Understanding Older Users' Acceptance of Wearable Interfaces for Sensor-based Fall Risk Assessment

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ABSTRACT
Algorithms processing data from wearable sensors promise to more accurately predict risks of falling – a significant concern for older adults. Substantial engineering work is dedicated to increasing the prediction accuracy of these algorithms; yet fewer efforts are dedicated to better engaging users through interactive visualizations in decision-making using these data. We present an investigation of the acceptance of a sensor-based fall risk assessment wearable device. A participatory design was employed to develop a mobile interface providing visualizations of sensor data and algorithmic assessments of fall risks. We then investigated the acceptance of this interface and its potential to motivate behavioural changes through a field deployment, which suggested that the interface and its belt-mounted wearable sensors are perceived as usable. We also found that providing contextual information for fall risk estimation combined with relevant practical fall prevention instructions may facilitate the acceptance of such technologies, potentially leading to behaviour change.

Author Keywords
Older adults; falls; wearable interfaces; usability.

ACM Classification Keywords
H.5.2 User Interfaces; J.3 Life and Medical Sciences: Health.

INTRODUCTION
Falls are the leading cause of injuries among seniors. Each year approximately 20% to 30% of seniors aged 65 and over experience a fall [45]. The outcome of a fall varies from a scratch to a fractured hip, and it may even lead to direct death in some cases. A fall not only physically harms the senior, but also causes a tremendous mental burden that leads to fear of falling, reduction in activity, and even greater isolation [2,41]. The direct annual costs associated with falls were estimated in 2010 to be $8.7 billion in Canada alone [39]. This has lead to a significant demand for feasible and affordable technological solutions.

CHI 2018, April 21–26, 2018, Montreal, QC, Canada

ACM ISBN 978-1-4503-5620-6/18/04…$15.00
https://doi.org/10.1145/3173574.3173693

The goal of such technological interventions is to help seniors maintain independent living and reduce the associated cost in terms of medical treatment and human resources. In the research community, fall detection is the most studied technique for tackling falls. Reliable fall detection systems can provide assistance to seniors after a fall has occurred, such as prompt response and minimizing post-fall damage. However, these systems do not prevent falls from happening in the first place. A proactive approach would be more valuable in terms of avoiding falls and reducing associated medical cost.

Our work focuses on sensor-based fall risk assessment (SFRA) solutions that offers an accessible way to measure the risk of falling. This information is particularly important for preventing falls in a timely manner. Conventional fall risk evaluations are often used to assist caregivers and families to develop interventions to help seniors reduce falls. However, these are typically conducted in a clinical setting, and thus rather inaccessible in the home.

Although research in SFRA is still incipient, a few proof-of-concept projects have shown encouraging results [40, 50]. These revealed how variables such as activity level or gait quality, obtained from wearable sensors through ambulatory monitoring can be applied to evaluate risks of falling and predict future falls. While this is very useful in improving the accuracy of wearable SFRA systems, comparatively little research is being carried out to understand user's acceptance of such solutions. Furthermore, we are yet to fully understand how to best design interactive systems that empower users to visualize fall risks based on the sensor data, as well as engage actively in a human-in-the-loop approach to calibrating and providing feedback into the underlying processing behind SFRA systems.

The research presented here is aiming to address this gap, through a field-based usability assessment of an SFRA system. For this, we have implemented an SFRA system consisting of a wearable sensor belt and fall risk detection algorithm. We have conducted a participatory design session with older adults that produced the specifications for a tablet-based mobile control interface wirelessly connected to the belt. A usability evaluation was then carried out through a field deployment of the belt + tablet combo. This SFRA system was well-received by the users, with potential for changing behaviours with respect to fall prevention by empowering users to better understand, monitor, and control the complex data and assessments generated by the wearable device. This may better support users' decision-making regarding the adoption of various interventions such as home hazard removal, withdrawal of certain fall inducing drugs, footwear modification, or even surgery [18]. Hence in this study, we bring to light evidence that quantifying and visualizing fall risk estimation had a positive effect on the participants, in terms of improving fall awareness, tendency to adapt fall prevention practices, and awareness of personal physical ability.

