90,93,96,97,99–108] enable *synchronous collaboration* and engagement between patients and clinicians via a range of interface types. In the study by Marisa Ferrari et al. [95], clinicians supervise participants in an exercise training with the use of the Nintendo Wii in a nursing home. Users were provided with immediate feedback of their in-game performance to improve their functional ability and balance. Although it is not made clear if patients were involved in the decisions made in this intervention, the fact

that both practitioners and patients are engaging in the intervention at the same time provides an opportunity for patients to be seen as more equal partners in their own care. Conversely, the remaining studies [83,91,92,94,95,98] are considered as *asynchronous* in that response from sourced movement data does not occur in real-time. The studies of Hilbe et al. [91], Majumder et al. [94] and Marisa Ferrari et al. [95] monitor older adults physical activities in an attempt to predict the likelihood of falling. Data such as abnormalities in walking patterns and critical patients leaving their bed are sourced from patients to prevent falls. As these systems monitor to improve health outcomes such as reduced fall risks, clinicians only intervene when the data collected suggests that the patient is at high risk of falling. No feedback is provided, as the purpose of these systems is simply to unobtrusively collect data that reflects ADLs, rather than perform activities to improve functional ability and balance to undertake ADLs.

4.6. Discussion

Pre-FPIs provide a useful way of preventing the onset of risks and treating fall risks using intervention types to reduce: functional ability deficits [40,74,80,81,85,89,92,94,95,107]; functional ability deficits and balance impairments [18,41,42,75,78,79,82,84,86–88,90,93,99,101–106,108]; and functional ability deficits and cognitive impairments [76,77,91,96,97,100]. However, limited attention is given to reducing both functional ability deficits and extrinsic risk factors [74] or focusing solely on reducing extrinsic risk factors [98]. A considerable number of Pre-FPIs have focused their efforts on alleviating intrinsic risks, with limited effort invested into providing support for overcoming extrinsic fall risks and the process of provision of assistive equipment in order to mitigate some of these extrinsic fall risk factors. This is despite the provision of specialist assistive equipment being one of the key interventions used to mitigate fall risks associated with functional decline.

The consensus of the fall technology literature reviewed indicates the increasing popularity and reusability of VR and game applications which aim to address the limitations of clinical interventions, particularly adherence and uptake issues. Based on results of studies presented in [40,42,74,76–78,80,81,85,88–90,93,100,101], games are often proposed as an adjunct to traditional interventions and are not typically designed to replace existing interventions. It seems that users are motivated by the use of exercise games as they can provide feedback on performance, thus creating a more stimulating and entertaining experience. Employing such technology reduces travel costs for older adults who travel to rehabilitation centres [112] and increases patient motivation to engage with proposed falls prevention intervention programmes. From the corpus of research reviewed [18,19,40–42,74–108], it seems that there are limited research efforts that utilise VR technology and games to augment fall education interventions aimed at reducing extrinsic fall risks with the exception of [74,98], which also lack the use of such technology.

Surprisingly, given the ever-increasing ubiquity of smart-phones with patients and clinicians, a relatively small number of Pre-FPI are deployed on smart-phones [19,78,83,92,94,98,101] compared to the majority, which are on desktop computers [41,42,74,76,77,80,85,86,91,93,96,97,104,106,107] or repurposed game consoles [18,40,75,79,81,82,84,86–90,99,100,102,103,105,108,109]. A possible explanation for this may be that game consoles more naturally possess the requirements and functionality that can be more readily repurposed for the function of developing rehabilitation exercise intervention applications. Nonetheless, smart-phones have shown promise in deploying Pre-FPIs, especially to help capture physiological data [18,19,40–42,74–79,81–100,102,103,105–108], but also in a much broader sphere,

hence the need to further explore their use to tackle both intrinsic and extrinsic risk factors. The advancements of smart-phones have increasingly become a portable device with unprecedented computational power similar to that of desktop computers.

One issue that stands out is the extent to which these systems allow patients and practitioners to collaborate. Whilst some of Pre-FPIs support asynchronous collaboration (i.e. not real-time collaboration) [19,78,79,82,92,94,98–100,102,104], the remaining studies [18,40–42,74–77,80,81,83–85,89–91,93,95–97,101,107] are synchronous, thereby giving an opportunity for patient and practitioner to collaborate as they are in an environment during the intervention. Given the long-term goal of health care delivery, particularly within the UK, to increase the extent to which patients are more equal partners in the delivery of care [47–49,113], it seems many Pre-FPIs are creating opportunities to support patient engagement in care and the decision making that is required whilst providing this care.

5. Post-fall prevention intervention systems

Post-fall prevention intervention systems (Post-FPIs) are typically used in the first instance to screen patients for fall risks after they have experienced a fall. Fall assessments are traditionally conducted within controlled environments, such as within a specialised falls clinic environment or alternatively within uncontrolled environments. The latter are often carried out as longitudinal assessments, where older adults are remotely monitored over a period of time in order to identify activity signatures that correspond to fall risks. Although Pre-FPIs have yielded many benefits for promoting health promotion activities to prevent the onset of fall risks, similar fall risk factors are diagnosed and treated via Post-FPIs. Table 3 provides a summary of Post-FPIs and their respective characteristics.

5.1. Fall risk factors

Post-FPIs and technologies that focus on preventing falls by screening and assessing for fall risks may also be considered as a function of two *fall risk factor* categories: *intrinsic* risk factors [39,114–130]; and *extrinsic* risk factors [38]. With regards to intrinsic risk factors, *functional ability deficits* are the sole focus of assessment in [114–119,121–123,125–130]. Majumder et al. [119] detect abnormalities in gait patterns, which are considered to be a common cause of falling in the older adult population. Users are notified of the likelihood of falling based on data collected and classified to determine whether or not the patterns of ADLs are abnormal. Redmond et al. [121] provide an unsupervised continuous fall risk assessment for older adults who live independently with a high risk of falling and who have been selected for clinical intervention. Staranowicz et al. [127] and Weiss et al. [128] present systems which monitor older adults' gait in real-time from ADLs and collate the motion data in order to predict falls so that older adults can receive early intervention. Zijlstra et al. [130] and Greene et al. [118] present approaches to monitor and assess fall risks for older adults performing clinical tests which emulate ADLs. Riva et al. [123] and Soaz and Daumer [126] analyse gait patterns to determine the association between features extracted from gait patterns with a history of falls in order to target older adults who are in need of clinical interventions. Almer et al. [114] develop a framework which was evaluated with a series of assessment tests (2-Minute Walk, Sit-to-Stand 5 and Timed Up and Go) by recoding movement data and using feature extraction techniques to determine fall risks in the movement data. Cuddihy et al. [117] monitor gait in older adults and notifies caregivers of any changes as they

Table 3
Post-fall prevention interventions.

Post-fall prevention system	Post-fall prevention interventions											
	Fall risk factors		Intervention types			Systems		Information sources			Interface type	
	Intrinsic	Extrinsic	Functional assessment	Cognitive assessment	Environmental assessment	Application type	Platform	Sensor location	Sensor purpose	Deployment environment	Multimodal interaction	Collaboration
Almer et al. [114]	Fun		X			S	Sm	U	Co	He + Hs	Nii + Ts	Async
Barelle and D. Koutsours [115]	Fun		X			S	DC	C	BS	He	Nii	Async
Brell et al. [116]	Fun		X			S	DC	C	BS	He	Nii	Async
Cuddihy et al. [117]	Fun		X			S	DC	C	Rp	He	Nii	Async
Du et al. [38]		EH			X	S	DC	C	BS	He	Nii	Async
Garcia et al. [39]	Fun + Cog		X	X		VR	DC	C	Rp	-	Nii	Sync
Greene et al. [118]	Fun		X			S	DC	U	BS	He + Hs	Nii	Async
Majumder et al. [119]	Fun		X			S	Sm	U	Co	He	Nii + Ts	Async
Rawashdeh et al. [120]	Fun + Cog		X	X		VR	DC	U	BS	Hs	NUI	Async
Redmond et al. [121]	Fun		X			S	DC	U	BS	He	Nii	Async
Regterschot et al. [122]	Fun		X			S	DC	U	BS	He	Nii	Async
Riva et al. [123]	Fun		X			S	DC	U	BS	.	Nii	Async
Schoene et al. [124]	Fun + Cog		X	X		G	DC	C	Rp	He + Hs	NUI	Sync
Singh et al. [125]	Fun		X			G	DC	C		He	NUI	Sync
Soaz and Daumer [126]	Fun		X			S	DC	U	BS	He + Hs	Nii	Async
Staranowicz et al. [127]	Fun		X			S	Sm	C	Co	He + Hs	Nii + Ts	Async
Weiss et al. [128]	Fun		X			S	Sm	U	Co	He	Nii + Ts	Async
Zhang et al. [129]	Fun		X			S	DC	U	BS	He	Nii	Async
Zijlstra et al. [130]	Fun		X			S	DC	U	BS	He	Nii	Async

also carry out assessments remotely and take preventive measures to alleviate fall risks. Singh et al. [125] and Barelle et al. [115] present an approach in extracting gait features from the walking patterns of older adults' to perform early diagnosis of functional decline for a more accurate estimation of fall risks. Post-FPIs presented in [39,120,124] address both *functional ability deficits* and *cognitive impairments* via the use of dual tasking. Schoene et al. [124] introduce a device that serves as a proxy to measure older adults with severe cognitive and physical impairments. Reaction time of stepping ability is used to predict potential risk of falls. The remaining Post-FPIs [38] focuses solely on the *extrinsic* risk factors. Du et al. [38] develop a robot to screen older adults' living environment for typical *environmental hazards* such as, to name a few, poor lighting, unstable furniture, lack of equipment in the bathroom and then provides that information to clinicians.

