Milla Immonen

RISK FACTORS FOR FALLS AND TECHNOLOGIES FOR FALL RISK ASSESSMENT IN OLDER ADULTS
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Risk Factors for Falls and Technologies for Fall Risk Assessment in Older Adults

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Abstract

Falls are a serious cause of morbidity and costs to society and frequent falls are associated with impaired quality of life of older people. Screening for high fall risk persons among the older population consumes resources and public funding. Novel, low-cost methods for identifying older persons at high fall risk are thus needed to be able to target preventive actions. The aim of this study was to examine whether individual clustering of chronic diseases is associated with higher fall risk and how technical solutions and connected data, with a special focus on the use of accelerometers, can be utilized in measuring acutely or incrementally appearing risk factors for falls in older adults. The research was carried out by collecting population-based survey data on older people (age 65-98) and by utilizing existing databases. A total of 918 people filled in a questionnaire including items on health status, lifestyle and falls. In addition, 42 volunteers participated in large-scale fall risk measurements. During the measurements, accelerometers were attached to the lumbar spine and front hip of the subject. A mobile application utilizing a separate accelerometer was developed to assess the risk of falls. The feasibility of the mobile application was tested with 11 volunteers of working age. In addition, an easy-to-use application for home-based training was developed and user experiences were collected from six older test subjects in Finland and ten older subjects in Spain. In Spain, four healthcare professionals evaluated the applicability and usability of the application. The results of the study showed that chronic diseases and multiple morbidity are associated with an increased risk of falling. Several technologies have been developed to assess the risk of a fall. Preliminary results indicated that a mobile application utilizing a separate accelerometer can detect deficiencies in walking style, which, in turn, may indicate an increased risk of falling. This study also showed that a sensor attached to the front of the hip could reliably assess some of the gait features associated with fall risk. Both the older people themselves and health care professionals felt positive about the home-based exercise application.

Keywords: accelerometers, chronic illnesses, fall risk, fall risk assessments, older adults
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Tiivistelmä

Yhteensä 918 henkilöä täytti täytyy yksiköitä varten kerättävää tietoa, jossa on tallennettu kaatumisesta sekä sen seurauksista.

Asiasanat: ikääntyneet, iäkkäät, kaatumisriski, kaatumisriskin arviointi, kiihtyvyysanturit, krooniset sairaudet, mobiilisovellus
To my family
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12th of December, 2019

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Abbreviations

AAL JP  Ambient assisted living joint programme
AiB    Ageing in Balance project
COP    Centre of Pressure
COPD   Chronic obstructive pulmonary disease
CSRT   Choice stepping reaction time
EU     European Union
EMG    Electromyographic
FAP    Functional Ambulatory Profile
FES-I  Falls efficacy scale international
FH     Frontal hip
FRI    Fall Risk Index
Frat-up Fall risk assessment tool
FROP-Com Fall risk of older people – community setting
Gasel  Gasel-project; Tailored Services for Elderly – Gamified remote service concept for promoting health of older people
IMU    Inertial Measurement Unit
LB     Lower back
MNA    Mini Nutritional Assessment
PA     Physical activity
PSD    Persuasive system design model
ROC    Receiver Operating Characteristics
SD     Standard deviation
SOF    Study of Osteoporotic Fractures
SPSS   Statistical Package for Social Sciences, IBM SPSS
std X, Y, Z Standard deviation X, Y, Z
STS    Sit-to-stand
STS-5  Sit-to-stand five times
SVM    Signal Vector Magnitude
THL    Finnish Institute of Health and Welfare
TUG    Timed Up and Go test
USD    United States Dollar
UWB    Ultra Wideband
VTT    VTT Technical Research Centre of Finland Ltd.
WHO    World Health Organization
Original publications

This thesis is based on the following publications, which are referred to throughout the text by their Roman numerals:


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1 Introduction

Falls among older people are a major public health and economic challenge. One third of people over 65 years old fall at least once a year (Lord, Sherrington, & Menz, 2001; Yoshida, 2012) and the number of falls per year increases with age and frailty level (WHO, 2007). The consequences of falls are serious. Falls are related to increased mortality, morbidity, reduced functioning, and premature nursing home admissions (Kannus et al., 1999; Rubenstein & Josephson, 2006). Not all falls are injurious, but even an non-injurious fall may have an effect on fear of falling (Patil, Uusi-Rasi, Kannus, Karinkanta, & Sievänen, 2014), which can lead to a negative cycle of reduced activity, reduced functionality, and need for help in daily activities (Delbaere, Crombez, Vanderstraeten, Willems, & Cambier, 2004; Li, Fisher, Harmer, McAuley, & Wilson, 2003). Hip fracture is one of the most serious consequences of falls and leads to impaired functional ability, decreased quality of life, and increased financial burden on society. The costs of hip fracture treatment are very high. The cost of care during the first year after a hip fracture was 30,258€ (range 26,332€ – 37,822€) during the years 2011-2013 in Finland ("PERFECT project/THL," 2018). The global average health and social care costs at 12 months after a hip fracture have been estimated at $43,669, with inpatient costs being the major driver (Williamson et al., 2017). Falls were also the leading category of unintentional injury death in 2016 for both genders in Finland (Kannus, Niemi, Parkkari, & Sievänen, 2019). The incidence rate of fatal falls has grown in Finland since 1971, and in 2016 were as high as 23 deaths per 100,000 persons for women and 26 per 100,000 persons for men (Kannus et al., 2019). On the other hand, the incidence rate of fall injuries that need hospital treatment has declined since the late 1990s in Finland for both genders and all age groups except the oldest women and men (≥90 years) (Kannus, Niemi, Parkkari, & Sievänen, 2018). However, the absolute number of injurious falls is expected to increase in Finland due to ageing of the Finnish population (Kannus, Parkkari, Niemi, & Sievänen, 2018).

As the population pyramid changes, resources for care are becoming increasingly limited. The cost of care of fall related injuries is increasing rapidly, and prevention is therefore becoming crucial. Screening for high fall risk persons among the older population consumes resources and public funding. Novel, low-cost methods for identifying older persons at high fall risk are thus needed to be able to target preventive actions. In addition, increasing public awareness of the
role of the individual in maintaining functional ability and preventing falls is becoming crucial.

Fall risk can be assessed by assessing balance, muscle strength, dizziness, posture, gait, drugs, environmental factors and cognitive impairment, as well as various medical factors (Lord et al., 2001). Technologies may function as a means to assess some of these risk factors and to detect high fall risk by automatic and continuous screening. Automatic and continuous monitoring of fall risk has potential in identifying those with high fall risk, and help target preventive actions. This may have potential in decreasing the costs of care and in raising public awareness.

A variety of technologies have been developed and studied to provide a means for screening for high fall risk (Ejupi, Lord, & Delbaere, 2014; Sun & Sosnoff, 2018). Some commercial products have also appeared on the market, but they are not widely used and are mainly targeted towards clinical use and demand time and resources from clinicians. Clearly, there is a need to provide tools to be embedded in the daily lives of older people to help them assess their own fall risk and to perform preventive actions in time. Integrating technologies into patient health records might enable changes over time to be detected. However, so far there is no scientific evidence on how this integration could be successfully conducted. Utilizing data mining and artificial intelligence in electronic health records for screening high fall risk patients offers potential in the future for targeting preventive actions at patients at risk, but the scientific literature in this area is so far scant. In an earlier study, Baus et al. developed a model for utilizing electronic health records for screening for high-risk patients (Baus et al., 2017). In addition, medical records can be used to develop a fall risk prediction model with moderate sensitivity and specificity (Oshiro et al., 2019).

The present study evaluates whether chronic diseases and multiple morbidity are associated with a higher risk of falling utilizing a population-based questionnaire of 918 subjects. In addition, the study collected information about existing methods and technologies for fall risk assessment and suggested a conceptual design for integrating technologies into patient health records. A mobile solution utilizing accelerometer sensors for assessing fall risk from human gait was presented and its feasibility for fall risk assessment was studied with a small test group. In addition, sensor location on the frontal hip in gait-based fall risk assessment was compared with the lower back using data from 42 older adults. Finally, the feasibility and usability of a fall prevention software for the use of older adults individually at home were evaluated by end-users in Finland and Spain.
2 Review of the literature

2.1 Falls in older people

Falls are common in older people. One third of people over 65 years old fall at least once a year (Lord et al., 2001) and the number of falls per year increases with age and frailty level (WHO, 2007). In Finland, injurious falls were the cause of more than 1,200 deaths of over-64-year-olds in 2017 (“Statistics Finland - Causes of death in 2017,” 2018). Falls increase mortality, morbidity, reduce functioning, and cause premature nursing home admissions (Kannus et al., 1999; Rubenstein & Josephson, 2006). A fall can also lead to a negative cycle of reduced activity leading to reduced functionality and need for help in daily activities (Delbaere et al., 2004; Li et al., 2003) as even a non-injurious fall may increase fear of falling (Patil et al., 2014). In the EU, fall related injuries are the cause of 2.3 million emergency visits per year, approximately 36,000 older people are fatally injured from falls per year, and the annual healthcare costs from falls are estimated at 25 billion € (Turner, Samantha; Kisser, Rupert; Rogmans, 2015). In the US, the total annual medical costs incurred from fatal and non-fatal falls are estimated at 50 billion USD (Florence et al., 2018). In Finland, the cost of care per hip fracture, the most common fall-related injury, was 30,258€ for the first year after the fall during the years 2011-2013 (“PERFECT project/THL,” 2018). The incidence of hip fractures decreased in Finland during the 20th century, but the amount of hip fractures is estimated to increase by 44% between 2016 and 2030 due to population ageing (Kannus, Niemi, et al., 2018). Falls and hip fractures can be prevented and their consequences reduced by preventive actions such as improving muscle strength, balance and coordination, or medication review (Cameron et al., 2010; Gillespie et al., 2009; Oakley et al., 1996). Fall prevention is a complex, multifactorial challenge (Rubenstein & Josephson, 2006), but the majority of individual fall risk factors can be minimized by preventive means (Gillespie et al., 2009; Satu Pajala, 2012; Robertson, Campbell, Gardner, & Devlin, 2002).

2.2 Risk factors for falls

The risk factors for falls have been widely studied (Ambrose, Paul, & Hausdorff, 2013; Downton, 1993; Lord et al., 2001; Rubenstein, 2006) and several classifications have been proposed. Commonly, fall risk factors are divided into
intrinsic and extrinsic risk factors (Bueno-Cavanillas, Padilla-Ruiz, Jiménez-Moleón, Peinado-Alonso, & Gálvez-Vargas, 2000; Lord et al., 2001; Perell et al., 2001; Rubenstein & Josephson, 2006). Intrinsic risk factors are patient-specific, such as age, gait and balance impairment, muscle weakness and medical conditions, whereas extrinsic factors are environmental, such as poor footwear or slippery floors (Bueno-Cavanillas et al., 2000; Lord et al., 2001; Rubenstein, 2006). Another categorization by the WHO has four categories of fall risk factors: biological, behavioral, environmental and socioeconomic (WHO, 2007). A third categorization model by Lord et al. groups the risk factors into six categories: psychosocial and demographic factors, postural stability factors, sensory and neuromuscular factors, medical factors, medication factors, and environmental factors (Lord et al., 2001).

Examples of fall risk factors are summarized in Table 1, which is adjusted from several sources (Bueno-Cavanillas et al., 2000; Lord et al., 2001; Perell et al., 2001; Rubenstein & Josephson, 2006). The factors most relevant to this study are examined in the following chapters.

<table>
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2.2.1 **Intrinsic risk factors**

As mentioned above, intrinsic risk factors include patient-specific causes, such as age, gait and balance impairment, muscle weakness and medical illnesses. Ageing induces many changes in physical ability; older people tend to have a stiffer, less coordinated gait than younger people and their posture control, body-orienting
reflexes, muscle strength and tone and stepping height all decline (Bueno-
Cavanillas et al., 2000). Ageing may also bring impairment of vision, hearing and
memory (Albert, 1997; Cruickshanks et al., 2003; Owsley, 2011).