We describe in this paper the user interface (UI) design insights we have gained from participatory design sessions with older adults (OAs). Based on the results of a field deployment, we reflect on what OAs who are otherwise physically healthy but concerned about long-term increases in fall risks need from a SFRA visualization UI. We then provide recommendations for the design of interfaces that monitor and control such wearable sensor-based devices.

BACKGROUND

Although falls are a widespread concern, currently there exists no universally effective prevention solutions, as falls are the result of a complex combination of risk factors and the effects of ageing [45] (e.g. environment, gait, balance, dizziness, vertigo [2]). While intervention programs can reduce falls through behaviour and environment changes [9,43,47], these are more difficult to implement.

Technology approaches have been proposed to address the implementation cost of conventional interventions, focusing on four directions: detection, prevention, risk assessment, and damage mitigation. Fall detection and, to a lesser extent, assessment, are the most active directions (e.g. intelligent home monitoring). Of increasing interest are wearable monitoring devices, which have improved considerably in accuracy [38] and acceptance by seniors [17,31], particularly compared to video based monitoring due to security and mobility concerns [15]. However, privacy concerns remain for wearable monitoring [34].

We briefly survey here prior technology approaches to fall prevention, in which we ground our own work. A complete review of relevant hardware and algorithmic advances can be found in [19]. We focus on wearable-based approaches because of their mobility, low cost, and easy deployment.

Automatic Fall Detection

Research on fall detection and response has been ongoing for more than 40 years. Developments of smaller and more capable sensors during the past decade have lead to an increase in the availability of user-friendly solutions, including for real-time detection [55]. Among these, Noury [37] developed a wearable sensor and a simple fall detection algorithm based on fused signals from an accelerometer, a position tilt switch, and a vibration sensor, in an attempt to differentiate Activities of Daily Living (ADL) from falling. Degen et al. [11] created a wrist-worn detector and used the norm of the acceleration vector to detect falls. It was the first design to consider the user experience of OAs using this device. The UI of the fall detector was kept minimal to be more usable by seniors. Unfortunately, although the device was easy to wear, it only performed well in detecting forwards falls.

Fall detectors developed in the late 2000s have achieved much better accuracy compared to their predecessors. Kangas et al. [25] showed that a waist-mounted fall detector using an accelerometer and threshold-based algorithms can successfully detect falls with a sensitivity of 97.5% and specificity of 100% for older adults aged 40-65. However, the detection of falls was performed offline. By 2010, many studies [6,20,28,54] reported successful fall detection with similar approaches described in Kangas' studies. However, many of these studies were not conducted "in the wild", and involved young participants simulating falls, while ADL data were collected from seniors.

Attempts were also made to evaluate fall detectors in real-world settings with older participants. Bourke [6] presented a vest that uses a threshold-based algorithm for real-time fall detection and alert. While promising, this was affected by usability issues and false alarms.

While much has been done on improving the sensor devices and algorithms, the usability challenge in wearable fall monitoring devices remains mostly undiscussed. The current research on fall detection is focused on creating more reliable algorithms, using different sensor types and placements [4,13,14,23]. The waist is identified to be most favourable since this location is closest to the body's centre of mass and the acceleration experienced at this site when a fall occurs tends to be similar across different fall types. Algorithms have also improved in accuracy, mostly through the use of machine learning [26], or by incorporating other risk factors such as cognition or gait dynamics [27], with promising results in settings such as smart homes [8]. Most algorithm research employs younger adults in simulated settings, which may not generalize to older adults [3,22,24]. Further deployments in realistic settings are needed.

Such deployments are now more affordable due to the increased ubiquity of wearable sensors (smartwatches, smartphones, etc.) Currently, smartphone-based detectors suffer from low accuracy [30]. Dedicated commercial solutions are more accurate, with accuracies of 75% fall detection, although false alarms are still a problem [56] as are the additional costs of human monitoring.

Prevention through Sensor-Based Fall Risk Assessment

A proactive approach that goes beyond detection may be far more valuable in terms of avoiding falls and reducing the associated medical cost. In particular, we examine the use of wearable sensors to anticipate risks of future falls. While conventional fall risk evaluations such as POMA [46], STRATIFY [38], and TUG [42] are successfully used to help seniors reduce falls, these are employed in clinical settings. For home settings, unsupervised sensor-based risk assessment tools may be more suitable [44].