5.2. Intervention types

Post-FPIs *intervention types* consist of *functional assessment*, *cognitive assessment* and *environmental assessment*. In particular, functional assessment is the main intervention type presented in [114–119,121–123,125–130] in order to determine intrinsic risk factors such as *functional ability deficits*. Majumder et al. [119] develop a smart-phone-based fall assessment system to monitor abnormal gait patterns from older adults performing physical activities that are constituted as ADLs. The gait patterns are collected from users over a period of time from walking and carrying out ADLs. Staranowicz et al. [127] propose a system which monitors the walking patterns of older adults' during their ADLs at home and identifies functional decline via the use of an autonomous robot. The systems proposed in [39,120,124] use cognitive assessment and functional assessment to assess functional ability deficits, balance and cognitive impairments. Patients are encouraged to conduct physical activities and cognitively demanding tasks to determine fall risks. Garcia et al. [39], for example, present a Kinect-based system to gather timing of movement to measure the reaction time of stepping ability tasks. This is referred to in this study as choice stepping reaction time (CSRT) and it is used to predict falls. As such, this approach measures physical abilities including strength and balance, and cognitive abilities such as attention and speed of processing. The remaining system presented in [38] conducts *environmental assessment* for fall risks. Du et al. [38] develop a robotic system that screens the patient's home, operated remotely by clinicians, with the robot being navigated around the home whilst checking for fall hazards. Essentially, this system automates home assessments that are typically conducted by clinicians.

5.3. Systems

Post-FPIs presented in [38,114–119,121–123,126–130] are all *static* systems, i.e. they do not provide the user with an interactive interface. Cuddihy et al. [117] propose a static system that measures gait based on ADLs performed by older adults. The system requires no form of interaction as its main function is to unobtrusively collect data in order to analyse gait patterns. Riva et al. [123] Soaz and Daumer [126] and Greene et al. [131] use wearable sensors, with no interface, to assess users' physical activities and balance to predict the potential risk of falling. Robinovitch et al. [132] use video cameras to record footage to identify falls or the environmental and behavioural factors that lead to falls. Almer et al. [114] and Majumder et al. [119] develop static applications to collect fall-like data from users to assess the data for fall-related behaviour. The applications used smart-phone sensors to extract features that are fall-like behaviour; however, the interface on the smart-phone was not used. Conversely, *game* and *VR* applications

presented in [39,120,124,125] are purpose-built or repurposed to screen older adults for intrinsic risks through game-play or simulation. Singh et al. [125] provide a balance game using the Nintendo Wii balance board to measure agility and balance in older adults. This system can also be used to reduce balance impairments as it empowers older adults to train frequently by providing visual feedback based on movement performed, converting real-life movement into virtual movement as part of an in-game narrative. The majority of the systems presented in [38,39,115–118,120–126,129,130] are deployed on a desktop computer platform, whilst the remaining systems in [114,119,127,128] are deployed on a smart-phone platform.

5.4. Information sources

The Post-FPIs presented in [38,39,114–130] exploit a range of *information sources* to gather data from patients. In particular, *users* one of the key *sensor locations* in [114,118–123,126,128–130] to gather information relating to the users' physical movement and to reduce the progression of fall risks. For example, Weiss et al. [128] use a bespoke wearable sensor to collect long-term gait patterns from older adults performing their ADL routine in order to capture properties and characteristics of fall risks in a real-life setting and complement conventional performance-based tests. Providing such a solution not only enables fall risks to be assessed remotely, but it also uncovers useful information regarding the quality and quantity of ambulation performed by older adults in the home. Conversely, *context* is exploited in [38,39,115–117,124,125,127] to source information unobtrusively from patients. Barelle et al. [115] develop an ICT-based home care system to monitor patients with gait impairments in order to diagnose early potential fall risks before a fall occurs and to respond with appropriate interventions. The system enables independent living at home by use of biomechanics data and indicators of gait impairments recorded in a schedule agreed with medical staff and patients based on health status and ADLs.

Sensor purpose consists of sensors tailored for reducing falls or built-in sensors repurposed for technology-based interventions. In particular, systems presented in [114,119,127,128] use *co-opted* smart-phone sensors as wearable devices to collect data from users. For example, Staranowicz et al. [127] and Weiss et al. [128] use accelerometer and gyroscope sensors on smart-phones to assess users' gait patterns for any abnormalities to notify users of potential falls. Users are not required to wear the smart-phone on any particular part of their body, however, it has to be on their person as the built-in sensors gather acceleration and movement data while users are walking. Almer et al. [114] present a smart-phone-based falls assessment application. The application collects data from built-in sensors such as accelerometer and gyroscope; it was evaluated using clinical assessment tests: the "2-Minute Walk", "Sit-to-Stand" and "Timed Up and Go" (TUG). *Bespoke* sensors are used in [38,115,116,118,120–123,126,129,130] to identify risk factors. For example, Greene et al. [118] propose bespoke body worn sensors to gather older adults movement data. The sensors are attached to the older adults' body whilst performing the berg balance scale (BBS) and the TUG tests. PostFPIs presented in [39,117,124] use *repurposed* sensors. For example, Singh et al. [125] use the Wii balance board as an input device to interact with a balance game to assess older adults balance.

Deployment environment refers to the range of environments in which Post-FPIs are deployed within, namely; the home environment, hospital setting or nursing home setting. The systems presented in [114,118,124,126,127] are deployed within the *home environment* and *hospitals*. The Post-FPIs presented in [38,115–117,119,121,122,125,128–130] are all deployed solely within the *home environment*. Brell et al. [116] conduct clinical tests using a robot

to collect data from patients performing ADLs in their home in order to diagnose fall risks. Other systems are deployed solely within the *hospital setting* [39,120]. Rawashdeh et al. [120], for example, propose a virtual 3D avatar system which reflects the movement of hospitalised patients that are prone to falls. There are no Post-FPIs that are deployed solely within the nursing home environment.

5.5. Interface type

Post-FPIs use *natural user interfaces* [120,124,125] to enable the user to interact with the system. Schoene et al. [124] propose a game which requires natural interactions such as foot movements to interact with the proposed game application. Singh et al. [125] provide an interactive interface to engage older adults to exercise independently and frequently without therapist intervention. The interface provides visual feedback during the intervention to enhance compliance to exercise more often and real-time feedback with regards to users' ability to maintain their balance. Post-FPI systems presented in [38,39,115–118,121–123,126,129,130] are *non-interactive interface* which provide a one-directional flow of data, without presenting feedback of the sourced data to patients. Regterschot et al. [122] use sensors to identify changes in mobility and fall risks to perform clinical tests, without providing an interactive medium to engage users in fall prevention interventions. Zhang et al. [129] use a pendant-worn sensor to detect chair transfers in order to unobtrusively assess fall risks in a non-interactive way. Older adults wear the pendant around their neck like a necklace for continuous monitoring. ADLs, particularly chair transfers, performed by older adults are the system's sole input to conduct fall risk assessments. A system's interface is often driven by the platform it is deployed on. Systems presented in [114,119,127,128], for example, use a combination of non-interactive interface and *touchscreen* built into smart-phones as the sensors collect data from patients, who use the touchscreen to activate in-system functions. Almer et al. [114] develop a smart-phone application with non-interactive interface to conduct assessment tests by obtaining motion data from patients using built-in sensors such as accelerometer and gyroscope, and touchscreen for users to authenticate into the system and to display the system's status and users information. The developed iOS application requires little interaction as it displays the current user and information about the device. The main engine, running the assessment tests, is deployed in the background, indicated by a green light, whilst the tests being performed are also displayed. The systems presented in [39,124,125] enable *synchronous collaboration* between patients and practitioners. Garcia et al. [39] and Singh et al. [125] carry out assessments through patients performing physical activities. Patients are presented with real-time feedback of balance scores and progress made during the assessment programmes. This real-time feedback component improves compliance for patients to regularly assess for fall risks. The remaining systems [38,114–123,126–130] provide *asynchronous* collaboration. Zijlstra et al. [130] monitor patients with mobility issues and fall risks whilst they perform sit-to-stand movements during chair transfers. Data is sourced from patient to provide a longitudinal profile of changes to ambulation and mobility issues during transfers in order to determine potential fall risks. No interface is presented to users, however, sensors are located on the torso of the patients and in and around their home furniture in order to measure power exertion and movement. Collecting longitudinal datasets such as [116] enables patients' movement data to be considered over a period of time. Conducting assessments in patients' homes enables both parties to collaborate to some extent, as patients are assessed remotely by clinicians without both parties having to physically be in the same environment. Rawashdeh