**Physical activity and falls**

In general, physical activity (PA) has been shown to reduce the risk of falling
(Gregg, Pereira, & Caspersen, 2000). However, some studies have indicated that
the most active group of older adults have a greater risk of falling than less active
older adults (B. K. S. Chan et al., 2007; Moayyeri, 2008). In contrast, some studies
have shown that fall risk decreases constantly with increasing amount of PA
(Heesch, Byles, & Brown, 2008; Peeters, Van Schoor, Pluijm, Deeg, & Lips, 2010).
Even though the most active group of older adults might have an increased risk of
falling, the fracture risk of older adults seems to decrease with increasing amount
of PA (Feskanich, Willett, & Colditz, 2002; Gianoudis et al., 2014; Moayyeri, 2008).
In a Finnish study, PA was found to be associated with a moderately elevated risk
for wrist fractures, which might be due to the higher number of outdoor activities
and Finnish weather conditions in the winter (Rikkonen et al., 2010).

**Balance and gait**

Human postural control is a complex motor skill derived from the interaction of
multiple sensorimotor processes (Horak, 2006). Maintenance of postural stability
and balance requires rapid processing of signals from visual, vestibular and
somatosensory systems, and balance may deteriorate when these systems
individually or collectively fail (Pothula, Chew, Lesser, & Sharma, 2004). The
somatosensory system provides information about the position and motion of body
segments in relation to each other and the support surface, and the visual system
provides information about the environment and body orientation (Hewston &
Deshpande, 2016). The vestibular system is part of the inner ear and signals motion
accelerations as the head translates and rotates in space (Angelaki & Cullen, 2008).
Pothula et al. (2004) studied unexplained falls from accident and emergency
patients and found that 80% of patients had vestibular symptoms. These patients
may have vestibular impairment or the symptoms may be caused by postural
hypotension, metabolic disturbances, thyrotoxicosis, anemia, a variety of
medications, or cardiovascular or cervical spine disease (Pothula et al., 2004).
Some diseases, such as type 2 diabetes, have been shown to increase the risk of vestibular dysfunction and falls (Hewston & Deshpande, 2016).

Gait, i.e. the pattern of walking of an individual, involves a large number of sub-systems, such as skeletal, joint, muscular, neurologic, vestibular, visual and proprioceptive systems. The gait cycle can be defined as the period of time between any two nominally identical events in the gait process, e.g. from the instant the foot strikes the ground to the instant the same foot strikes the ground again. The gait cycle can be divided into stance and swing phases and both of these further into several sub-phases. In the stance phase the foot is on the ground and in the swing phase the foot is moving forward through the air. The stance phase lasts from initial ground contact to toe-off (Adams & Cerny, 2018; Whittle, 2007). Functional ambulatory profile (FAP) is a summary score (range 0-100) that quantifies the gait based on specific temporal and spatial gait parameters (Nelson, 1974).

The relationship between balance and gait characteristics and falls has been widely studied. Postural instability has been found to increase the risk of falls of older people (J. W. Muir, Kiel, Hannan, Magaziner, & Rubin, 2013; Oliveira et al., 2018). In a study using force-platform balance tests among 434 community dwellers it was found that the participants in the highest center of pressure (COP) movement tertile had a two- to fourfold risk of indoor falls compared to participants in the lowest COP tertile of the test (S. Pajala et al., 2008). Inability to complete the tandem stance was also a significant predictor of fall risk (S. Pajala et al., 2008). Gait characteristics have been found to be associated with fall risk in recent studies (Rispens et al., 2014; H. Similä, Immonen, Merilahti, & Petäkoski-Hult, 2015; Van Schooten et al., 2015). One recent study concluded that the best prediction model for future falls comprised the amount of gait (daily number of strides), gait characteristics describing complexity, intensity, and smoothness, and the interaction between these characteristics (Van Schooten et al., 2015).

Muscle strength

Muscle mass and muscle strength decline with age even in healthy older people (Hurley, 1995). Lower limb muscle weakness leads to poor balance, abnormal gait patterns and reduced general mobility (S. Lord & Stumnieks, 2005) and increases the risk of falls (Stephen R. Lord, Ward, Williams, & Anstey, 1994). In addition to the lower body, muscle weakness in the upper body is also associated with increased fall risk (Arvandi et al., 2018; Moreland, Richardson, Goldsmith, & Clase, 2004). A recent cross-sectional study with 1,028 participants by Ahmadiahangar et
al. found an increased fall risk among groups with low and moderate quadriceps muscle strength compared to a group of high quadriceps muscle strength (Ahmadiahangar et al., 2018). These findings suggest that lower limb muscle weakness is an important risk factor for falls. Weakness of upper body muscles has also been connected to high fall risk in older adults (Arvandi et al., 2018). In a study by Yang et al. (2018), handgrip strength was found to be the most significant independent factor of fall episodes (N.-P. Yang et al., 2018). In another study, greater rate of decline in grip strength over time was significantly associated with higher fall risk (Xue, Walston, Fried, & Beamer, 2011). Low hand grip strength has also been suggested to predict fractures in osteoporotic patients (Cheung et al., 2012). Recently, weakness in abdominal trunk muscle has also shown to be been connected with fall risk (Kato et al., 2019).

**Chronic conditions and falls**

Chronic conditions have been found to be related to falls in several studies (Cimilli Ozturk et al., 2017; Gale, Cooper, & Aihie Sayer, 2016). Patients with Parkinson’s disease have increased fall risk (Pickering et al., 2007; Stolze et al., 2004). Lee et al. found in their systematic literature review that heart failure is connected with a higher amount of falls (K. Lee, Pressler, & Titler, 2016). Cognitive impairments have also been found to increase fall risk (Allali et al., 2017; Tinetti, Speechley, & Ginter, 1988). Diabetes patients have been shown to have increased prevalence of falls and the fall risk is higher in insulin-treated patients (Hewston & Deshpande, 2016; Sarodnik, Bours, Schaper, van den Bergh, & van Geel, 2018; Y. Yang, Hu, Zhang, & Zou, 2016). People with rheumatoid arthritis have been suggested to have greater fall risk (Brenton-Rule, Dalbeth, Bassett, Menz, & Rome, 2015). Depression has been found to increase the fall risk of older people (Deandrea et al., 2010; Gale et al., 2016; Paliwal, Slattum, & Ratliff, 2017). Furthermore, Kistler et al. (2018, 2019) have found in their two studies that chronic kidney disease increases the risk of falls (Kistler, Khubchandani, Jakubowicz, Wilund, & Sosnoff, 2018; Kistler, Khubchandani, Wiblishauser, Wilund, & Sosnoff, 2019).

**Frailty** is a condition where the older adult seems to be in a cycle of declining energy. Definitions of frailty vary. According to Fried et al. frailty is defined presence of at least three of the following five criteria: shrinking, weakness, poor endurance, slowness, and low physical activity (Fried et al., 2001). Similar criteria are included in the most frailty definitions (N. M. de Vries et al., 2011). Some frailty definitions include social aspects, such as lack of social contacts (N. M. de Vries et
al., 2011). In addition, using biomarkers to diagnose frailty in older adults is emerging (Calvani et al., 2015; Saedi, Feehan, Phu, & Duque, 2019). Several screening tools exist, but there is a lack of agreement between the screening instruments, which has slowed implementation of these frailty definitions (Walston, Buta, & Xue, 2018). Frailty is not a chronic disease per se, but frail persons have been found to have an elevated risk of falls (O. J. de Vries, Peeters, Lips, & Deeg, 2013; K. E. Ensrud et al., 2007; Kristine E Ensrud et al., 2009).

The prevalence of multiple chronic conditions increases with age (Excoffier, Herzig, N’Goran, Déruyt-Luyet, & Haller, 2018; Sakib, Shooshtari, St John, & Menec, 2019; Wolff, Starfield, & Anderson, 2002) and in the literature co-occurrence and multi-morbidity patterns of diseases among older adults have been identified (Davis, Chung, & Juarez, 2011; P. G. Lee, Cigolle, & Blaum, 2009; Marengoni, Rizzuto, Wang, Winblad, & Fratiglioni, 2009). Number of diseases or number of health conditions has been found to be associated with history of falls, with the prevalence of falls rising with the number of diseases (Ek et al., 2018; Sibley, Voth, Munce, Straus, & Jaglal, 2014; Teixeira, Araújo, Duarte, & Ribeiro, 2019). Multiple chronic diseases have also been found to be associated with physical functioning difficulties (Stenholm et al., 2015). Only a few studies have evaluated the relationship between multi-morbidity patterns and falls (Ek et al., 2018; Paliwal et al., 2017; Sibley et al., 2014).

2.2.2 Extrinsic risk factors

Extrinsic risk factors for falls are features of the environment that cause loss of balance or slipping, such as uneven ground, loose rugs, pets, lack of supporting fittings in the bathroom, slippery surfaces, or poor footwear (Callis, 2016; Lord et al., 2001). Additionally, some lifestyle factors have been categorized as extrinsic factors, such as being married, which has been found to protect against falls in some studies and to be neutral in some other studies (Kwan, Straus, & Holroyd-Leduc, 2016). Medicines are categorized in some sources as intrinsic and in some sources as extrinsic factors (Bueno-Cavanillas et al., 2000; Lord et al., 2001; Rubenstein, 2006).

2.3 Fall risk assessment

The purpose of fall risk assessment is to identify persons at high risk in order to implement preventive measures, such as interventions or environmental
modifications, to reduce the risk of falls. The choice of fall risk assessment method depends on the target group, e.g. their age and housing situation (Rubenstein & Josephson, 2006). Multidimensional fall risk assessment can include several aspects, such as: history of falls, medical problems, medications, mobility assessment, examination of vision, gait and balance, lower extremity joint function, basic neurologic examination, muscle strength, mental status, assessment of cardiovascular status, functional performance tests, and environmental assessment (Lusardi et al., 2017; Park, 2018; Rubenstein & Josephson, 2006). Different fall risk assessment scales are used and these vary between nations, health care units and organizations. In Finland, the National Institute of Health and Wellbeing has made recommendations for fall risk assessment and fall prevention (Satu Pajala, 2012) and recommends a protocol to be used in health care for assessing fall risk. Regardless of the used protocol, full-scale fall risk assessment and screening for high fall risk patients among the older adult population is time consuming and a burden on health care resources.

2.3.1 Clinical measurements

Several different fall risk assessment scales have been developed and validated for the use of health professionals. The Downton fall risk index estimates the overall fall risk and probability of future falls (Downton, 1993). Downton’s index covers several different aspects of fall risk; history of falls, medication, sensory deficits, mental state and walking capability. FROP-Com is another multifactorial fall risk assessment tool, which covers 13 risk factors with 26 questions (Russell et al., 2009) and has demonstrated good reliability and a moderate capacity to predict falls (Russell, Hill, Blackberry, Day, & Dharmage, 2008). The Berg Balance Scale evaluates postural control (Berg, Wood-Dauphinee, Williams, & Gayton, 1989) and has a good discriminative ability to predict multiple falls according to receiver operating characteristics (ROC) analysis (S. W. Muir, Berg, Chesworth, & Speechley, 2008). Fear of falling and confidence in performing different daily activities can be measured with the Falls Efficacy Scale - International (FES-I) (Yardley et al., 2005), which has two versions: a 16-item and a shortened 7-item version. Both scales have been found to predict falls (Cumming, Salkeld, Thomas, & Szonyi, 2000; Delbaere et al., 2010). The Timed Up and Go (TUG) test is a simple test in which the person is asked to stand up from a chair, walk a short distance, turn around, walk back to the chair and sit down, and the total time taken is measured (Podsiadlo & Richardson, 1991). TUG assesses functional ability and
balance, but has not been shown to be able to predict falls (Barry et al., 2014). The Short Physical Performance Battery (SPPB) tool assesses physical performance with three components that measure balance, gait and lower body muscle strength (Guralnik et al., 1994) and it has been suggested to be able to discriminate between fallers and non-fallers (Veronese et al., 2014). In the Sit-to-Stand (STS) test, subjects are instructed to stand up from a chair five times as quickly as possible, and the time taken to complete the repetitions is recorded. STS was originally designed for assessing lower body strength, but it was later proven that STS performance also depends on multiple physiological and psychological processes and represents a particular transfer skill (Stephen R. Lord, Murray, Chapman, Munro, & Tiedemann, 2002). Furthermore, STS has been found to identify people with balance disorders (Whitney et al., 2005).