Although research in sensor-based fall risk assessment is still in its early stage, research has shown encouraging preliminary results. Marschollek et al. [33,38] proposed an unsupervised method to classify fallers from non-fallers, using inertial sensor data to extract gait and dynamic balancing parameters, with classification accuracy of up to 80%. van Schooten et al. [48,49] utilized inertial sensor data collected at participants' trunk to evaluate fall risk in an unsupervised setting, yielding and accuracy of 82%.

Although less common as fall detection, these studies have shown that wearable-based fall risk assessment is feasible, and can potentially assist seniors (and their caregivers) in realistic settings such as at home. It is expected that such approaches will eventually be able to incorporate unsupervised algorithms using motion data, further increasing the convenience of such systems.

Usability of Wearable Fall Monitors

Aside from technical challenges, user acceptance of fall detection and prevention technologies are critical to creating feasible solutions, as is the case in general with assistive technologies for older adults [40] and in particular with multimodal/multi-sensor interfaces [34]. With respect to health monitoring, seniors indicated that balancing ease of use with extended mobility and ability to afford independence is important for the adoption of monitoring devices [15, 31]. Moreover, seniors are concerned by lack of control over false alarms, especially when these are sent to caregivers automatically [17]. The user requirements highlighted by the above studies suggest that usability challenges must be addressed in order to implement a fall monitor that is practical, unobtrusive, well-received by seniors, and ultimately achieves health benefits.

While today's research on fall detection and prevention using wearable sensors has largely been focused on creating and improving algorithms and devices, there is certainly a need for studying the acceptance of such implementation for older users. Establishing detailed user requirements and design requirements will also direct future research on fall monitors in terms of user interface, sensor placement, and data visualization.

GOALS AND SCOPE

Our research aims to fill the identified gap of lacking real-life evaluations of design requirements supporting users' needs with respect to monitoring, controlling, and understanding data collected from wearable sensor-based fall risk assessment (SFRA) systems. Our work draws from gerontechnology research [49] on sensor-based algorithms that quantifies changes in risks vs. detecting imminent falls. The oldest seniors are at higher risk of imminent falls; however, it is the younger seniors who experience an increase in awareness of such risks while maintaining an active lifestyle. Our target demographic is this latter group, which exhibits significant concerns about frailty-inducing events such as falls – a more frequent concern for healthy OAs than e.g. cognitive decline [1,45].

In particular, we aim to explore the most effective fall risk data visualization and information delivery mechanisms on mobile interfaces through participatory design with older users. For this, we hypothesize that:

H1. A wearable SFRA system that quantifies numerically and visualizes the risk of falling can lead to acceptance and adoption of this technology by older users
H2. The fall risk information that the SFRA system provides leads to improved fall risk awareness

In other words, H1 focuses on usability, and H2 focuses on effectiveness of the SFRA system. We answer these hypotheses trough the following research questions:

Q*1. What is the most acceptable and comprehensible way to present information regarding the risk of falling (and changes in such risks) for older users?*
Q2. How acceptable and usable do OAs consider the belt and visualization display to be for daily use?
Q3. How much do older users value the information regarding their risk of falling and how much does it help them to be aware of their own behaviours regarding fall prevention?

Q1 will refine the definition of good usability for the SFRA system; Q2 will support the validation of H1, while Q3 will produce evidence to support validation of H2. We also expect that answering these will yield design considerations for such systems. The field evaluation provides answers to Q2, and the participatory design sessions and interview sessions to Q1 and Q3. We expect that these short-term findings will help inform further deployments that will demonstrate long-term acceptance and behaviour change.

IMPLEMENTATION

Our main goal is to evaluate a wearable SFRA system in terms of technology acceptance and the effect of improving fall risk awareness. For this, we developed a custom SFRA system and conducted a field study. We first describe the design and implementation of hardware and software infrastructure of the custom wearable SFRA system. Next, we describe the first phase of the study. The purpose of the first phase of the study is to guide the development of a mobile UI interfacing with the SFRA system to display fall risk information. We then describe the design, procedures, and findings of the second phase of the study – a field evaluation of the SFRA system with older users in real-life settings, and report on design considerations.