et al. [120] develop a system that senses patients' movement and posture data from sensors attached to different parts of the body (wrist, ankle and chest). The data is sent to a base station in which it is processed in real-time. The processed data is used to animate a 3D avatar that mirrors patients movement. Clinicians respond to abnormalities on the 3D avatar that indicate that patients are at risk of falling. However, no data is directly fed back to patients as its sole purpose is to monitor movement.

5.6. Discussion

Post-FPIs assess patients for intrinsic and extrinsic fall risks using physical, cognitive and environmental assessment interventions. After reviewing these systems, the following observations are drawn with regards to assessing fall risks. The majority of the post-fall prevention systems assesses intrinsic risk factors such as functional ability deficits [114–119,121–123,125–130]; functional ability deficits and cognitive impairments [39,120,124], with limited attention given to extrinsic risk factors [38] which can also result in serious fall injuries. Post-FPIs use a range of intervention types to assess fall risks. Functional assessments [114–119,121–123,125–130] were solely used to assess functional ability to determine risks of falling, whereas [39,120,124] use both functional assessments and cognitive assessments to assess multifactor risks.

While Post-FPI systems play a crucial role in reducing the risk of falling, particularly assessing fall risks, few systems address extrinsic factors [38]. In fact, only one system, [38] has focused on assessing the home environment for extrinsic risks. This system involves a robot to assess the patient's home. A clinician is able to operate the system remotely by navigating the robot around the home whilst going through a checklist of factors. Despite the apparent benefits, the system is not fully autonomous, which makes it prone to handling errors that can affect its reliability, in addition to still needing clinicians time to conduct the assessment tasks remotely.

The consensus of the Post-FIP systems indicates that majority of systems are static in nature and offer no means for users to interact with the systems [38,39,114–119,121–123,126–130]. Therefore, it appears, that limited efforts are spent on systems which provide an interactive means to assess fall risks [120,124,125]. Another challenge yet to be explored in this domain is the patient–clinician collaboration. The majority of systems provide synchronous collaboration [38,39,114,115,117–120,122,123,125–130] where data is sourced from older adults and the response is provided in real-time. The rest of the studies reviewed here present systems that are asynchronous [116,121,124], meaning that data sourced from older adults is not clinically assessed at the time it was performed.

6. Fall injury prevention intervention systems

Fall injury prevention intervention systems (FIPs) aim to detect and respond to falls after they have occurred and prevent or minimise *fall related injuries* that may occur as a consequence of falling. Unlike Pre-FPIs and Post-FPIs, they do not typically focus on overcoming the intrinsic/extrinsic risk factors that may lead to a fall occurring, but rather focus on responding to a fall after it has occurred. These systems typically aim to monitor patient activity with the goal of providing a channel of communication between older adults and clinicians. There are three main *intervention types* that these systems target. *Activity monitoring* involves monitoring patient movements either obtrusively or unobtrusively while they perform ADLs to identify abnormalities in patient daily occupations. *Fall detectors* monitor patient activity in order to identify the discrete occurrence of a fall. In the event of abnormalities or the occurrence of a fall, clinicians can be alerted via an alert for *medical assistance* after a fall has occurred [63]. Many systems have

been proposed over the years and categorised based on their sensors, underlying algorithms and computational techniques used to detect this phenomenon.

Table 4 summarises fall injury prevention systems proposed in the falls technology domain.

6.1. Fall risk factors

All FIPIs presented in [43–45,133–171] focus on minimising *fall related injuries* that may occur as a result of experiencing a fall. For example, Abbate et al. [43] propose a system to monitor patient movement automatically using an artificial neural network and feature extraction machine learning technique which alerts emergency services and other preloaded emergency contacts after a fall has been detected. Mastorakis and Makris [155] present a system using an algorithm which uses a large training dataset which includes falls data and a range ADLs in order to more accurately detect falls when they occur and avoid false positives. Ferrari et al. [143] monitor and track patient movement in hospital, if a fall is detected, the system automatically sends an alarm to clinicians when patients attempt to leave their beds without aid or displays an increase in activity levels. Transmitting this type of data to nurses in the hospital enables them to provide care and assistance when it is needed. Zhang et al. [169] put forward a system that unobtrusively detect falls that occur at night-time where the older adult is unconscious and hence may find it difficult to move without aid. An alarm is generated to inform clinicians of a fall. Cao et al. [44] prevent injuries which occur as a result of lying on the floor after a fall for a long period of time, this is achieved by patients wearing the smart-phone and using the built-in accelerometer sensor to detect falls when they occur. A threshold algorithm was developed which can be adapted to the patient demographic information, such as age, gender, height and weight to increase the detection accuracy of motion outputted from patients' movement.

6.2. Intervention types

The FIPIs presented in [43–45,133–171] use a full range of *intervention types* i.e. *activity monitoring, fall detector and medical assistance* to detect and reduce fall related injuries occurring. For example, Abbate, Avvenutia, Bonatesta, Colaa, Corsinia and Vecchiaia [40] and Abbate, Avvenuti and Light [133] develop filtering techniques to distinguish falls from ADLs in order to specifically identify falls when they occur, gather data profiles about older adult's movements, and automatically send alerts to clinicians in the event of a fall. Cao et al. [44] monitor older adults' activities and acceleration of movement to determine if the older adult is currently experiencing a fall. If a fall is identified, an SMS message is sent to the older adult's carer provide immediate assistance to their client. Bagnasco et al. [136] classifies three different fall types which are front fall, backward fall and lateral fall, which occur as a result of performing ADLs. This approach increases the accuracy of identifying fall events so that they can receive adequate support from clinicians. Kepski and Kwolek [147,148], Yu et al. [45] and Koshmak et al. [149] all provide a means of either obtrusively or unobtrusively monitoring older adults within their living environment to identify falls. Once a fall has been identified, an alarm is triggered for caregivers to provide medical support to older adults who have fallen. Laguna and Finat [150], Werner et al. [168] and Koshmak et al. [149] monitor older adults movement remotely and detect falls when they occur. Paoli et al. [157] and Leone et al. [152] provide notifications to caregivers in the case of a fall and enable them to have authorised access to monitor older adults. Mastorakis and Makris [155] monitor older adults activities to identify a fall by using an algorithm with a 3D

bounding box which calculates the velocity of width, height and depth in order to establish if the activity performed by users is a fall or an ADL. An alarm is sent to clinicians in order to provide immediate assistance to fallers.

Mehner et al. [156] detect falls automatically in order to provide rapid medical support so that fall related injuries will be reduced and to physically help older adults off the ground, particularly in cases where older adults knock their head and are unconscious or not able to seek help. He et al. [145] classify data sourced from monitoring older adult activity. The motion is then split into five sub-patterns which include vertical and horizontal motion, lying, sitting, standing, and falls in order to accurately detect falls by employing a feature extraction technique. Once a fall is detected, an automatic multimedia messaging service (MMS) is sent to preloaded contacts which include the patient's GPS coordinates and auto-generated image of a Google map pinpointing the location of the fall. Cabestany et al. [138] automatically detect falls both inside and outside the living environment and then sends an alert to a call centre, informing them that a fall has occurred. Shim et al. [164] monitor patients in bed in order to detect bed-side falls in an assisted living environment. If patient movement is detected around the bed, it is then necessary to consider it as a potential fall and a caregiver is then notified. Lee and Carlisle [151] provide a mechanism that sources data about the activities of older adults; if a fall occurs, it is then reported to emergency services. Terroso et al. [166] detect a fall, either in or out of the home and send an automatic message to family members and other stakeholders involved in the patient's care. Ren et al. [161] enable caregivers of patients to have access to a centralised cloud server, where data sourced from patients activities are transmitted to it. This enables patients to receive medical attention, in some cases, prior to a fall occurring or soon after the event. A fall is detected by distinguishing ADLs from simulated activities that are stored in the cloud server as fall events. Finally, Sahota et al. [162] reduce bedside falls of patients in hospital by monitoring their activities. If the patients leave the bed, an alarm is triggered and sent to the nursing team of the hospital, providing the location of the patient who has fallen.