### 2.3.2 Technologies for fall risk assessment

Technologies provide means to make fall risk assessment easier and more effective. Possible technologies for fall risk assessment and their capabilities in assessing different factors for falls are summarized in Table 2.

FRAT-up is a recently proposed predictive tool for multifactorial assessment of fall risk of older people living in the community. It consists of questions related to medication, diseases, sensory deficits, age, gender, functional capability and memory (Cattelani et al., 2015) and calculates the probability of falling within the next 12 months.

Fall risk assessment scales can be extended with sensor-based analysis methods. Wearable movement monitors enable fall risk assessment outside the clinic in unsupervised environments, but also present challenges in terms of design, implementation protocols and signal analysis (Shany, Redmond, Narayanan, & Lovell, 2012).
<table>
<thead>
<tr>
<th>Technologies</th>
<th>Balance</th>
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<th>Medical background</th>
<th>Fall history (fall detection)</th>
<th>Sensory deficiencies falling</th>
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<tr>
<td>Wearable sensors</td>
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<td>Optical motion capture</td>
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<td>Gait mats</td>
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<td>Smart phones</td>
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<td>Depth cameras, radars</td>
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<td>Game consoles</td>
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<td>Electronic health records</td>
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*indoors only
Typical sensors used for balance and gait assessment are force plates, optical motion capture systems, gait walkways, gait mats, insoles and wearable sensors, such as accelerometers and gyroscopes (3D inertial measurement units (IMU)) (Ni Scanaill, Garattini, Greene, & McGrath, 2011; Vienne, Barrois, Buffat, Ricard, & Vidal, 2017). Additionally, risk assessments utilizing smart phones have been developed and tested (Habib et al., 2014). Depth cameras and radars can also be used for assessing mobility, balance and gait (Stone & Skubic, 2013; F. Wang, Skubic, Rantz, & Cuddihy, 2014).

Cheap, small and wearable sensors, such as accelerometers and gyroscopes, are used for measuring and analyzing body movement (Cuesta-Vargas, Galán-Mercant, & Williams, 2010; Lopez-Nava & Munoz-Melendez, 2016). Accelerometers are inertial sensors that consist of a mass reacting to movement or gravitation proportionally to acceleration (Shany et al., 2012). The actual component of movement-related acceleration needs to be separated from the gravitational component, and the gravitational component can also be used to define the postural orientation of the sensor (Kavanagh & Menz, 2008; Shany et al., 2012). There are several types of accelerometers available: piezoelectric, piezo resistive, and variable capacitive accelerometers, all of which apply the same principle of operation of a mass that responds to acceleration by causing a spring or an equivalent component to stretch or compress proportionally to the measured acceleration (Hooke’s law) (Kavanagh & Menz, 2008; Shany et al., 2012). Triaxial accelerometer devices have three sensitive axes mounted orthogonally to one another and the output voltage given by the accelerometer can be converted into m/s² values based on calibration (Shany et al., 2012).

Examples of accelerometer use include measuring physical activity, sleep, exercise, step count and energy expenditure (Murphy, 2009). Different daily and physical activities can also be recognized from the data (Attal et al., 2015; Pärkkää et al., 2006).

Digital or web-based questionnaires provide a means for assessing fall risk at home. Questionnaires can be used for assessing subjective fall-risk, fear of falling, fall history, or daily health situation (Rubenstein, Vivrette, Harker, Stevens, & Kramer, 2011). Only a few studies so far have been conducted to evaluate the effectiveness or feasibility of digital questionnaires. A web-based FRAT-up questionnaire was evaluated by Cattelani et al. (2015), who suggested that the questionnaire performance was comparable to externally validated state-of-the-art tools (Cattelani et al., 2015). Obrist et al. (2016) tested a monthly online questionnaire to assess fall risk with 134 older adults. The authors concluded that
the online survey was feasible and that the questions were understood well, but the response rate was low, and the discrimination between fallers and non-fallers was moderate (Obrist, Rogan, & Hilfiker, 2016). Ibrahim et al. (2017) combined in their study a TUG assessment with a questionnaire and found that the combination of a questionnaire with another assessment tool may better discriminate fallers and non-fallers (Ibrahim, Singh, Shahar, & Omar, 2017).

Recently, increasing interest has emerged in applying game consoles to fall risk assessment, but few studies about their feasibility or effectiveness exist (Clark et al., 2010; Marston et al., 2015; Vieira, Pereira, Freitas, Terroso, & Simoes, 2015). Game consoles can have various integrated or attachable sensors; Microsoft Kinect uses a depth camera, whereas Nintendo Wii Fit uses a balance board. Game-based fall risk assessment enables several advantages; the user does not feel that they are being monitored, their movements are natural, and games can be designed to be persuasive towards better performance. In a study by Yamada et al. Nintendo Wii Fit was able to recognize dual tasking problems, which have been suggested to be associated with fall risk (Yamada et al., 2011).

Electronic health records can provide additional insight into overall fall risk. Several intrinsic and extrinsic factors can be studied by utilizing electronic health record data, such as age, gender, chronic diseases, previous falls, medical conditions, impaired memory or cognition, sensory deficiencies, and drug prescriptions. Baus et al. developed a model for utilizing electronic health records for screening for high-risk patients (Baus et al., 2017). Recently, it was demonstrated how medical records can be used to develop a fall risk prediction model with moderate sensitivity and specificity (Oshiro et al., 2019). In an earlier study, a decision tree prediction model was developed for fall risk assessment utilizing medical databases and a database of 135,433 individuals. Age, female sex, previous fall, nocturia, anti-depressant use, and urinary incontinence were the strongest predictors of the risk profile (Rafiq et al., 2014).

**Balance and gait**

Accelerometry has been widely used in gait and movement analysis (Bautmans, Jansen, Van Keymolen, & Mets, 2011; Moe-Nilssen & Helbostad, 2004). Acceleration signals can be used to detect the timing of gait events, such as initial contact and final contact (González, López, Rodriguez-Uría, Álvarez, & Alvarez, 2010). Most current mobile phones contain accelerometers, which can be utilized for fall risk assessment. Recently, a review was made of studies of mobile
applications that evaluate dynamic and static balance (Roeing, Hsieh, & Sosnoff, 2017). The review included studies that had measured static balance or a clinical measure of balance with a mobile phone and concluded that the reviewed studies did not prove the ability of these applications to predict fall risk and that applications should be designed with special consideration for the user’s level of function. The usability in those populations should also be tested (Roeing et al., 2017). Utilizing the accelerometers embedded in mobile phones for gait or balance analysis is challenging because the mobile phone needs to be adjusted to a certain location on the body to obtain accurate measurements of gait or sway (H. Chan et al., 2011; Tacconi, Mellone, & Chiari, 2011).

Wireless embedded sensor systems integrated into shoes enable the assessment of gait features and critical weather conditions affecting fall risk, and many studies have tested shoe sensors (Bamberg, Benbasat, Scarborough, Krebs, & Paradiso, 2008; Hausdorff, Rios, & Edelberg, 2001; Majumder, Zerin, Ahamed, & Smith, 2014; Nakajima et al., 2011; Talavera et al., 2015). Shoe sensors provide possibilities to detect gait speed, stride-to-stride fluctuations and the walking style of the user. Hausdorff et al. (2001) studied the use of force-sensitive insoles for analyzing gait features and found the solution to be feasible for obtaining stride-to-stride measures of gait timings and that stride time variability was higher in subjects who subsequently fell than those who did not experience a fall during the 12-month follow-up period (Hausdorff et al., 2001). Another study by Talavera et al. tested wireless shoe insoles for gait analysis and found their fall risk index results to be comparable with clinical fall risk assessments (Talavera et al., 2015). Smart insoles have also been suggested to be able to distinguish between normal and abnormal walking patterns (Majumder et al., 2014).

Floor sensors or smart floors are able to detect similar gait features to wearable sensors. Rantz et al. (2012) found in their study utilizing floor sensors that gait velocity and functional ambulation profile (FAP) measured with a floor sensor were significantly correlated with clinical fall risk measures (Rantz et al., 2012).

Depth cameras can be used in homes for gait and balance analysis and can provide continuous and unobtrusive information. Rantz et al. (2015) used Microsoft Kinect to obtain gait characteristics and found that gait velocity and stride length correlated with clinically valid fall risk assessments (Rantz et al., 2015). Depth cameras are also able to measure stride parameters of people using an assistive walking device (Stone & Skubic, 2013). Depth cameras have been found to provide reliable gait and balance assessment (Clark et al., 2015; Dehbandi et al., 2017; Kim & Kim, 2018).
Ultra-wideband (UWB) radio technology can use a very low energy level for short-range, wide-bandwidth communications over a large range of the radio spectrum. UWB radar uses transmitting antennas and receiving antennas for the reflected signal (X. Wang, Dinh, & Teng, 2012). Humans cause changes in the frequency, phase and time of arrival of the reflected signal and, thus, human movement can be detected with UWB radars. A recent study demonstrated that UWB radars can be used for measuring sway in quiet standing, although a large-scale study is needed to further validate this finding (Joshi, Knoefel, Goubran, & El-Tanany, 2017). Doppler radars have been tested in a study by Wang et al. (2014) for unobtrusive health measurements and quantitative gait measurements, and the results show that a dual radar setting provides a clear advantage over the single radar system and that dual radar setting was more accurate for walking speed and step time measurement (F. Wang et al., 2014).

In a choice stepping reaction time (CSRT) test, the subject stands on a platform with four horizontal rectangular panels, one in front of each foot and one to the side of each foot. The panels are randomly illuminated, one at a time. The subject is instructed to step onto the illuminated panel as quickly as possible, using the left foot only for the two left panels (front and side) and the right foot only for the two right panels. The panels contain a pressure switch to determine the time of foot contact. CSRT is measured as the time period between the illumination of a panel and the foot making contact with it. In a study by Lord et al., CSRT was found to be significantly associated with neuropsychological, sensorimotor, and balance measures and to be an independent and significant predictor of falls. The authors also found that poor lower limb muscle strength impairs CSRT (S. R. Lord & Fitzpatrick, 2001).

Schoene et al. (2011) utilized a dance mat, which uses pressure sensors to detect steps, to test choice stepping reaction time (CSRT) and concluded that the dance mat device is a valid and reliable tool for assessing stepping ability and fall risk in older community-dwelling people (Schoene, Lord, Verhoef, & Smith, 2011).

**Muscle strength**

Muscle strength can be reliably assessed with direct muscle strength measurements or indirectly with measures that indicate weak muscle strength (Moreland et al., 2004). Pijnappels et al. (2008) used dynamometers in their study to measure the muscle strength of various muscle groups. The study concluded that the capacity to generate maximum extension force by the whole leg (e.g., in a leg press apparatus
or during jumping) was the best classification method for categorizing older people into groups of fallers and non-fallers (Pijnappels, van der Burg, Reeves, & van Dieën, 2008). Electromyographs (EMG), used to detect the electrical activity of muscle cells when the cells are activated, have been rarely used in previous studies to separate fallers from non-fallers. However, Chorin et al. (2016) studied Sit-to-Stand tests utilizing EMG and found that gastrocnemius lateralis muscle activity patterns measured with EMG differed between fallers and non-fallers (Chorin, Cornu, Beaune, Frère, & Rahmani, 2016).

**Chronic conditions and falls**

Most previous studies of technologies dealing with chronic conditions focus on computerized models that utilize health databases. Such a model developed by Baus et al. (2017) for screening for high fall risk patients includes chronic conditions. In their model, dementia, epilepsy and rheumatoid arthritis patients have higher odds of having documented falls (Baus et al., 2017). In a recent study, Oshiro et al. (2019) successfully demonstrated how medical records can be used to develop a fall risk prediction model with moderate sensitivity and specificity. The final fall prediction model in the study by Oshiro et al. also includes the following chronic conditions: mental disorder, Parkinson’s disease, urinary incontinence, depression, osteoarthritis, and osteoporosis (Oshiro et al., 2019).

### 2.4 Fall prevention

Falls of older adults are caused by many different factors, and preventing falls means eliminating or reducing the effect of these factors early enough. Prevention of falls can include the following interventions separately or together: 1) exercise/physical therapy programs aimed at improving balance, gait, and strength, 2) withdrawing or minimizing psycho-active medications, 3) management of orthostatic hypotension, 4) management of foot problems, 5) changes in footwear, 6) modification of home environment, 7) patient and caregiver education, 8) vitamin D supplementation in patients with vitamin D deficiency or high risk of fall, 9) cataract surgery and 10) dual chamber cardiac pacing (A. Lee, Lee, & Khang, 2013). Versatile exercise has been shown to prevent falls (Cameron et al., 2010; Gillespie et al., 2009). A recent review of several studies involving exercise programs aimed at fall prevention concluded that exercise as a single intervention can prevent falls in community-dwelling older people (Sherrington et al., 2017).
Specifically, exercise programs that challenge balance and are of a higher dose had larger effects, but further investigation is needed to study the impact of exercise as a single intervention in clinical groups and aged care facility residents. Promising results were found indicating the ability of exercise to prevent falls of people with Parkinson’s disease and cognitive impairment (Sherrington et al., 2017).
3 Purpose of the study

Falls are a major public health and economic concern in ageing societies and have serious effects on the quality of life of older adults and their families, friends and caregivers. There is an urgent need to find solutions for screening individuals at high fall risk. Current technical solutions include measuring characteristics of gait, measuring time spent on getting up from a chair, and measuring static postural sway with force platforms or other sensor solutions. Most of the available solutions have been designed for clinical use and are not suitable for continuous assessment during the daily life of older adults. Thus, sudden changes in functional capability, which may be precursors to a fall, may remain undetected. The aim of this study was to examine if individual clustering of chronic diseases is associated with higher fall risk and how technical solutions and connected data can be utilized in measuring acutely or incrementally appearing risk factors for falls in older adults.

The specific aims of the study were to:

- Reveal the possible associations between chronic diseases and occurrence of recent falls, and between individual clustering of chronic diseases and occurrence of recent falls
- Describe and evaluate existing technical solutions for fall risk assessment and to propose how to integrate them into electronic health records
- Evaluate the feasibility of an accelerometry-based mobile fall risk assessment solution for daily-life settings of older people
- Find out whether gait variables calculated from the acceleration signal for fall risk assessment differ from each other when measured from two different locations; on lower back and right side frontal hip
- Collect and study end-user feedback on the usability and feasibility of a home exercise technology aimed at reducing fall risk of older adults
4 Subjects and Methods

A summary of the subjects, study design and methods is presented in Table 3. The data collection protocols and analysis methods are elaborated in the following sections.

4.1 Subjects

The study population in study I was collected in a population-based Gasel project, “Tailored Services for Elderly - Gamified remote service concept for promoting health of older people”, led by the University of Oulu, Finland, and conducted in an international consortium during 2014-2016. The GASEL study population consisted of a random sample of 1,500 older adults obtained from the Finnish Population Register Centre. The sampling criteria were: aged 65 or more by the end of 2014, speaking Finnish as a native language, and having a permanent living address in Oulu, Finland in November 2014. The questionnaire was piloted among eleven volunteer seniors. All participants were sent a paper questionnaire by mail at the beginning of November 2014. A reminder and another copy of the questionnaire were sent to non-responders four weeks after this. Respondents were offered the possibility to answer and return the questionnaire either electrically or on paper. Altogether 1,400 questionnaires were mailed and 918 responses were received. The questionnaire covered different wellbeing related factors, demographic status, diseases, medication, use of technology, attitudes toward technology, health literacy, personality, exercise, daily activities and functional capability.

The material for publication II, state-of-the art literature, were collected from Google scholar, IEEE Explorer databases, and the ResearchGate and Mendeley online platforms.

In study III, a test group of 12 voluntary subjects, eight male and four female, were recruited among VTT’s employees. The test subjects were not involved in the development of the solution. One subject had paralysis of the left foot, otherwise the test subjects were healthy and without restricted mobility. One subject wore high-heeled shoes, the rest had flat shoes.
<table>
<thead>
<tr>
<th>Study</th>
<th>Design</th>
<th>Age</th>
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<th>Measurements</th>
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<tbody>
<tr>
<td>I</td>
<td>Population-based questionnaire (Gasel)</td>
<td>65-</td>
<td>918</td>
<td>Questionnaire on demographics, health, diseases, medication, physical activity, habits, functional capability, falls</td>
</tr>
<tr>
<td>II</td>
<td>Boolean searches of databases: fall risk, fall risk assessment, and technologies and sensors for fall risk assessment. Conceptual design for a cloud-based service for monitoring and assessing fall risk. Example end user application for fall risk assessment (Gasel &amp; AiB &amp; VTT internal project)</td>
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<tr>
<td>III</td>
<td>Software description, field test (AiB &amp; VTT internal project)</td>
<td>47.7 ± 11 years</td>
<td>12</td>
<td>Accelerometer</td>
</tr>
<tr>
<td>IV</td>
<td>Fall risk assessments wearing two accelerometers; on lower back and front right hip (AiB):</td>
<td>mean 74.2 years (64-85 years)</td>
<td>42</td>
<td>AIB: Accelerometer, medical condition habits, falls history, physical activity, fall risk assessments, muscle strength (grip &amp; lower body)</td>
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<tr>
<td>V</td>
<td>Iterative software development. Software use by older adults and professionals. Telephone interviews after four months use in Finland and final questionnaire for users in Finland and Spain. (AiB)</td>
<td>65-84 years (FI)</td>
<td>6 older users in Finland and 10 in Spain.</td>
<td>61-82 years (ES)</td>
</tr>
</tbody>
</table>
The study populations in studies IV and V were collected in the Ageing in Balance (AiB, 2012-2015) project, which was part of the European Ambient Assisted Living Joint Programme (AAL JP). In total, 42 subjects were recruited among residents of a retirement home in Tampere and from a senior physical exercise group in Oulu. Inclusion criteria for the study were age 64 years or more, living independently, no cognitive impairment, and able to perform simple physical exercises independently. Exclusion criteria were use of a wheelchair, being bed bound, or having a medical condition or functionality deficit that prevents the individual from doing simple physical exercises.

The Ethics Committee of Human Sciences of the University of Oulu (statement 6/2014) approved the study I protocol. A personal letter including the questionnaire described the voluntary nature of participation, the confidentiality of the data and the presentation of the results. A completed questionnaire was regarded as consent to participate. The protocols of study IV and V for field tests in Oulu and Tampere were approved by the Ethics Committee of Human Sciences of the University of Oulu (statement 2/2014) and by the Hospital La Fuenfria in Madrid, Spain, in study V. All of the subjects in studies III, IV and V were volunteers who gave their written informed consent.

4.2 Methods

4.2.1 Population-based GASEL study (I, II)

Data collection in Study I was performed by a comprehensive postal questionnaire including items on demographics, health and wellbeing, diseases and medical history, medication, use of technology, attitudes toward technology, health literacy, personality, volume of physical activity, daily living activities, and functional capability. Current diseases were determined by the question: “Do you currently have any of the following conditions as diagnosed by a medical professional?” and the answer options “yes” or “no.” Diseases queried in the questionnaire included liver disease, kidney disease, diabetes, rheumatoid arthritis, coronary heart disease, elevated blood pressure, blood circulation problems in the brain, blood circulation problems in the legs, hypothyreosis, hyperthyreosis, cancer, asthma, chronic obstructive pulmonary disease (COPD), heart failure, osteoporosis, Parkinson's disease, mild, moderate or severe cognitive impairment, eating disorder, depression, other mental illness, and other disease (with an open answer option).
To collect information on the frequency of recent falls of the respondents, the following question was used: “Have you fallen during the last three (3) months? (A fall is defined as an event that results in a person coming to rest inadvertently on the ground or floor or other lower level).” The answer options were: “no” and “yes, __ times.” Alcohol use was determined by the question: “Do you drink any alcoholic beverages, even occasionally? (e.g. beer, cider, mild wines, wines, or spirits),” and the answer options “I do not” or “Yes, I do, on average __ units per week.” One unit of alcohol was defined as equivalent to a standard glass of beer (285 ml), a single measure of spirits (30 ml), a medium-sized glass of wine (120 ml), or 1 measure of an aperitif (60 ml). Level of daily physical activity was determined by a question based on Pyky et al. (2015): “Approximately how much do you move per day (e.g., cycling, walking housework, hobbies, leisure activities, etc.)?” The response alternatives were <1 h, 1–2 h, and >2 h (Pyky et al., 2015). Smoking habits were determined by the answer options: 1) I don't smoke at all, 2) I quit smoking in year __, 3) I currently smoke __ cigarettes a day, 4) I use snuff or other tobacco products other than cigarettes. Living arrangements (living with someone or alone) were also inquired. Perceived sleep quality was determined by the answer options: 1) good, 2) satisfactory, and 3) poor. Ability to stand up from a chair was determined by the question: “Can you rise from a chair independently without using your arms or hands? and the answer options 1) I am able to rise independently and without using my hands, 2) I am able to rise independently using my hands on first try, 3) I am able to rise using my hands after several tries, 4) I need minimal assistance to rise and 5) I need moderate or maximal assistance to rise.” The SOF Index (Study of Osteoporotic Fractures) (Kristine E Ensrud et al., 2009) was used with modifications to identify individuals with frailty symptoms. The modifications and the reasons for them are described in detail in our earlier study (Keränen et al., 2017). The modified items were: 1. Weight loss irrespective of intention to lose weight (score = 1, if at least 1 kg weight loss in 3 months) (original SOF Index: if weight loss is more than 5% of body weight), 2. Can you rise from a chair independently without using your hands?” (score = 1 if unable) (original SOF Index: inability to rise from a chair five times without using the arms or hands), and 3. Poor energy was determined by the question: “Which of the following best describes how energetic you have felt in the last month?” (score =1 if the response is “I feel moderately tired, exhausted or weak” or worse) (original SOF index: if answer to the question “are you full of energy” is “no”). The subject was categorized as frail if their SOF index was 2 or 3; intermediate if their SOF index was 1; and robust if their SOF index was 0. Possible malnutrition was
assessed using Mini Nutritional Assessment (MNA) (Guigoz, Vellas, & Garry, 1996) including items on decrease in nutrition, weight loss, mobility, stress or acute illness, neuropsychological problems (dementia or depression), and BMI. The person is considered malnourished if their total MNA score is 0-7 points, at risk of malnutrition with 8-11 points, and as having normal nutrition with 12-14 points. Compared to the original MNA questionnaire, weight loss was determined in our study by the question: “In the last 3 months, has your weight 1) Decreased by ___ kg (score =0 if more than 3 kg, score = 2 if between 1 kg and 3 kg), 2) Stayed the same (score=3), 3) Increased by ___ kg (score =3) or 4) I don't know (score =1). In addition, the question regarding psychological problems was modified: moderate to severe memory disorder, mild memory disorder, other neurological illness, and depression were determined by the question: “Do you currently have any of the following conditions as diagnosed by a medical professional?” and the answer options “yes” or “no.” Moderate or severe memory disorder and depression is interpreted as 0 points in MNA, mild memory disorder as 1 point, and no memory disorders or depression as 2 points.