6.3. Systems

Application types of all FIPIs presented in [43–45,133–169,171] are *static* typically offering no form of rich interaction or visual feedback based on the activity monitored by these systems. Martín et al. [154], Dai et al. [139], Tang et al. [165] and Fang et al. [142] all gather data from older adults through mechanisms which detect falls based on the movements being made by older adults in real-time. There is no interface present, as the sole purpose is to detect falls and send an automatic message or call automatically to preloaded emergency contacts. FIPIs appear to be heterogeneous with regards to the devices, systems and techniques that underpin them. One of the main objectives of successful FIPIs is to distinguish fall events from ADLs. This has proven to be an on-going challenge and often the primary point of focus of contemporary systems. Much effort has been invested in improving classification algorithms and detection techniques to be able to consistently distinguish fall events from ADLs; however, this is perhaps at the expense of focusing attention on developing more interactive, analytical and informative user interfaces for such systems.

FIPIs are deployed on a range of *platforms* including *desktop computer* [134–136,143,144,148,152,153,157–164,168,169]; *smart-phone* [44,45,133,137,139–142,145,146,149,154–156,165–167,171] platforms. Unlike other system categories, there appear to be no FIPIs deployed on game console platforms. An example of systems deployed on a smart-phone platform is that of Abbate et al. [43] and Abbate et al. [133] who develop a fall detection system on a smart-phone where patients are required to have

Table 4
Fall injury prevention interventions.

Fall injury prevention systems	Fall injury prevention interventions										
	Fall risk factors	Intervention types			Systems		Information sources			Interface types	
		Fall related injuries	Activity monitoring	Fall detector	Medical assistance	Application type	Platform	Sensor location	Sensor purpose	Deployment environment	Multimodal interaction
Abbate et al. [43]	X	X	X	X	S	DC + Sm	C + U	Co + BS	He	Nii + Ts	Async
Abbate et al. [133]	X	X	X	X	S	Sm	C + U	Co	He	Nii + Ts	Async
Albert et al. [134]	X	X	X	X	S	DC + Sm	U	ES	He	Nii + Ts	Async
Aud et al. [135]	X	X	X	X	S	DC	C	BS	He	Nii	Async
Bagnasco et al. [136]	X	X	X	X	S	DC	U	BS	He	Nii	Async
Busching et al. [137]	X	X	X	X	S	Sm	U	Co + BS	He	Nii + Ts	Async
Cabestany et al. [138]	X	X	X	X	S	DC + Sm	C + U	Co + BS	He	Nii + Ts	Async
Cao et al. [44]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
Dai et al. [139]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
Della Toffola et al. [140]	X	X	X	X	S	Sm	C + U	Co	He	Nii + Ts	Async
Fahmi et al. [141]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
Fang et al. [142]	X	X	X	X	S	Sm	U	Co + BS	He	Nii + Ts	Async
Ferrari et al. [143]	X	X	X	X	S	DC	U	BS	He	Nii	Async
Fourlas and Maglogiannis [144]	X	X	X	X	S	DC	U	BS	He	Nii	Async
He et al. [145]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
He et al. [146]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
Kepski and Kwolek [147]	X	X	X	X	S	DC + Sm	C + U	Co + BS	He	Nii	Async
Kepski and Kwolek [148]	X	X	X	X	S	DC	C	Rp	He	Nii	Async
Koshmak et al. [149]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
Laguna and Finat [150]	X	X	X	X	S	DC + Sm	U	Co	He	Nii + Ts	Async
Lee and Carlisle [151]	X	X	X	X	S	DC + Sm	U	Co + BS	He	Nii + Ts	Async
Leone et al. [152]	X	X	X	X	S	DC	C	BS	He	Nii	Async
Li et al. [153]	X	X	X	X	S	DC	C	BS	He	Nii	Async
Martín et al. [154]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
Mastorakis and Makris [155]	X	X	X	X	S	Sm	C	Co	He	Nii	Async
Mehner et al. [156]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
Paoli et al. [157]	X	X	X	X	S	DC	C	BS	He	Nii	Async
Papadopoulos and Crump [158]	X	X	X	X	S	DC	U	BS	He	Nii	Async
Planinc and Kampel [159]	X	X	X	X	S	DC	C		He	Nii	Async
Rantz et al. [160]	X	X	X	X	S	DC	C	Rp	He	Nii	Async
Ren et al. [161]	X	X	X	X	S	DC	U	BS	He	Nii	Async
Sahota et al. [162]	X	X	X	X	S	DC	C	BS	He	Nii	Async
Shieh and Huang [163]	X	X	X	X	S	DC	C		He	Nii	Async
Shim et al. [164]	X	X	X	X	S	DC	C	BS	He	Nii	Async
Tang et al. [165]	X	X	X	X	S	Sm	U	BS	He	Nii + Ts	Async
Terroso et al. [166]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
Viet et al. [167]	X	X	X	X	S	Sm	U	Co	He	Nii + Ts	Async
Werner et al. [168]	X	X	X	X	S	DC	C	BS	He	Nii	Async
Yu et al. [45]	X	X	X	X	S	Sm	C	Co	He	Nii	Async
Zhang et al. [169]	X	X	X	X	S	DC	C	BS	He	Nii	Async

the smart-phone on their person as a wearable device. The system consists of three fundamental components: (1) a device that collects physiological data via wearable and environmentally embedded sensors; (2) a filtering technique to process the sensor data to distinguish it between falls and ADLs; and (3) communication of an alert in the event of a fall occurring.

6.4. Information sources

FIPs exploit a range of *information sources* in order to detect falls. *Sensor location* defines where the sensors are located to source information typically located either on the user or are embedded within the *context* or environment in which the falls are being detected. The sole location of sensors used by the FIPs presented in [44,134,136,137,139,141–146,149–151,154,156,158,161,165–167,171] is on the user. For example, Cao et al. [44] require users to wear a smart-phone device on their body, repurposing the built-in accelerometer in order to monitor the movement of the patient. Another example, that of Terroso et al. [166] uses a wearable accelerometer sensor which sends data on patient movement to the smart-phone application and server. The sensor communicates to the smart-phone application via Bluetooth in order to enable the analysis to be carried out, the geographical location to be logged via the smart-phone GPS sensor, and the message to be sent. Fang et al. [142] propose an android-based fall detection system which requires users to either attach the smart-phone to their chest, waist or thigh to detect the significant change in acceleration in order to accurately detect a fall. Fahmi et al. [141] use built-in accelerometer and orientation sensors which are built into the mobile device to measure the position and acceleration of the user to understand a range of fall characteristics and accurately detect a fall when it occurs.

Context is the main information source used in [45,135,148,152,153,155,157,159,160,162–164,168,169]. Data is unobtrusively collected from patients and is arguably less intrusive than approaches which place sensors on the body of the patient. For example, Kepski and Kwolek [148] use the Kinect to detect falls in a living environment. This approach enables older adults to be tracked in 3D, and is a low-cost solution. Although environmentally embedded sensors unobtrusively source information based on user movement, the system is limited by spatial coverage and is unable to monitor patient movement wherever they go, unless the environment is instrumented by a number of sensors; although this may address such a challenge, doing so is often not practical. Yu et al. [45] use a single camera to monitor community-dwelling older adults in their home in order to detect a fall based on posture. However, in some scenarios wearable sensors and context sensors are used to improve the level of accuracy of detecting falls. The systems proposed in [43,133,138,140,147] all use both the *user* and *context* as an information source. For example, Cabestany et al. [138] propose a small sensor device which require users to attach around their waist or hip to achieve optimal accuracy using a developed algorithm. The device is developed so that it is easy for users to wear while performing ADLs. The context-based device is deployed as a bed sensor to detect falls that occur in instances where users are not wearing their sensor. If a fall has occurred, an alarm will be generated. If there is no physical response from the user, a notification from the sensors is sent to the smart-phone application and a message is then sent to emergency services.