**Statistical analysis**

All analyses in Study I were performed with SPSS (IBM SPSS for Windows, version 24, IBM Corp., Armonk, NY, USA). The individual was classified as a faller if he or she had fallen at least twice during the last three months (Masud & Morris, 2001). To summarize the participants’ characteristics and to analyze the statistical significance of the differences between fallers and non-fallers, descriptive statistics were used. The statistical significance of the differences in dichotomous variables between fallers and non-fallers was analyzed by cross-tabulation and the Chi-square test. Mann-Whitney U-test was used for continuous variable age, and t-test for BMI. If the respondent had answered yes or no to at least one of the diseases, the answers to the other disease questions were interpreted as “no.” If none of the diseases were answered yes or no, the respondent’s disease data were interpreted as missing. Alcohol use was categorized in three categories: no alcohol, light drinker (1-3 drinks per week), moderate (4-7 drinks per week for women and 4–14 drinks per week for men), and heavy (≥8 drinks per week for women and ≥15 drinks per week for men). The statistical significance of the differences in disease and lifestyle variables between fallers and non-fallers was analyzed by cross-tabulation and Chi-square tests. Binary logistic regression
analysis with age adjustment was performed to analyze the statistical significance of the relationship between number of diseases and recurrent falls.

A two-step statistical procedure was used to analyze whether different combinations of chronic conditions were associated with recent falling. Parkinson’s disease, hyperthyroidism, liver diseases, kidney diseases, eating disorder and mental illnesses (other than depression) were not included in the cluster analysis due to low prevalence, and “other diseases” was not included due to the vague definition and variety of these diseases. First, an agglomerative hierarchical clustering with Ward’s linkage method was performed to identify sub-groups of individuals based on their responses to the chronic disease questions (Cornell et al., 2009). Hierarchical clustering means that each subject begins as an individual cluster, which gradually merges with the most similar other clusters until a single cluster containing all subjects is obtained. This hierarchical clustering produces a tree-like structure, i.e. dendogram. Secondly, binary logistic regression with age and gender adjustment was performed to study the relationship between chronic disease clusters and recurrent falls.

4.2.2 State-of-the-art review (II)

The state-of-the-art literature review in study II was made by performing Boolean searches in Google Scholar, IEEE Explorer, ResearchGate and Mendeley. Journal and conference articles, books and book chapters related to fall risk, fall risk assessment and technologies and sensors for fall risk assessment were selected according to their extent. Additionally, specific technologies were searched for separately, such as “ultra-wideband radar and fall risk assessment.” Literature, that presented results of utilizing technologies for fall risk assessment were selected. The selected publications addressing falls, fall risk and fall risk assessment date from 1975-2018 and those addressing technologies for fall risk assessment from 2003-2018. Novel sensor technologies as well as movement analysis has advanced during this timeframe.

4.2.3 Software development and field studies (II, III, V)

Articles II, III and V include software developed for end users. In publications II and III a mobile fall risk assessment solution was used, and in publication V a Windows application for a touch screen PC was used.
Mobile fall risk assessment solution (publications II and III)

A mobile fall risk assessment solution utilizing accelerometer data was developed in an internal project of VTT Technical Research Centre of Finland Ltd by utilizing accelerometer data and results collected in the AiB project (H. Similä et al., 2015; Heidi Similä, Immonen, & Ermes, 2017). The software was developed for the Android operating system utilizing accelerometer data received via Bluetooth® LE connection from a Movesense device manufactured by Suunto. The functionalities of this software are described in publications II and III. The application was developed to demonstrate the fall risk assessment algorithm. The desired functionalities of the software were specified and the application utilizing Movesense sensor was developed iteratively for the Android operating system. The application was designed to be easy to use for the users. The process for assessing an individual’s fall risk is as follows: 1) name of the individual is defined and added to the system, 2) username is used to login to the system, 3) available Movesense sensor is selected and the Bluetooth connection is established, 4) instructions for conducting the test are shown to the user, 5) user starts the measurement by pushing a button, 6) user stops the test or the test is stopped automatically if the preset duration or collected data set is achieved, and 7) data is analyzed and the result is shown to the user. The 12 voluntary subjects recruited were asked to walk three times as follows: 1) Walk normally at your normal pace, 2) Walk dragging your feet on the floor, and 3) Walk slower than your normal pace (publication III).

Home technology for fall prevention (publication V)

Software for older users was developed iteratively to prompt and coach the users in taking actions that promote fall prevention and in exercising with video guidance. The end users took part in the design process and first evaluated the initial use case scenarios (H. Similä, Immonen, García Gordillo, Petäkoski-Hult, & Eklund, 2013). A persuasive system design model (PSD) was utilized in a workshop with researchers to design the functionalities of the system, and the design process and results were published by (Harjumaa & Muuraiskangas, 2014). The main functionalities are: a) automatic reminders of exercises, b) video exercise guidance, c) individually tailored schedule for exercises, d) diary for tracking past exercises and daily step counts, e) wellness monitoring through scheduled questions (e.g. “how did you sleep”), f) manually adding any other performed exercise. A physiotherapist and two physiotherapy students developed the exercise plan. The
videos were loaded to the application from the commercial product Physiotools’ video library. For the first version, we used existing video exercises from the Physiotools video library, and for the second version additional exercise videos were recorded by the two occupational therapy students and added to the Physiotools video library. The exercises included balance, muscle strength and stretching exercises. The exercises had three difficulty levels. Screenshots of the developed software are shown in Figure 1. The system also included a separate accelerometer device, which the users could carry attached to the body with an elastic belt. When the accelerometer was not in use, it was attached to the USB port of the device to charge the battery and to transfer the raw data from the device to the system. Step count was shown for the user in the user interface.

The tests in Finland were conducted following the procedure described in Figure 2. In the final tests, six users who had used the system for more than two weeks were asked questions about the usefulness and ease of use on a Likert scale. In addition, open questions regarding exercise adherence, whether the person exercised more because of the device and opinions about the most useful functionalities, missing functionalities, whether they prefer real life contact better, willingness to buy the device and software, the exercise program, the nutritional hints and wellness-related questions presented by the application, and other comments.
The system was also evaluated and feasibility-tested in Spain by professionals and ten older adults who had fallen during the last year. The older adults were recruited
among medical service clients in northwest Madrid. The participants filled in questionnaires about their background and their motivation to actively engage in balance improvement and balance exercises. A physician assessed the fall risk of the participants. The participants tested the system for the following predetermined scenarios mimicking system usage at home: 1) performing video-guided home exercise, 2) viewing the diary of performed exercise, 3) manual addition of an exercise to the diary and 4) automatic reminders and questions on the screen, and 5) activity monitoring with the sensor. A physiotherapist guided the users through the tests. The physiotherapist observed the use of the system and the users were interviewed afterwards about their first impressions, expectations, ease of use, usefulness and further improvement ideas.

In Spain, professionals also evaluated the usability and feasibility of the system by answering the same questions.

### 4.2.4 AiB data collection (IV)

Extensive fall risk measurements were conducted with 42 older persons three times during a year in Oulu and Tampere in Finland. Fall risk measurements include scientifically validated assessments, such as Berg Balance Scale, Activities-Specific Balance confidence scale, Falls Efficacy Scale International, walk tests, and sit to stand. Thorough descriptions of the collected fall risk measures are provided in our earlier publications (Heidi Similä et al., 2017; Heidi Similä, Mäntyjärvi, Merilahti, Lindholm, & Ermes, 2014). Accelerometer data and depth camera data were collected during the fall risk assessments. Sensor data were collected from two different locations in the body, lower back and right frontal hip. The tests also included corridor walking, which was performed twice in a corridor over 20 m in length, and gait data was collected with accelerometers for use in study IV.

### 4.2.5 Gait acceleration measures and data analysis (III, IV)

The acceleration measures used in studies III and IV were collected with separate accelerometer sensors. In study III, a Movesense device manufactured by Suunto (www.suunto.com) was used. The Movesense device is based on the Nordic Semiconductor nRF52832 Bluetooth® LE System-on-Chip (SoC). The sensor is an accelerometer/gyro combo ST LSM6DS3, which supports 12.5/26/52/104/208 Hz sample rates and ±2/±4/±8/±16 g full-scale acceleration ranges. The Movesense
device is a small (36.6 mm x 36.6 mm, 10 g) button-like item. The data from the Movesense button was sent to an Android mobile phone over a Bluetooth® LE connection. The Movesense sensor was attached to the vertebral column of the lower back of the subjects firmly with an elastic belt.

Another sensor product was used in study IV, a GCDC X16-2 (www.gcdataconcepts.com) accelerometer sensor with a sampling rate of 100HZ ±16G. Two GCDC sensors were attached to subjects; one at the center of the lower back between the L3-L5 vertebrae with an elastic belt and the other with another elastic belt on the front of the body on the right hip. Real-time clocks embedded in the sensors were synchronized with the computer clock before each test session. To ensure uniform positioning, the sensors were always attached by the same researcher. The acceleration signals from both sensors were used in the analysis in study IV.

In studies III and IV the subjects were asked to walk along a corridor. In study III, the walking distance was approximately 10 meters and the subjects were asked to perform three different walks: 1) Walk normally with your own normal style and speed, 2) Drag your feet while walking to demonstrate a person with mobility or balance problems, 3) Walk slower than your normal pace. In study IV, the floor of the corridor that the subjects were asked to walk along was marked with tape a couple of meters after the beginning and before the end of the corridor. One researcher annotated the beginning of the walk, crossing the first tape, crossing the second tape, and end of the walk.

Data analysis

The data analyses in studies III and IV were carried out using Matlab version R2017a (MathWorks, Inc.; Natick, MA, USA) and, additionally, in IV, SPSS for Windows version 24.0 (IBM Corp., Armonk, NY, USA) was used.

Acceleration data in studies III and IV were filtered to remove the gravitational acceleration from each of the three sensor axes (3rd order elliptic infinite impulse response filter, cutoff at 0.25 Hz, passband ripple 0.01 dB, stopband at -100 dB). The filtered signals were subtracted from the original accelerations to calculate body accelerations in the mediolateral (x), vertical (y), and anteroposterior (z) directions. The following equation is used to calculate the signal vector magnitude (SVM) for the sample n.

\[
SVM[n] = \sqrt{(x[n])^2 + (y[n])^2 + (z[n])^2}.
\]  

(1)
SVM can be used to evaluate the degree of movement intensity (Karantonis, Narayanan, Mathie, Lovell, & Celler, 2006; Khusainov, Azzi, Achumba, & Bersch, 2013). Five linear acceleration features and three temporal features were calculated from the body accelerations. The linear features include standard deviations of x, y, z, and SVM signals and average SVM. To analyze temporal features, steps were first detected from the vertical acceleration signal by calculating a 10-point moving average, then threshold crossings were detected (0.15 times the maximum value of the signal under investigation) and local maxima were detected in the original signal between the indices of consecutive threshold crossings. Average step time, standard deviation of step times, and asymmetry between left and right step were calculated from the time incidents of the detected steps. Step time is the time between two consecutive peaks. The mean and standard deviation of the step times in seconds were calculated. These linear and temporal features mentioned above are often calculated in accelerometry-based fall risk assessment studies (Jennifer Howcroft, Kofman, & Lemaire, 2013; Rispens et al., 2014).

The features mentioned above were used in study III to form a fall risk index (FRI), which is the weighted \( \sum_{i=0}^{N} \omega_i X_i \); 

\[
FRI = w_0 + w_1 X_1 + \cdots + w_N X_N, 
\]

The FRI values for study III were calculated for one feature, standard deviation of vertical acceleration, which has been found to predict balance and fall risk with scientific significance in previous studies (Menz, Lord, & Fitzpatrick, 2003; Heidi Similä et al., 2017; Van Schooten et al., 2015).

Statistical analysis in study III included comparison of differences in feature values between different walking styles using one-way analysis of variance (ANOVA), F-test and Tukey-Kramer for post hoc multiple comparisons.

In study IV, the difference in the amount of steps detected by the two sensors was evaluated in terms of frequency and percentage of agreement between the sensors. Pearson correlation between the feature values derived from the lower back and front hip sensors was determined in order to compare the effect of sensor location on those features.
5 Results

The main results of the substudies are summarized in Table 4.

<table>
<thead>
<tr>
<th>Study</th>
<th>Study description and material (project name)</th>
<th>Main result of the study</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Association between chronic diseases and falls. Association between disease clusters and falls. Questionnaire data from 918 Finnish adults aged 65 to 97.</td>
<td>Recurrent fallers had higher number of diseases. Osteoporosis cluster and multiple chronic disease cluster had significantly increased risk of recurrent falls</td>
</tr>
<tr>
<td>II</td>
<td>Literature review of technologies for fall risk assessment and conceptual design of technologies for monitoring and assessing fall risk. Prototype end user application for fall risk assessment.</td>
<td>Conceptual design of a fall risk assessment system utilizing various sensors. Mobile solution for fall risk assessment.</td>
</tr>
<tr>
<td>III</td>
<td>Mobile solution for fall risk assessment. Software description and user tests with 12 persons to evaluate the feasibility of the mobile solution for detecting gait disturbances.</td>
<td>Acceleration features were significantly different (p &lt; 0.01) between normal walk and dragging walk, and between normal walk and slow walk. Average step time was significantly different between normal and slow walk (p &lt; 0.05). The features did not differ significantly between dragging and slow walks. Standard deviation of step times or asymmetry between right and left step times did not differ significantly between the walks.</td>
</tr>
<tr>
<td>IV</td>
<td>Gait analysis from two accelerometer sensor locations on lower back and front right hip to study the relevance of the sensor location. Data on 42 individuals aged ≥ 64 years collected in a field test.</td>
<td>Most of the analyzed gait features from the two locations have a strong correlation, indicating that these features are not sensitive to sensor location around waist level. Poor agreement between the two sensors in measuring step time and step symmetry.</td>
</tr>
<tr>
<td>V</td>
<td>Iterative software development and feedback from software use by older adults and professionals in Finland and Spain.</td>
<td>Mostly positive than negative feedback from the older and professional end users. The users wished to be able to monitor how the exercises are performed and receive direct feedback.</td>
</tr>
</tbody>
</table>
5.1 Chronic diseases and falls (I)

In total, 119 (13%) subjects reported that they had fallen at least once during the last three months: 73 subjects (8%) once, 27 (2.9%) two times, 11 (1.2%) three times, 4 (0.4%) four times and 5 (0.5%) more than five times. Subjects who reported recurrent falls were significantly older (median 71 years, quartiles 68 and 77 years) than subjects who did not report any falls or reported having fallen only once (median 71 years, quartiles 68 and 77 years), (p=0.025). Recurrent fallers were also categorized as frail more often (n=16, 40%) than non-fallers (n=46, 5.9%), (p<0.001) and a smaller proportion of fallers were able to get up from a chair without using hands or getting help (n=17, 39.7%) than non-fallers (n=690, 81.3%) (p<0.001). Fallers were more often at risk of malnutrition according to MNA assessment (n=9, 37.5%) than non-fallers (n=67, 13.1%), with a statistical significance of p=0.004. A higher proportion of fallers had low BMI (BMI<20, n=4, 9.1%) or high BMI (BMI>30, n=10, 22.7%) than non-fallers (n=18, 2.2% and n=150, 18.5% respectively). Fallers reported to have poor self-reported sleep quality more often (n=8, 19.6%) than non-fallers (n=16, 7.6%) (p=0.023).

The proportion of subjects having at least one chronic disease was slightly higher among fallers (n=40, 93%) than non-fallers (n=672, 83.1%), although the difference is not statistically significant (p=0.223). The association between number of chronic diseases and recurrent falls is shown in Table 5. Participants with five or more chronic diseases had higher odds for recurrent falls during the last three months than participants with less chronic diseases according to binary logistic regression.

Eight clusters were selected for the final cluster solution. Participants who were healthy with a low number of chronic conditions formed Cluster 1. Participants in Cluster 2 more frequently had elevated blood pressure and cancer than participants in the other clusters. Cluster 3 participants had co-morbidity of coronary heart disease, heart failure and diabetes. Cluster 4 included participants with asthma and COPD. Cluster 5 included participants with hypothyroidism and diabetes. Cluster 6 included participants with osteoporosis. Cluster 7 included participants with blood circulation problems in the legs. Cluster 8 included participants with multiple chronic conditions; diabetes, rheumatoid arthritis, coronary heart disease, elevated blood pressure, blood circulation problems in brain and legs, asthma, COPD, heart failure and cognitive impairments.
Table 5 Association between number of chronic diseases and recurrent falls as odds ratio (OR) and 95% confidence interval (95% CI), adjusted for age.

<table>
<thead>
<tr>
<th>Variable</th>
<th>OR (95% CI)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>No chronic diseases</td>
<td>reference</td>
<td></td>
</tr>
<tr>
<td>One chronic disease</td>
<td>0.74 (0.15-3.71)</td>
<td>0.711</td>
</tr>
<tr>
<td>Two chronic diseases</td>
<td>1.97 (0.50-7.79)</td>
<td>0.336</td>
</tr>
<tr>
<td>Three chronic diseases</td>
<td>3.45 (0.90-13.17)</td>
<td>0.070</td>
</tr>
<tr>
<td>Four chronic diseases</td>
<td>3.02 (0.64-14.13)</td>
<td>0.161</td>
</tr>
<tr>
<td>Five chronic diseases</td>
<td>13.65 (3.33-56.02)</td>
<td>0.000</td>
</tr>
<tr>
<td>Six or more chronic diseases</td>
<td>9.62 (2.31-40.06)</td>
<td>0.002</td>
</tr>
<tr>
<td>Age 65-74</td>
<td>reference</td>
<td></td>
</tr>
<tr>
<td>Age 75-84</td>
<td>0.88 (0.42-1.86)</td>
<td>0.741</td>
</tr>
<tr>
<td>Age ≥85</td>
<td>1.75 (0.70-4.39)</td>
<td>0.234</td>
</tr>
</tbody>
</table>

OR = odds ratio, CI = confidence interval

The prevalence of each chronic condition in each cluster is presented in Table 6. Nearly all chronic conditions were represented in each cluster, with the exception of Cluster 1. Clusters 2-7 had a dominance of one to three conditions and cluster 8 had a high prevalence of multiple diseases. Cluster 1 was labelled “low chronic disease”, Cluster 8 “multiple chronic diseases” and the other clusters were labelled according to the dominance of the diseases. The revealed clusters also differed in demographic characteristics and geriatric conditions. Relative to Cluster 1, other cluster participants were older, less physically active, more frail, and had more geriatric conditions, such as dizziness or urinary incontinence. Relative to the other formed clusters, Cluster 8 was older, less physically active, more overweight (BMI <30), more often at risk of malnutrition, and had a higher prevalence of geriatric conditions, such as dizziness and incontinence. Binary logistic regression analyses indicated that Clusters 6 (osteoarthritis) and 8 (multiple chronic disease) were significantly associated with increased risk of recurrent falls adjusted for age and gender (OR=5.49, p=0.028 and OR=14.26, p=0.002 respectively). The association of Cluster 3 (coronary heart disease, heart failure, diabetes) with increased risk of recurrent falls is also approaching borderline significance (OR=4.76 =p=0.059). The other revealed clusters were not significantly associated with higher risk of recurrent falls.
### Table 6 Chronic diseases by cluster

<table>
<thead>
<tr>
<th>Cluster</th>
<th>1 Low chronic disease</th>
<th>2 Elevated blood pressure, cancer</th>
<th>3 Coronary heart disease, heart failure, diabetes</th>
<th>4 Asthma, COPD, arthritis</th>
<th>5 Hypothyroidism, diabetes</th>
<th>6 Osteoporosis</th>
<th>7 Blood circulation problems in legs</th>
<th>8 Multiple chronic disease</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>138</td>
<td>227</td>
<td>100</td>
<td>64</td>
<td>59</td>
<td>176</td>
<td>66</td>
<td>32</td>
</tr>
<tr>
<td>Diabetes</td>
<td>0.7%</td>
<td>33.5%</td>
<td>42.0%</td>
<td>12.5%</td>
<td>39.0%</td>
<td>17.6%</td>
<td>22.7%</td>
<td>84.4%</td>
</tr>
<tr>
<td>Rheumatoid arthritis</td>
<td>0.0%</td>
<td>7.5%</td>
<td>2.0%</td>
<td>9.4%</td>
<td>0.0%</td>
<td>4.0%</td>
<td>0.0%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Coronary artery disease</td>
<td>0.0%</td>
<td>5.3%</td>
<td>88.0%</td>
<td>17.2%</td>
<td>3.4%</td>
<td>9.1%</td>
<td>22.7%</td>
<td>59.4%</td>
</tr>
<tr>
<td>Hypertension</td>
<td>1.4%</td>
<td>69.6%</td>
<td>58.0%</td>
<td>57.8%</td>
<td>49.2%</td>
<td>48.3%</td>
<td>43.9%</td>
<td>87.5%</td>
</tr>
<tr>
<td>Circulatory disorder in brain</td>
<td>0.0%</td>
<td>8.8%</td>
<td>6.0%</td>
<td>6.3%</td>
<td>0.0%</td>
<td>7.4%</td>
<td>1.5%</td>
<td>43.8%</td>
</tr>
<tr>
<td>Circulatory disorder in legs</td>
<td>0.0%</td>
<td>3.5%</td>
<td>5.0%</td>
<td>15.6%</td>
<td>10.2%</td>
<td>11.4%</td>
<td>100.0%</td>
<td>78.1%</td>
</tr>
<tr>
<td>Hypothyroidism</td>
<td>0.0%</td>
<td>4.0%</td>
<td>15.0%</td>
<td>14.1%</td>
<td>98.3%</td>
<td>5.7%</td>
<td>7.6%</td>
<td>28.1%</td>
</tr>
<tr>
<td>Cancer</td>
<td>0.0%</td>
<td>18.1%</td>
<td>2.0%</td>
<td>1.6%</td>
<td>5.1%</td>
<td>5.7%</td>
<td>7.6%</td>
<td>31.3%</td>
</tr>
<tr>
<td>Asthma</td>
<td>0.0%</td>
<td>1.8%</td>
<td>6.0%</td>
<td>95.3%</td>
<td>6.8%</td>
<td>9.1%</td>
<td>4.5%</td>
<td>40.6%</td>
</tr>
<tr>
<td>COPD</td>
<td>0.0%</td>
<td>1.3%</td>
<td>1.0%</td>
<td>17.2%</td>
<td>1.7%</td>
<td>2.8%</td>
<td>1.5%</td>
<td>31.3%</td>
</tr>
<tr>
<td>Heart failure</td>
<td>0.0%</td>
<td>4.8%</td>
<td>37.0%</td>
<td>4.7%</td>
<td>5.1%</td>
<td>2.8%</td>
<td>6.1%</td>
<td>71.9%</td>
</tr>
<tr>
<td>Osteoporosis</td>
<td>0.0%</td>
<td>0.9%</td>
<td>0.0%</td>
<td>1.6%</td>
<td>8.5%</td>
<td>27.8%</td>
<td>3.0%</td>
<td>18.8%</td>
</tr>
<tr>
<td>Moderate or severe cognitive impairment</td>
<td>2.9%</td>
<td>0.9%</td>
<td>2.0%</td>
<td>1.6%</td>
<td>1.7%</td>
<td>5.7%</td>
<td>0.0%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Mild cognitive impairment</td>
<td>0.0%</td>
<td>21.6%</td>
<td>11.0%</td>
<td>9.4%</td>
<td>8.5%</td>
<td>8.5%</td>
<td>9.1%</td>
<td>53.1%</td>
</tr>
</tbody>
</table>

Values are percentages % among the cluster

### 5.2 Technologies for measuring and reducing fall risk

Technological solutions for assessing and reducing fall risk are presented in studies II, III, IV and V.
5.2.1 Conceptual framework for a cloud service for monitoring and assessing fall risk (II)