All fall injury prevention systems use devices that have different *sensor purpose* to sense activity signatures that represent fall events. *Bespoke sensors* are used in [135,136,143,144,152,153,157,158,161,162,164,165,168,169] to identify fall events. For example, Bagnasco et al. [136] design a bespoke wearable device that triggers an alarm after a fall, then transmits the data to a base station

via Zigbee, a communication protocol that creates a wireless personal area network with low-powered devices. On the other hand, systems presented in [44,45,133,139–141,145,146,149,150,154–156,166,167,171] use *co-opt* smart-phone sensors to detect falls. For example, Abbate et al. [43] develop a fall detection system on smart-phones that track the movement of patients, identifies a fall and then automatically sends a notification to emergency services. Although there are benefits in using smart-phone sensors, for example, the built-in accelerometer and gyroscope to obtain information from the patient, it is recognised that users have to be willing to wear the device, which can be considered intrusive. Alternatively, there are sensors repurposed to suit detecting falls. *Repurposed* sensors in [148,160] have various forms, such as camera, pressure, and audio or are devices that are brand specific, for example, the Microsoft Kinect. For example, Kepski and Kwolek [148] develop a fall detection system which repurposed the Kinect as an input device to source information from older adults functioning in their living environment. The systems presented in [43,137,138,142,147,151] use *co-opted sensors* and *bespoke sensors* and are considered as distributed systems.

Deployment environment refers to the living environment in which FIPs are deployed. *Home environment* [43–45,133–169,171] relate to FIPs that are developed to detect fall events among community-dwelling older adults. For example, Della Toffola et al. [140] develop a robotic system to be deployed in the patient home. This system monitors older adults and responds rapidly to fall events that occur in the home. A sensor network, which is part of the system, is used to determine where the patient has fallen in the home. The nodes within the network are connected via wireless signal which sends an alert to the robot in case of a fall. The robot then communicates the alert to the clinicians who intervene with medical assistance.

6.5. Interface types

All FIPs use *multimodal interaction* which comprises the way in which information is collected from users, how they control the system, and the in-built touch mechanisms that are embedded into handheld devices. *Non-interactive interface* are used in [43–45,133–171] with no interface presented to the user, but uses sensor devices to source information from users and is employed to control the fall prevention system. For example, Kepski and Kwolek [148] develop a fall detection system using the Kinect as an input sensor device that was used to source information from users in the living environment. Although in a gaming context the Kinect provides users with feedback based on their performance, this system is a non-game application and is used purely for monitoring user movements, hence no specific input required nor an interface presented for users to control the system. Shieh and Huang [163] develop a video-like surveillance system which uses cameras to monitor high risk locations within the home to capture daily movement performed by users. This system is uni-directional as no user interaction is required as multiple cameras are unobtrusively deployed throughout the living environment for a wider coverage and to collect vision data from users in order to detect falls. Li et al. [153] focus on detecting a fall using acoustics in the living environment and automatically sends a notification to the caregiver when the detected fall occurs. Della Toffola et al. [140] monitor ADLs of older adults who are at risk of falling. The system detects falls, but recognises that fall detection is prone to false positives, and hence, a robot is deployed in the environment in an attempt to address these issues and to intervene if a fall is detected. An alarm is sent out to emergency services, caregivers and clinicians. Rantz et al. [160] deploy a camera-based intervention to prevent falls in hospital rooms, preserving patients' privacy and unobtrusively capturing activities that lead to a fall and notify

clinicians of a fall. The systems presented in [43,44,134,137–139,142,145,146,149–151,154,156,165–167,171] use both *non-interactive interface* and *touchscreen* to enable users to use the systems via movement and touchscreen gestures. An example of this is He et al. [145] who present a fall detection system on the Android smart-phone. The embedded sensors on the smart-phone are utilised to collect information on the user's movement. If a fall is detected an alarm message with the time and the patient's location is sent out to clinicians and other preloaded contacts. This system has a natural user interface, as the sensors are embedded into the smart-phone; the user is required to attach the smart-phone to their waist, as required for the built-in accelerometer. On the other hand, the touchscreen function gives the user the option of disabling the system by closing the application or an alert is automatically sent to practitioners.

Collaboration between patients and practitioners in FIPIs occurs as a result of data being sent to practitioners as a consequence of a fall event being detected. However, the collaboration between the two parties is *asynchronous* [43–45,133–171]; these systems do not offer any real-time communication functions to the practitioner in order to communicate with the patient immediately after the fall has occurred. All systems simply alert the practitioner that a fall has occurred, but do not provide any further scope for communication, within the bounds of the system, after the alert has been sent. An example of this is Abbate et al. [43] and Dai et al. [139] who develop systems which enable asynchronous collaboration between the faller and clinician as a notification is sent to the clinician in case of a fall. Even if an older adult has fallen, an opportunity for collaboration does not occur in real-time, but rather when clinicians respond by providing medical assistance to patients.

6.6. Discussion

FIPIs are all commonly used to detect falls and prevent fall-related injuries with the use of intervention types such as activity monitoring, fall detector and medical assistance, which all are interdependent. The falls prevention technology literature appears to be saturated with systems developed to monitor activity, detect falls, and send an alert if a fall is detected. Despite the abundance of FIPI systems in the research literature and the significant benefits in the deployment of such systems, there are a number of challenges that may potentially impact their use in practice. Accurate detection of falls is one such challenge particularly distinguishing the kinematic differences between ADLs and fall events is an ongoing area of research. Preserving users' privacy is also considered challenging [160]. Repurposed camera sensors have an advantage over wearable sensor devices as image processing techniques can be applied to preserve users' privacy. This also offers an unobtrusive way of sourcing information and creates a means of monitoring patients to verify whether or not they have fallen. Repurposed camera sensors are only able to monitor predefined spaces within the living space, however, this can be a benefit in comparison to wearable sensors as, they can source data directly from users without users having to attach a device to their body [148].

Whilst the risk of falling cannot be eradicated due to the inevitable nature of falls occurring as a result of ageing, effective fall prevention measures can be implemented to help minimise the risks from the outset. The majority of the research efforts in falls preventing technology have focused on using and developing machine learning techniques and optimising algorithms to enhance the sensitivity and specificity of accurate fall detection when they occur, with limited efforts expended on the design and interface functionality of these systems. The consensus of the FIPI studies indicate that these systems provide static applications with the sole purpose of detecting falls when they occur,

rather than providing interactive applications that engage patients in interventions that would reduce fall risks. In most FIPI studies, there is a singular focus on reducing fall-related injuries as such injuries happen in the event of fall.

7. Cross falls prevention interventions

Cross falls prevention intervention systems (CFPIs) target the full range of interventions covered by Pre-FPIs, Post-FPIs and FPIs, thus providing an integrated approach to the delivery of falls prevention interventions to patients. Table 5 presents a summary of CFPIs proposed in the research literature.

7.1. Fall risk factors

All CFPIs solely target intrinsic fall risk factors [37,73,172–174], with the exception of [73] which targets both intrinsic and extrinsic fall risk factors. With regard to CFPIs that solely target intrinsic risk factors [37,172–174], *functional ability deficits* are the sole focus of these studies. They are also considered in the study of Shi and Wang [73], which also addresses extrinsic factors. An example of a study which focused on intrinsic risk factors is that by Silva et al. [37] who propose a game to assess older adults' gait in order to delay onset of strength and functional decline. Similarly, Chen and Gwin [172] and Ranasinghe et al. [174] focus on intrinsic factors such as poor postural transition, gait, history of falling, and other fall-related risk activities, which affect one's functional ability and ultimately may lead to falls.

The cross falls prevention interventions presented in [73] focus on both intrinsic and extrinsic risk factors, especially *environmental hazards*. This is exemplified in the work undertaken by Shi and Wang [73] who develop a smart-phone application that provided tips to increase awareness of fall hazards in the home. The tips include illustrations of exercises and ideas about how to improve the home so as to avoid environmental hazards such as poor lighting in the hallway, kitchen and bathroom.

7.2. Combination of intervention types

A few systems [73,173] use *intervention types* often associated with Pre-FPIs and FIPIs to prevent the onset of fall risks or identifying risks to avoid fall-related injuries. For example, Shi and Wang [73] increase awareness of environmental fall risks, assess and detect fall risks when they occur and alert older adults and carers to take preventive measures in a timely fashion. Cortés et al. [173] develop assistive technology to increase independence around the home and to help alleviate the burden on caregivers and family members. The proposed walking aid has embedded sensors, which collect the usage data and sends it to clinicians. Two of the five CFPIs [172,174] use intervention types that are often employed by Post-FPIs and FIPIs. For example, Chen and Gwin [172] and Ranasinghe et al. [174] propose systems that monitor older adults' physical activities to identify fall risks. Once a fall has occurred clinicians are sent a notification to either reduce the potential risk or to assist in the case of a fall. Silva et al. [37] assess the intrinsic risk factors such as functional ability deficits, and more specifically walking patterns, for quality and to provide a form of exercising (for example, dancing), to encourage physical activity to counter the potential risk of falling.

7.3. Systems

The *application types* employed by [73,172–174] are all *static* and the remaining system [37] is an interactive *game* application, which provides a form of interaction and feedback to the user. Ranasinghe et al. [174] propose a static system to be used within

hospitals and residential care homes. Users are required to wear a device to enable monitoring of movement in the environment. Shi and Wang [73] develop a smart-phone application, using built-in sensors, which did not require any form of user interaction as it was merely a data collection tool coupled with suggesting knowledge tips on reducing environmental risks within the home and how to get into a recovery position after a fall to prevent any adverse effects thereafter. Chen and Gwin [172] design a wearable sensor device, which collects data from users' performing ADLs and an algorithm to detect fall events. There is no interactivity required for this device to function, as the device's function is to collect data. Finally, Cortés et al. [173] develop a system to assist users living independently by attaching sensors on assisted equipment for clinicians to monitor the usage of the equipment. Silva et al. [37] develop a game-based application, which require users to interact with the dancing game using the built-in sensors on a smart-phone to enable older adults to interact with the game application, ensuring that the physiological data of users matches the movement required in the dancing game. The game then provides the user with visual and audio feedback.

Two out of five systems [37,73] are deployed on a *smart-phone platform*. Shi and Wang [73] and Silva et al. [37] develop systems that use built-in smart-phone sensors to source data directly from users. Systems in [174] are deployed on the *desktop computer platform*. Ranasinghe et al. [174] develop a desktop application used to identify activity signatures of fall risks in real-time from wireless sensors and deployed within the living environment, to process and store the data and alert clinicians to address a fall risk.

7.4. Information sources

The *information sources* in [37,73,172–174] support a wide range of fall prevention activity. Sensors are often used to gather information from various sources and therefore have different *sensor locations*. The majority of CFPs [37,73,172,174] source information directly from *users*. Chen and Gwin [172], for example, propose a device that automatically assesses and detects fall risk factors by older adults wearing the device on their body to continuously monitor physical activities. The device gathers acceleration data in 3D space and plots this to X, Y and Z axes, reflecting the body pose of the user respectively. Ranasinghe et al. [174] propose a wearable sensor. Users are required to attach it to a piece of clothing to enable the device to monitor their activities in real-time to classify high risk tasks. Silva et al. [37] present a smart-phone-based system where an accelerometer sensor is used to source data from older adults. The smart-phone is attached to their lower back so that the system recognises physical activities being performed during game play. The remaining system, that of Cortés et al. [173] uses *context* in which user functions coupled with movement to collect data. The same study proposes a system that uses wearable devices to capture data from users and the context to ascertain the state of users in order to respond with support. Sensors are also attached to assistive equipment, such as walking aids, to help keep track of movement and general use of the equipment and to keep clinicians informed.

All sensors capture data directly from users or the context in which they function. With regards to *sensor purpose*, a range of systems [172–174] use *bespoke sensors*, which are developed specifically for gathering data obtrusively or unobtrusively to track users' movement. For example, Ranasinghe et al. [174] utilise a wearable sensor device to unobtrusively monitor older adults in real-time, preserving their privacy, and enabling clinicians to source data from them remotely. Chen and Gwin [172] and Cortés et al. [173] both propose bespoke devices which require older adults to attach the devices to their body. Cortés et al. [173] built-in sensors into assistive equipment to enable monitoring of

fall risks. The remaining systems [37,73] use *co-opted* of smart-phones sensors to source information from users. For example, Silva et al. [37] require users to wear their smart-phone as a wearable device to provide movement to control and interact with the game. Shi and Wang [73] also exploit built-in smart-phone sensors to monitor older adults in order to detect fall events as and when they occur.

In terms of *deployment environment*, the majority of CFPs [37,73,173] are deployed within the users' *home environment*. Silva et al. [37] propose a hybrid system to be deployed within the older adults' home to enable clinicians to administer clinical tests and monitor adherence to unsupervised exercises. Cortés et al. [173] deploy a system, within the patients' home to reduce fall risks and increase assisted living via the use of artificial intelligence and robotic solutions. Conversely, the study by Ranasinghe et al. [174] deploys technology-based interventions to reduce risks in *hospitals* for older adults who are admitted into acute care, especially if they are cognitively impaired, which therefore warrants the need to monitor them during their stay in hospital or residential care.

7.5. Interface types

The *collaboration* which is afforded by CFPs [37,73,172–174], as with other fall prevention systems, is *asynchronous*. Patients (typically in an unobtrusive way) generate physiological and movement data which is sent to clinicians who respond with medical assistance or establish the likelihood of users falling. Shi and Wang [73] develop a game to increase levels of engagement with home-based exercises to reduce fall risks and enable clinicians to monitor those risks and carry out clinical tests. Ranasinghe et al. [174] enable nurses to respond with help to patients who attempt to transfer on and off items of furniture, such as the toilet and bed unassisted without caregivers' help, which could lead to falls.

All systems [37,73,172–174] use a particular form of *multimodal interaction* to interact with technology-based interventions. *Natural User Interface* appear to be a common form of interaction [37,73,172–174] as it enables users to perform physical activities and gestures to control an in-game avatar and various objects in a virtual environment. CFPs in [37] uses *touchscreen* and *natural user interface* for users to manipulate the systems by performing gestures to interact with the touchscreen on a smart-phone. The system responds to those gestures by providing feedback to users. In the study of Silva et al. [37], the user attaches the smart-phone to their body so that the system can track their dance moves. Users are provided with both audio and visual feedback, as data their dance moves is transmitted to the movement of a character during gameplay. Shi and Wang [73] develop a smart-phone application for the user to interact with via the built-in touchscreen. Chen and Gwin [172] require natural gestures and movement from older adults to operate their system, enabling clinicians to monitor patients remotely.

7.6. Discussion

The CFPs presented in this section [37,73,172–174] deploy a full range of techniques typically associated with Pre-FPIs, Post-FPIs and FIPIs to assess, detect, and respond to fall risks. As a result of combining these techniques, multiple fall risks are responded to, often allowing for more comprehensive interventions to be provided compared with systems that target one particular intervention type. The only cross fall prevention system that reduces both intrinsic and extrinsic risks is [73], which enhances awareness of environmental fall hazards supplemented with guidance of how to conduct exercise movements to increase adherence. All cross-prevention systems [37,73,172–174] use a natural user interface,

Table 5
Cross falls prevention interventions.

Cross fall prevention systems	Cross falls prevention interventions											
	Fall risk factors		Combination of intervention types				System		Information sources		Interface type	
	Intrinsic	Extrinsic	Pre-fall prevention	Post-fall prevention	Fall injury prevention	Application types	Platform	Sensor location	Sensor purpose	Deployment environment	Collaboration	Multimodal interaction
Chen and Gwin [172]	Fun			X	X	S	DC	U	Bs	-	Async	Nii
Cortés et al. [173]	Fun	X			X	S	DC	C + U	Bs	He	Async	Nii
Ransinghe et al. [174]	Fun			X	X	S	DC	U	Bs	Hs	Async	Nii
Shi and Wang [73]	Fun	Eh	X		X	S	Sm	U	Co	He	Async	Nii + Ts
Silva et al. [37]	Fun		X	X		G	Sm	U	Co	He	Async	NUI + Ts

enabling users to interact with computerised content by performing a range of natural gestures [175]. Movement data is analysed, for signatures that correspond to fall risks, via the use of computational techniques and advanced processing capabilities. CFPIs that are deployed on smart-phones [37,73,172–174] exploit their inherent natural user interface and touchscreen interface. From the systems presented here [37,73,172–174], it can be inferred that patients play a major role in their care by engaging with these interventions via the use of sensors and the communication functions of the systems. Perhaps the complexity of these systems and the increased overhead required to design and deploy such systems are the reasons that only a small number of such systems have been presented in the research literature to date.