We proposed a fall risk assessment system utilizing various sensors in study II. An illustration of the proposed system is shown in Figure 3. In the proposed system, various sensors collect information on gait, activity, sleep, environment and health factors. The information gained from these sensors is collected in a Personal Health Record (PHR). In Finland, the My Kanta Personal Health Record (Kanta PHR) is a national repository for health and wellbeing related information collected by citizens. Data from wearables and apps can be stored in the application provider’s (third party) data storage systems. Fast Healthcare Interoperability Resources (FHIR) interface facilitates access to health and wellbeing related data in third-party storage. The proposed fall risk assessment system utilizing sensor data applies data mining, fall risk calculation logic, and data interpretation. The system can also provide recommendations for the user or responsible bodies. Intended users of the system include doctors, nurses, physical therapists, older adults and their relatives and caregivers, and relevant decision makers. Preferences regarding the functionalities and user interfaces of the system vary between different users. Finnish citizens will in the near future have the option of sharing their My Kanta PHR data with social welfare and healthcare professionals. Health researchers and decision makers will also be able to access the collected data subject to the individual’s consent to use the data in anonymized form. Researchers will benefit from access to such a large amount of data on daily living in refining fall prediction models. For decision makers at the national level, information on the physical condition of citizens is crucial to be able to implement population-wide preventive actions and predict future service needs. Self-assessment of fall risk is possible utilizing the data collected from sensors and health records. The system can also provide historic overviews of changes in physical condition over time and produce alerts if sudden or acute changes in physical condition are detected.
Fig. 3. Illustration of the fall risk assessment system utilizing the Finnish Personal Health Record (PHR) system MyKanta and Patient Data Repository (PDR)

5.2.2 Mobile fall risk assessment solution (II, III)

To demonstrate a fall risk assessment solution for older end-users, a mobile fall risk assessment solution was developed. The application was developed for Android operating systems using acceleration data received from a Movesense device over Bluetooth® LE connection. The older user is guided to perform a self-evaluation of fall risk, or a nurse or other care personnel is guided to perform a fall-risk assessment for a client. In the fall risk assessment test, the user is guided to walk a distance of roughly 10 meters. The acceleration data collected during the walk are analyzed by the application, and the Fall Risk Index (FRI) (see equation 2) result is shown to the user. Screen shots of the application are shown in Figure 4. The developed prototype only stores the data locally on the mobile phone, but the solution can be enhanced to support the conceptual design presented in the previous chapter. FRI values can be combined with other personal data and the FRI can be used as complementary information in holistic assessment of an individual’s fall risk.
5.2.3 Accelerometers in measuring fall risk from gait (III, IV)

Gait features and FRI of different walking styles collected with the mobile fall risk assessment solution

In the comparison between different walking styles, the following acceleration feature values differed with statistical significance ($p < 0.01$) when compared with normal walk and acted dragging walk, and between normal walk and acted slow walk: standard deviation of $x$, $y$ and $z$ and SVM signals and average SVM. Average step time was significantly different only between normal walk and slow walk ($p < 0.05$). There was no statistically significant difference between the features obtained from acted dragging walk and acted slow walk. The standard deviation of step times and asymmetry between right and left step times were similar between the different walking styles.

The mobile fall risk assessment solution’s Fall Risk Index (FRI) values are shown in Figure 5. The FRI values calculated from normal walk for all but one subject are lower than the FRI values calculated from dragging walk and slow walk. Subject 8 wore high heels and had higher FRI measures than the others. Subject 9
had a paralyzed foot and was the only subject with a slightly lower FRI value in dragging walk than normal walk.

Fig. 5. Fall Risk Index (FRI) values calculated for each subject with different acted walking styles; normal, dragging and slow.

**Sensor location**

Accelerometer data collected from sensors on the lower back and frontal hip of 42 subjects were included in the comparison of gait features. The participants had good balance, with a mean Berg Balance score of 53 (range 34-56). Calculation of the number of steps differed between sensors on the lower back and frontal hip; one to six less steps were detected by the sensor on the front hip compared to the sensor on the lower back for 19 subjects, and the detected number of steps was same for 20 subjects. For three subjects, the used method detected more steps from the front hip than the lower back.

Visualizations of the standard deviations of the acceleration signals in the mediolateral (x), vertical (y), and anteroposterior (z) directions from each of the 42 subjects are shown in Figure 6. The vertical measurements align well with each other and anteroposterior acceleration differed most between the sensors on the lower back and frontal hip.
A comparison of gait feature values obtained from the sensors located on the lower back and frontal hip are shown in Table 7. The listed numbers are group means, group standard deviations, Pearson correlations, and p-values. There was a statistically significant correlation between the standard deviation of mediolateral (x), vertical (y), and anteroposterior (z) acceleration, and the mean and standard deviation of SVM and mean step time. No correlation was found between the two sensors in the standard deviation of step time and step asymmetry. The highest correlation between the sensors was achieved with mean SVM values, which means that the total acceleration is similar measured from both locations. This feature is shown in Figure 7 for all subjects.
Table 7. Mean gait feature values from accelerometer sensors on lower back and front hip, and Pearson correlation between the two sensors.

<table>
<thead>
<tr>
<th></th>
<th>N=42</th>
<th>Mean LB* (SD)</th>
<th>Mean FH* (SD)</th>
<th>Pearson Corr.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std X</td>
<td></td>
<td>0.207 (0.060)</td>
<td>0.233 (0.062)</td>
<td>0.755</td>
<td>0.000</td>
</tr>
<tr>
<td>Std Y</td>
<td></td>
<td>0.324 (0.103)</td>
<td>0.320 (0.977)</td>
<td>0.866</td>
<td>0.000</td>
</tr>
<tr>
<td>Std Z</td>
<td></td>
<td>0.215 (0.585)</td>
<td>0.232 (0.658)</td>
<td>0.729</td>
<td>0.000</td>
</tr>
<tr>
<td>Std SVM</td>
<td></td>
<td>0.216 (0.593)</td>
<td>0.204 (0.059)</td>
<td>0.840</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean SVM</td>
<td></td>
<td>0.388 (0.103)</td>
<td>0.415 (0.104)</td>
<td>0.952</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean Step Time (s)</td>
<td>0.469 (0.0405)</td>
<td>0.478 (0.0428)</td>
<td>0.908</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Std Step Time (s)</td>
<td>0.039 (0.040)</td>
<td>0.062 (0.041)</td>
<td>0.019</td>
<td>0.230</td>
<td></td>
</tr>
<tr>
<td>Step Asymmetry</td>
<td>5.54 (5.644)</td>
<td>11.61 (13.20)</td>
<td>0.072</td>
<td>0.649</td>
<td></td>
</tr>
</tbody>
</table>

* LB = lower back, FH = front hip

Fig. 7. Mean SVM for sensors on the lower back and front hip of all subjects, © 2018 IEEE.

5.2.4 End user experiences of home technology for preventing falls (V)

In a telephone interview of six Finnish end users of the first version of the software, we found that the three users had used the device almost daily and three users had used it little or irregularly. Five out of six had performed the video-guided exercise more than once a week. Some problems were reported regarding setting up the
device and its subsequent use. Four users considered the device pleasant to use and two said they felt neither negative nor positive about the device. One user wished for a feature to be able to view statistics or historical data on responses given to questions related to sleeping or eating. In the interview, one person commented that the software was easier to use compared to other technologies. Four users commented that the device had increased their motivation to exercise, whereas two commented that it did not motivate them to exercise because they were already active before using the device. Two users felt a sense of obligation to use the device. One user mentioned that “It is good that the device forces me to exercise, otherwise I wouldn’t exercise at all” and was delighted to find that her muscle strength had increased during using it. All of the device users had enjoyed the exercises.

In the final assessment of six female end users, the device users had used the device for a period ranging from 4.3 months to 16.3 months. All users were physically active in addition to using the device: they walked, did Nordic walking or cycled daily. Five persons attended group exercises once or twice per week and two exercised at a gym weekly. The results of the Likert scale questionnaire given in the final assessment are shown in Figure 8. In addition, two users mentioned that they had exercised more than usual because of the device, one user reported exercising somewhat more, and one user said that the device had not changed the amount that they exercise. The users were unable to come up with any ideas for further development of the device.

In the test session of Spanish older end users, nine users considered the home solution to be practical, good and straightforward, and eight users thought it was easy to use. Some users commented on the lack of feedback on whether the exercises are performed correctly or not. Ideas for further development addressed the content of the exercises, and one user also suggested improving the activity log. The physiotherapists who observed the test session expressed concern regarding the safety of the exercises due to the system not providing feedback on whether the exercises were performed correctly. Furthermore, they considered that the older users are not interested in doing the exercises if they are not monitored by a health professional.

The professional users in Spain offered further development ideas: they wanted to be able to customize the exercises to each user, track the duration of the exercises, and have a feedback option during exercises. They also suggested that an avatar mimicking the end users' movements would be beneficial. The professionals also requested a decision support system for classifying users automatically into suitable
exercise difficulty levels. The users suggested that patient health records could be used to obtain data from medical assessments.

Fig. 8. End user responses regarding usability and usefulness

<table>
<thead>
<tr>
<th>Statement</th>
<th>0%</th>
<th>10%</th>
<th>50%</th>
<th>90%</th>
<th>100%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exercising with the help of the device I can reach better balance faster.</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Exercising according to the guidance of the device will enhance my balance.</td>
<td>3</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Because I have the device, I do more balance exercises.</td>
<td>4</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Device allows me to exercise balance more efficiently</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Device allows me to exercise balance more easily</td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>I think that the device is/was beneficial for me</td>
<td>4</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>It was easy to learn how to use the device</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>The device functionalities corresponded to my expectations</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>The instructions and information provided by the device were clear and understandable to me.</td>
<td>5</td>
<td>1</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using the device could be easily integrated into my everyday life.</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>It would be easy to learn to take advantage of the device for improving and maintenance of balance.</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>I think the device is easy to use.</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

- Fully agree
- Somewhat agree
- Neither agree or disagree
- Somewhat disagree
- Fully disagree
6 Discussion

The present study introduced and evaluated various technological solutions for assessing fall risk of older persons. The study revealed that individual clustering of chronic diseases was associated with increased fall risk. In addition, the study showed that it is possible to develop feasible and acceptable methods for screening older individuals at high fall risk utilizing various technological solutions, especially accelerometers.

The risk of recurrent falls has been shown to increase with age (Downton, 1993; Lord et al., 2001; Masud & Morris, 2001; Rubenstein, 2006). Our findings are consistent with those of previous studies, showing that the proportion of recurrent fallers increased with age in study I. The number of frequent fallers was also higher among people with low BMI, low activity, self-reported poor sleep quality, inability to get up from a chair without help, frailty according to the SOF index, and malnutrition according to MNA. Multiple chronic diseases seem to be associated with a higher amount of recurrent fallers. Older persons with five or more diseases increased the risk of recurrent falls compared to the no disease group with age adjustment. With hierarchical clustering, we formed eight separate clusters and found that the cluster with multiple chronic diseases had a significantly higher risk of having fallen during the last three months than the cluster of low chronic diseases. The osteoporosis cluster also had a statistically significant higher risk of recurrent falls. Elevated blood pressure was distributed almost evenly among the clusters with the exception of the multiple chronic disease cluster, which had a higher prevalence of elevated blood pressure. Our results partially align with previous studies in the field. A population-based study in Canada revealed that clusters of hypertension and COPD patients had higher risk of falling than a low chronic diseases cluster (Sibley et al., 2014). Positive association between the number of fall episodes and heart attack, angina, stroke, asthma, COPD, CKD, arthritis, depression, and diabetes among fallers was found in another study in the US (Paliwal et al., 2017). Hierarchical clustering was also used by Ek et al., (2018) with a follow-up period of five years. They found that people with an unhealthy lifestyle and a high burden of chronic diseases had increased risk of falling over a longer follow-up period (5 and 10 years) (Ek et al., 2018). The results of both the above studies and the present study indicate that it is possible to identify individual clusters of diseases that increase fall risk. Moreover, a larger data set, for example utilizing data from electronic health records of diagnosed diseases and injurious falls, would allow the results to be adopted for screening high fall risk patients.
among the population and to target preventive actions towards persons in need. A model of utilizing electronic health records for screening high-risk patients has been developed by Baus et al. (2017), and another recent study has successfully demonstrated how medical records can be used to develop a fall risk prediction model with moderate sensitivity and specificity (Oshiro et al., 2019).