8. Challenges and future research directions

In summary, taking a broader view of the typical functions that each category of system fulfils, the majority of Pre-FPIs [18,19,40–42,74–79,81,82,84–90,93,96,97,99–103,105,106,108] deploy 3D technology and games as a means to augment evidence-based exercises, focusing on intrinsic fall risk factors, such as functional ability deficits and balance impairments. A large number of Pre-FPIs [18,19,41,78–80,82,84,86,90,93,99–106] are deployed within the home environment to overcome issues of non-compliance with exercising and eradicate the travelling costs to rehabilitation centres. Most of the post-FPI systems are static [38,39,114–119,121–123,126–130]. However, the remaining systems provide an interactive means of engaging older adults during fall risk assessment programmes [120,124,125]; specifically focusing on intrinsic fall risks. Post-FPI systems [38,114–122,124–130] are also often deployed within the home environment. With regards to FIPIs, the majority of these systems focus on falls detection, often via a database of simulated fall behaviour to help distinguish between fall events and ADLs. All approaches, to some extent, detect falls obtrusively or unobtrusively focusing on older patients. Technology-based falls prevention research has tended to focus on detecting falls as a result of its inevitable occurrence, particularly in older people. Nevertheless, Pre-FPI and Post-FPI systems have shown promise in reducing the onset of fall risks, rather than injuries that occur in the event of a fall. CFPI systems provide a comprehensive fall prevention approach as they include a combination of intervention types of Pre-FPI, Post-FPI and FIPi [37,73,172–174]. Smart-phone features are strongly being used across all system types. These portable, low cost, and increasingly ubiquitous devices are being used as a solution in deploying fall prevention systems, which is in line with a growing number of older adults now becoming more familiar with smart-phones [176], and consequently one can assume that smart-phones will continue to be part of future fall prevention systems.

Effective management of falls is a complex endeavour, particularly when considering the multiple intrinsic risks, namely social and physical factors and extrinsic risks such as slippery surfaces, poorly fitted or abandoning assistive equipment, poor lighting, unsafe stairs and loose rugs [2,29]. It is recognised that in order to reduce the risk of falling, particularly in an older adult population, targeting extrinsic risk factors is equally as important as targeting intrinsic risk factors [2]. The effective management of fall risks in order to enable older adults to live independently within their homes for longer is seen as being extremely beneficial to the patient in terms of maintaining independence and quality of life [20]. Despite the key role extrinsic fall risk factors play in ensuring that the goal of independent living is realised, and that fall risk factors are suitably managed, it is apparent that extrinsic risk factors are rarely considered and targeted by contemporary fall prevention intervention systems. Of the 104 fall prevention

systems [18,19,37–45,73–108,114–130,133–169,172–174], only 4 systems [38,73,74,98] target extrinsic risk factors. FPI systems in particular, by definition, do not target extrinsic factors at all, as their sole focus is to detect falls so as to reduce fall-related injuries.

There is a need for new research to explore how technology-based applications can be applied to better address and manage extrinsic fall risk factors. Furthermore, when exploring the extent to which existing systems facilitate the process of collaboration and shared decision making between patient and practitioner, it seems that the majority of systems do not invest significantly into delivering such functionality. Pre-FPIs appear to be the category delivering the largest proportion of systems which offer synchronous communication between patient and practitioner and hence patient–practitioner collaboration [18,19,40–42,74–82,84–90,93,96,97,99–108]. The collaboration which is supported, however, is synchronous and hence does not optimally support real-time patient–practitioner discussions/interactions about the fall risks encountered or indeed how these may be better managed and overcome. In the rare cases that the system does facilitate asynchronous patient–practitioner communications [83,91,92,94,95,98], the system functionality does not tend to actively support and facilitate shared decisions to be made about the patient's care or enable the patient to provide input into the decisions made about their care.

As a consequence of carrying out this survey, a number of challenges have emerged which should be addressed by the falls prevention technology research domain.

8.1. Challenges to Pre-FPIs

Challenge 1: Lack of research effort focused on reducing extrinsic risk factors, which are of equally major concern for patients who exhibit intrinsic risks and live independently. In many instances, falls occur as a result of multiple risk factors including intrinsic and extrinsic risk factors. Many interventions prevent both types of risks in order to increase the effectiveness of preventing a fall. Although there are Pre-FPIs that have produced promising results for addressing intrinsic fall risk factors to date, there are a limited number of systems that reduce both functional ability deficits and extrinsic fall risks and solely reduce extrinsic fall risks.

Challenge 2: Lack of fall education interventions used in Pre-FPIs to reduce fall risks. There are a small number of Pre-FPIs that use fall education interventions to reduce fall risks, not least as a singular intervention system. While the vast majority of Pre-FPIs that utilise 3D technology and games for preventing intrinsic fall risks has shown promising results, there is an absence of using such technology to augment fall education interventions, with the exception of two [74,98]. These two systems specifically provide advice for patients to avoid environmental hazards. Bell et al. [74], as well as focusing on reducing functional ability deficits, also addressed environmental risks, noted down in paper-based form, such as decreasing clutter, furniture, spills and the impact these could have on older adults in their living environment. Otis and Menelas [98] look at specific characteristics of the environmental conditions in which older adults function and notified them of a potential risk of falling. Despite this, Pre-FPI systems enable patients to self-manage and reduce falls by engaging in unsupervised health promotion activities. Fully realising the patient–practitioner collaboration paradigm is a challenge, as patients are not given the opportunity to be involved in any decision-making or interventions that reduce extrinsic factors of falling. Furthermore, Pre-FPI systems are of major benefit in that they provide an intuitive way for patients to engage in

home-based exercises, and give practitioners the ability to monitor patient's physical health remotely.

In response to Pre-FPI challenges, the following research directions and recommendations are proposed:

Recommendation 1: Identify new opportunities and develop new technology-based applications to support patients and practitioners in their efforts to overcome extrinsic risk factors. One promising area of technology that may provide opportunities to overcome this challenge may be found within the interactive 3D virtual reality and gaming domain. For example, interactive 3D gaming applications which simulate the range of extrinsic fall risks that occur at a patient's home may help to improve patient's awareness of risks and encourage the development of strategies to overcome these risks if they occur in real-life. However, it is important that such solutions are applied in a meaningful way in order to target extrinsic risk factors that relate to patients personal home environment in which they function. This is particularly important when considering the notion of ageing-in-place, which focuses on enabling patients to remain in their home for longer. Therefore, addressing extrinsic risk factors via the use of technology could reduce fall events that occur as a result of multiple risk factors or solely based on extrinsic risk factors.

Recommendation 2: Develop technology-based applications which enable and support fall prevention intervention education and promotion activity. Taking a pro-active approach to educating patients, who may still be at low risk of falling, around fall risks is likely to increase their awareness of potential risks and encourage behaviour change that may reduce their risk of falling in the future. Given the distinct lack of applications which take such an approach, coupled with the potential benefits, there is a need for more focused technology-based research in this area. Furthermore, for those who have been prescribed assistive equipment to help with performing daily activities and reduce fall risks, educating patients on the need for equipment might be developed to increase adherence and successful uptake of assistive equipment in the home to help with mobility issues and the onset of fall risks. Interactive 3D gaming and virtual reality simulations of fall risks again, may offer promising platforms to deliver educational interventions. Educational interventions deployed on mobile platforms such as smartphones and tablet-based applications may also be an area of potential opportunity for such applications, particularly given the popularity and ever increasing ubiquity of such devices.

8.2. Challenges to Post-FPIs

Challenge 3: Current systems do not consider or support the delivery of environmental assessment interventions to reduce fall risks. The majority of the systems produce personalised applications by sourcing information obtrusively or unobtrusively, using sensors, directly from the patient's physical movement in accordance with clinical assessment tests. Although these systems enable patients to self-assess their functional abilities and cognitive function, there is little consideration given to assessing the environment in which the patients function, with the exception of one system [38]. This is particularly important as systems proposed in the literature are directing their efforts to ageing-in-place, independent living and remote assessment but they do not take into account the fall hazards that may be apparent within the patient's home environment.

Challenge 4: Existing Post-FPI systems do not enable patients and practitioners to interact and collaborate whilst fall risk assessments are carried out using Post-FPIs. The majority of Post-FPI systems

provide remote synchronous but static communication mechanisms and hence do not provide patients or practitioners with a means of interacting with each other whilst using these systems. Typically, systems produce static reports on the predefined criteria the system is set up to report on, with no option for the patient to provide additional contextual detail which may be useful for interpreting the data in a more personalised and appropriate way. Post-FPI systems therefore would benefit from offering more collaborative functions that provide an opportunity to enable patients, to some extent, to collaborate with clinicians and help interpret the data that these systems generate.

In response to these challenges, the following future research direction recommendations are proposed:

Recommendation 3: Incorporate environmental assessment interventions into Post-FPI systems. Whilst falls often occur as a result of multiple fall risks, it appears that Post-FPIs would benefit greatly from assessing extrinsic risk factors by incorporating environmental assessment interventions into Post-FPIs.

Recommendation 4: Develop Post-FPIs which allow patients and practitioners to engage and collaborate with each other as part of the assessment process. From the falls prevention systems reviewed, it appears that providing patients with an interactive means could help to increase compliance to fall risk assessments by presenting real-time feedback and a mechanism that supports richer interactions and collaboration between patients and practitioners.

8.3. Challenges to FIPIs

Challenge 5: Existing FIPIs are often unable to demonstrate effective and reliable differentiation between fall events and daily activities in order to accurately detect falls, particularly within real-life settings. As such, much effort has been expended on developing algorithms and computational techniques to improve the level of sensitivity and specificity in accurately detecting falls via user-worn or camera-based sensors. This still, however, remains an on-going research challenge. There are a small number of FIPI systems that have been evaluated with real-life falls due to ethical reasons, however, the remaining systems are unable to demonstrate the effectiveness and reliability of the proposed system in real-life settings. Hence this raises issues relating to the ecological validity of the proposed systems. In overcoming such issues, most FIPI systems simulate fall like behaviour in order to gather signatures of fall events in a database to increase detection accuracy.

Challenge 6: Preserving the privacy of patients when using FIPI systems that utilise cameras to detect falls. While the use of cameras as an alternative to user-worn sensors provides an unobtrusive way of monitoring patients, there still remains the challenge of user's privacy being breached.

Challenge 7: FIPI systems that use cameras to monitor patients only cover a limited space within the monitored environment. Using cameras as an alternative to user-worn sensors presents no restriction of where it is installed, however, the camera devices are limited in covering a certain amount of space in its view. Instrumenting the environment with multiple cameras may increase space coverage of the environment, but will increase cost and in some instances it may not be feasible to do so. Monitoring patients and detecting falls using camera sensors still remains an on-going research challenge, with limited coverage and effort in optimising image processing techniques to mask user privacy. Also, older adults may forget to wear

user-worn sensors, which require effort in reminding users to wear the user-worn sensors.

Challenge 8: The majority of FIPIs are static and provide no form of user interaction. In most studies, developing machine learning techniques and optimised algorithms has been the focus in order to increase the accuracy of fall detection, however little consideration has been given to the interface functionality of the systems. There is a lack of interactive applications to engage patients during interventions that could reduce fall risks. However, much less effort regarding the interaction has been explored in this intervention. All systems attempt to alleviate fall related injuries that occur after a fall, these injuries are more severe upon the impact.

In response to these challenges, the following recommendations are proposed:

Recommendation 5: Develop, deploy and evaluate FIPI systems under real-life conditions. Falls are a complex phenomenon and are yet to be fully understood. Patients' physiology in relation to real-life falls differs, which makes gathering simulated fall like behaviour problematic and the robustness of which may be considered to be questionable. Therefore, if FIPI systems are to be ecologically valid, accurate and reliable such systems would need to be evaluated within real-world settings.

Recommendation 6: New approaches to deploying camera-based digital video footage of patients within their home environment, whilst also protecting and preserving privacy of patients must be developed. Some promising avenues via which this may be achieved lie within the image processing and face recognition research domain. For instance, there needs to be more development of algorithms that dynamically remove and selectively scramble or distort image detail at the point of capture, which may be considered to potentially compromise the patient's privacy. Furthermore, providing clear prompts of when cameras are monitoring to reassure users that their privacy is not being breached at other times may help with the acceptance of such technology. Developing techniques to selectively activate cameras or broadcast footage, only when a potential fall is detected, could also be a potential solution for preserving user privacy.

Recommendation 7: Invest effort into developing hybrid sensor networks to detect falls. Instrumenting the patients' living environments with multiple types of sensors has shown promise in the research literature as a potential solution and addresses drawbacks of certain sensors by installing another. Camera sensors that are used by fall prevention systems are deployed in the patient's environment to detect fall events or fall related injuries, however such sensors are limited in coverage, which in some cases, depending on the location of the fall, render it ineffective. However, the advantage of using cameras is that users are not required to wear any sensors on their body. User-worn sensors are not limited in covering the environment, but require users to attach a device on their body in order to detect falls.

Recommendation 8: Develop systems which support richer and more engaging mechanisms for user interaction. Little effort seems to have been invested into considering the user interface design of FIPIs, or indeed the specific user-centred interaction requirements of older adult users and clinicians. Systems do not appear to make any significant attempt to develop system interfaces that support patient/practitioner collaboration and interactive information sharing. Therefore, investing effort into user-centred design of system interfaces is likely to improve the level of engagement and acceptance of such systems, which in turn is likely to impact on their longer term success.

8.4. Challenges to CFPIs

Challenge 9: CFPI systems face similar challenges to other fall prevention systems in that there is a lack of effort in reducing extrinsic risk factors. Fall risks are categorised as intrinsic and extrinsic, both of which are equally of major concern and become a risk to older patients who live independently.

Challenge 10: CFPIs incorporate intervention techniques associated with Pre-FPIs, Post-FPIs and FPIs as a comprehensive prevention that can target multiple fall risk factors. The majority of CFPIs prevent multiple fall risks by utilising Pre-FPIs, Post-FPIs and FPIs intervention techniques. Although multiple fall risks are responded to, developing CFPI systems is an overly complex task which brings with it significant time and cost overheads.

In response to these challenges, the following recommendations are proposed:

Recommendation 9: Develop CFPIs which support patients and practitioners in their efforts to overcome extrinsic risk factors.

Recommendation 10: Develop pragmatic CFPI systems which reduce multiple fall risks whilst also minimising the development and deployment overhead associated with such systems. Combining intervention techniques to target multiple fall risks often provides more effective falls prevention as fall events occur as a result of multiple risk factors. However, the challenge is to identify CFPIs which also minimise the resource overhead required for developing these comprehensive solutions.

9. Concluding discussion

This paper presents a conceptual falls prevention technology model, which includes fall prevention interventions, the information sources they exploit and their collaboration functions. The conceptual model of falls prevention technology was derived from and used to survey a range of fall prevention technology systems that have been proposed within the literature in a specified time period. Fall prevention interventions were found to belong to one of four system sub-types; *pre-fall prevention* (mitigating the early stages of fall risks through health promotion), *post-fall prevention* (assessing fall risks), *fall injury prevention* (reduces post-fall injuries) and *cross-prevention* (combination of multiple interventions used to reduce fall risks) used in practice. The *application types* are categorised (*static, interactive, games* and *virtual reality*) and the *platforms* (*desktop computer, game console* and *smart-phones*) in which they are deployed. The fall prevention technology systems that exploit *information sources* were also categorised (user and context) and the purpose of sensors used to source information (*bespoke, repurposed* and *co-opted*) and *deployment environments* where the systems are installed (*home, nursing home* and *hospital*). The interface type that each system used were also categorised (*natural user interface* and *touchscreen*) and their respective *collaboration functions* (*synchronous* and *asynchronous*) which occurred between older adults and clinicians either offline, sharing an interface during an intervention or online sourcing data remotely.

Although pre-fall prevention systems has shown promise in reducing intrinsic risk factors, there is a lack of research energy which has been expended on reducing extrinsic risks, partly from using education interventions to increase fall hazard awareness, which is mainly a component of a multifactorial intervention. This is due to the sole focus of such systems aiming to increase adherence to and uptake of exercise interventions.

Post-fall prevention systems are prominent for augmenting traditional clinical tests used to assess functional abilities and cognition, but there appears to be benefits to reducing extrinsic risks in

order to make it more of a comprehensive prevention, due to the collaborative nature of existing systems that are deployed in older adults home to self-administer assessments. As such, post-fall prevention systems enable older adults to self-assess for intrinsic risks, which in turn enable clinicians to conduct their assessments remotely by deploying a system in the patients' homes. However, extrinsic risks and personalising the home to aid mobility and reduce fall risks by self-assessment has yet to be explored.

Fall injury prevention systems appear to be prominent in the literature amongst other systems as it is focusing mainly on detecting falls. As such, falls are inevitable and detecting falls when they occur to prevent fall-related injuries is essential, however, other areas of preventing fall risks are of major concern.

To address and overcome the challenges faced by pre-fall, post-fall, fall injury and cross fall prevention systems, this study has proposed a range of recommendations for fall prevention systems. It is proposed that future fall prevention systems would benefit even more from addressing extrinsic risks, particularly how equipment could be successfully adopted by clinicians conducting home assessments effectively and older adults being able to self-assess their needs for assistive equipment in the absence of clinicians in the home. To this end, exploring how home furniture are accurately measured by stakeholders involved in home assessments could ensure the correct fit of equipment in the home, which could lead to successful uptake of and adherence to using equipment. Providing an innovative way of educating fall prevention to older adults using fall hazards typically found in the home has been suggested as a potential area of research. Moreover, systems would benefit from focusing on enabling patients to self-assess and provide self-care against fall risks and to enable collaboration for shared-decision making between patients and practitioners.

Conflict of interest

The authors declare that they have no competing interests.

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