In study II we proposed a conceptual design that collects data from various wearable and ambient sensors and devices, and utilizes the data collected in patient health records. When an elevated risk of falling is noticed, the user or responsible bodies are able to receive recommendations for preventive actions. Automatic fall risk assessment and fall prevention still require important development improvements. An optimal solution or combination of sensors or information is still undefined. Another undefined aspect is how the collected information can be integrated into health care paths and processes. Targeted attention and efforts should also be given to usability and the way information is presented to users. Personal data should only be used with consent from the users. In earlier studies it has also been found that low-cost, portable and objective measuring instruments are feasible for use with older adults and have the potential to identify persons at high fall risk (Ejupi et al., 2014; Sun & Sosnoff, 2018). In addition, sensor-based solutions have the potential to be used in the daily lives of older adults to enable continuous monitoring (Ejupi et al., 2014; Sun & Sosnoff, 2018). However, recent studies conclude that the predictive ability of the technologies needs to be validated (Ejupi et al., 2014; Rajagopalan, Litvan, & Jung, 2017; Sun & Sosnoff, 2018).

A mobile solution for fall risk assessment was introduced in studies II and III. In preliminary user tests in study III, the obtained gait feature values were predictable, showing significant differences between normal and dragging/slow gait. The difference in average step time between normal and slow walking was the only significant temporal feature, and is a logical finding. However, because the problematic gaits were acted out, other features not found to be significant by the preliminary study should not be discarded based on these results. Further studies should be made to evaluate their significance. Fall Risk Index (FRI) values were systematically higher for dragging or slow walking compared to normal walking, with the exception of slightly lower FRI for dragging walking from the subject with a paralyzed foot. In addition, one subject who wore high heeled shoes during the test received the highest FRI value for normal walking compared to the other subjects, although dragging and slow gait increased her FRI value, as with all subjects. Shoes may have an effect on gait (Wiedemeijer & Otten, 2018) and thus also FRI value, and this should be taken into account in test situations. In the used
application, it is possible to make an initial measurement (baseline) for each subject and monitor the change in gait features for each person over time. The results are promising and wider data collection using the solution should be planned to further evaluate the solution. The advantage of the presented gait-based solution is that it only requires the attachment of a single sensor by the user and the test is easy to perform, which may increase the adoption of the solution by older users. However, a study involving older users should be made to assess the feasibility and usability of the solution. The presented solution and other gait analysis based methods enable monitoring of incremental and sudden changes in fall risk in daily life settings, which is not possible with clinical assessment scales. The data or FRI results collected by the solution could also be given to health professionals who could make decisions on preventive actions against falls. A larger data set collected from older adults with a follow-up period should be collected and analyzed to further enhance the FRI calculation. A recent study by Manor et al. (2018) presented a mobile solution for fall risk assessment utilizing the inertial sensor in mobile phones. In that study, the application instructed the user to perform gait tests and dual-tasking tests with multimedia and text instructions. The results showed that measuring stride times with the app was valid and reliable during both normal and dual-task walking and in both laboratory and non-laboratory environments, but the study did not investigate the same gait features that were included in our studies (Manor et al., 2018). A mobile application for fall risk assessment was developed and tested by Pergolotti et al. (2019). The application was designed to measure postural sway and motor reaction time, utilizing the gyroscope sensor in mobile phones. The solution was found to be feasible for fall risk assessment, and postural sway measured with the solution correlated significantly with the 30-second Sit-to-Stand test, and motor reaction time correlated significantly with the Timed Up and Go test (Pergolotti et al., 2019). In a recent systematic review of novel sensing technologies by Sun and Sosnoff (2018) the authors concluded that the variation in measured parameters, assessment tools, sensor sites, movement tasks, and modelling techniques, prevents making a firm conclusion on the ability of sensing technologies to predict future falls. However, they consider it feasible that these assessments can be undertaken regularly in both clinical and non-clinical settings (Sun & Sosnoff, 2018). Similar to our study, the need for testing the solution with older users is recognized in other related studies (Manor et al., 2018; Pergolotti et al., 2019; Sun & Sosnoff, 2018). Inertial sensors also enable instrumentation of other fall risk assessment scales, such as the Sit-to-Stand (Doheny et al., 2011) and Timed Up and Go (Greene et al., 2010) tests. However, both of the latter assessment
methods require two sensors, on the sternum and right thigh (Doheny et al., 2011) and on the anterior of each shank (Greene et al., 2010), respectively. Gait-based assessment has the advantage of requiring only one sensor, which may increase the usability, adoption and acceptance of the solution by potential older users.

In study IV we compared the gait features extracted from the accelerometer signal collected from the lower back and front right hip and found that some features did not differ between the two sensors. The analyzed features have been connected with high fall risk in earlier studies. The linear acceleration features (standard deviation of x, y and z) had a strong and significant correlation between the lower back and frontal hip, as well as standard deviation and mean SVM and mean step time. This means that these features were not sensitive to sensor location at waist level. In our study, mean SVM had the highest correlation between the two sensors, leading to the preliminary conclusion that the total amount of acceleration can be captured well from waist level irrespective of sensor location. Features that were not significantly correlated between the two sensors included standard deviation of step times and step time asymmetry. Step detection was less accurate from the frontal hip sensor than the lower back sensor. Asymmetry of right and left step times requires a sensor attached to the centerline of the body. The sensor on the right side is more sensitive to right side steps and this may lead to false detection of side difference. Partially similar results were found in an earlier study, where similarities were found for mean step time and mean step length from sensors on the waist and lower back, and not found for step time asymmetry (Del Din et al., 2016). In another study, a mobile phone was placed in the front pocket of test subjects to measure gait, and stride times during walking under different experimental conditions were accurately measured (Manor et al., 2018). Our study was conducted with a relatively small study group of older adults and all subjects were physically active and in good physical condition. In addition, our data were collected in a test session, and a study utilizing data collected during actual daily living is needed to utilize the results. Our results indicate that also other sensor locations may be suitable for fall risk assessments in addition to the lower back, which is most commonly used in fall risk assessment (J Howcroft, Kofman, & Lemaire, 2013). For older users, it might be easier to attach the sensor to the front hip than the lower back.

In study V we collected feedback on the developed home solution for fall prevention from older people and professionals. The feedback included more positive than negative responses from both the older and professional end users. The users in Finland stated that they had done more physical exercise because of
the system. It should be noted that our test subjects were in good physical condition and were already physically active, which may have an effect on the results. In Spain, the test users thought that the system might affect their balance. The Spanish users also would have preferred to get feedback on whether the exercises were performed correctly or not. Our test groups in Spain and Finland were relatively small and further research is needed on the effectiveness of technical interventions. However, technological solutions have great potential to promote exercising at home and a recent review found that among older adults adherence to technology-based exercise solutions is high (Valenzuela, Okubo, Woodbury, Lord, & Delbaere, 2018). Video games for exercising (exergames) are a showing promising results as a means of increasing physical activity and improving health and physical function in older adults (Primack et al., 2012; van Diest, Lamoth, Stegenga, Verkerke, & Postema, 2013). An earlier review by (Skjæret et al., 2016) collected information about technologies utilizing exergaming for delivering exercising and rehabilitation to older adults. Based on the findings, the authors provided the following recommendations for future development of exergaming: personalization is needed, the solutions should address multiple physical functions, they need to be safe for the users, and there is a need for studies with longer follow-up time (Skjæret et al., 2016).

Combining clinical fall risk assessments with sensor data might provide more information about fall risk, but only a few studies utilizing a combination of information can be found from the literature. The combination of clinical fall risk factors and body-worn inertial sensor data has been found to lead to better accuracy compared to clinical or sensor data alone (Greene, Redmond, & Caulfield, 2017). In another study by Howcroft et al. (2017), the ability of several wearable sensors and sensor combinations to predict falls of older adults was tested. The best input data for fall prediction was gained with multi-sensor gait assessment with a combination of accelerometers located on the posterior pelvis, head, and left shank. Regarding single-sensor models, the best predictor in the Howcroft et al. study used a posterior pelvis accelerometer, dual-task gait data, and a neural network. The results of the study also showed that sensor-based models outperformed clinical assessment-based models (Jennifer Howcroft, Kofman, & Lemaire, 2017). A recent systematic review by Bet et al. (2019) examined studies utilizing wearable sensors for fall detection and fall risk assessment. According to the review, in current research accelerometers are the most popular wearable sensors for measuring elevated fall risk among older adults. Machine learning is a growing area of interest in studies addressing the use of wearables for fall risk assessment, although feature
extraction was the most used method in the reviewed studies (Bet, Castro, & Ponti, 2019).

This study has some limitations. In study I, the number of falls during the preceding three months was quantified by retrospective inquiry, which is prone to information loss. In addition, there was no information on whether the chronic diseases were diagnosed before or after the falls. In addition, we were not aware of how the chronic conditions were treated or how the subjects adhered to the treatment plans. The collected information also was self-reported, which may affect the reliability of the responses. Furthermore, possible cognitive impairment of the senior participants was not taken into account. Parkinson’s disease is commonly known to increase fall risk, but in our study sample the prevalence of Parkinson’s was low and thus not included in the clustering. Further research with a larger population sample, for example utilizing patient health records, is needed to increase the reliability of the results. However, our results are promising in showing that individual clustering of diseases may reveal high fall risk persons among the older population and that persons with multiple chronic diseases have higher fall risk. The size of the study groups in publications III, IV and V were relatively small, which limits the generalizability of the results. Further studies with larger study groups are needed to validate the results and to enhance the FRI calculation in study III. In study III, the walking styles were acted, and the test subjects were at working age. Another study with older people having actual gait deficits or mobility problems is needed to further validate the results. Our results do, however, provide a clear preliminary indication that the mobile solution is able to detect problematic gait. In addition, the subjects in study V were in good physical condition, which may have an effect on the subjects’ willingness to use the solution and positive attitudes towards exercising with the solution. The effectiveness of the solution or the intervention program were not studied in this study and further studies including a larger and more heterogeneous group of older adults is needed.

Several aspects need to be taken into account in the design of technological solutions for fall risk assessment and fall prevention, such as heterogeneity of the group of older adults, need for personalization, usability aspects, health literacy aspects, visualization of the results, privacy and security, adjusting the solutions to the daily life of older adults, and cost-effectiveness of the solutions. In the case of prevention, it is also important to determine who will be responsible for the costs of the solutions. However, the solutions presented above provide promising results regarding the use of technological solutions for fall risk assessment and the
potential of such solutions to provide cost-effective methods for screening for high fall risk patients among older populations.
7 Conclusions

This study provides new knowledge on the association between multimorbidity and risk of falling among older people, and on the possibilities of different technologies for screening older individuals at high risk of falling. The study is multidisciplinary and broadens the current outlook on fall risk assessment technologies. A positive association between multiple chronic diseases and fall risk was found among the population-based sample of older people. Accelerometry-based technologies were found to be feasible for fall risk assessment. Based on the aims of this study, it can be concluded that:

- Chronic diseases and multiple morbidity are associated with elevated fall risk. The study suggests that it is possible to identify individual clusters of diseases that increase fall risk.
- Technologies and data analysis methods can be used for automated measurement of known fall risk factors, and automatic fall risk assessments can be integrated into electronic health records. However, optimal solutions or optimal combinations of sensors and information, and how to integrate the information into health care paths and processes remain undefined.
- Mobile applications utilizing a separate accelerometer sensor are feasible for measuring deficits in gait, which may in turn indicate elevated fall risk.
- Linear gait features derived from accelerometer signals do not differ between sensors located on the lower back and frontal hip. Step time calculation, step count, and gait asymmetry features were not reliably recorded from the side of the body.
- Feedback on the developed home-based fall prevention technologies was mainly positive from both older adult and professional end users.
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Original publications

I Immonen, M., Similä, H., Haapea, M., Enwald, H., Keränen, N., Kangas, M., Jämsä, T., & Korpelainen, R. (manuscript 2019). Association between chronic diseases and recurrent falls among older people in Finland – a population-based GASEL study, manuscript, submitted to BMC Geriatrics


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Original publications are not included in the electronic version of the dissertation.

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