The SFRA system developed for this study consists of two central pieces: a wearable device for data collection, and a mobile device for fall risk information display. We decided to focus on walking, as prior research suggests that motion is a reliable modality for collecting fall risk data [48]. Our implementation relies on a server-client architecture, with data collected by the server being uploaded to a processing unit (e.g. laptop or tablet in the participant's home), which in turns provides fall risk assessment data to a tablet-based UI that is used by the participant. This architecture has been selected to minimize the battery drain on both the wearable sensor and the tablet, and to be deployable in homes without reliable connectivity. To reliably obtain gait features, previous studies have recommended using 100 Hz for accelerometer sampling [6,12,21,49,57,58], which is not easily found among consumer devices. Therefore, we have built a custom wearable device that can provide easy integration with mobile devices as well as high quality motion data with a high sampling rate. The custom hardware is designed in the form of a belt, as shown in Figure 1. The belt form factor was chosen for its familiarity among the target demographic and its social acceptance, for its ability to be worn around the waist (ensuring accurate motion data collection as recommended in [50]), and for its meeting of usability recommendations [40].

The case for the electronics is 3D printed using the Dremel Idea Builder and PLA filament. It is designed as an easy-to-wear 9mm closing belt buckle. Our custom device collects accelerometer data at high frequency (200 Hz) using a FLORA LSM9DS0 9-DOF Accelerometer + Gyroscope + Magnetometer. Data is synced with a tablet using an Adafruit Feather M0 Bluefruit LE (Low Energy Bluetooth). The 3.7v 2000mAh Li-Ion battery can last more than a day. Motion data is collected by the wearable device and stored on the device's SD card. On request of the mobile app, it transmits the stored motion data to the mobile device. The data is then sent to the server for fall risk estimation (only when motion is detected, in order to save bandwidth).

The algorithm used to assess the fall risk is developed by van Schooten et al. [48,49], and used here with permission from these authors. The algorithm accepts input of raw accelerometer data in three directions of walking motion. The algorithm is coupled with the method of Zijlstra et al. [59] to identify valid walking data, which relies on the fact that the shape of the forward acceleration signal can be roughly predicted during stepping. The output is converted to a numerical 1 to 10 scale indicating the risk of falling. We have opted for this algorithm as it works as a long-term predictor of risks instead of detecting imminent falls.

FIELD STUDY – PARTICIPATORY DESIGN

Participatory design is shown to be an effective approach to gather design requirements and improve the quality of digital technology design in the early stage of the design process by engaging older adults [29]. We invited participants to share their design ideas for the mobile UI that will help older adults to visualize fall risk information.

Figure 1: The custom-built wearable hardware (in the form of a belt).

This captures users' perspectives into designing interfaces to display the risk of falling. The input from older participants (potential users of wearable SFRA systems), is used to inform the design of the display interface.

Participants

Five participants (Table 1) participated in this phase – a number in line with studies of similar methods or users [35,52]. The recruitment was carried out through flyers posted on the university campus, local libraries, and community centres. Inclusion criteria were at least 55 years of age and comfortable using mobile touchscreens.

ID	Age	Gender	Familiar with Mobile Device	User of Mobile Device	Familiar with Wearable	Uses Wearable Devices
P1	61	M	High	Yes	Yes	Yes
P2	67	M	Medium	No	No	No
P3	59	F	Medium	Yes	Yes	Yes
P4	57	F	High	Yes	Yes	No
P5	62	F	High	Yes	Yes	No

Table 1: Demographic information for Phase I. All participants were cognitively able, but concerned about long-term prevention of falls.

The study was designed with ethical guidance from the Canadian Tri-Council Policy (TCPS2), and approved as low-risk by our university's Research Ethics Board. We have taken additional steps to protect participants, such as instructing them to not rely on the prototype's assessments, and providing referral info for a fall specialist.

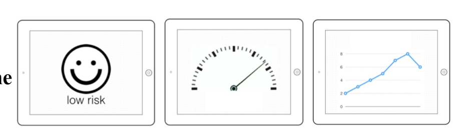
Protocol and Instruments

Participatory design [29,52] is used, in the format of one-on-one sessions with an older participant. Each session has three parts: "Information gathering and sharing"; "Scenario generation"; and "Feature and scenario envisioning". First is a discussion to familiarize the participants with the topics of falls and technologies, which they will be using later in a paper-and-pencil design activity. Participants are asked to share their understanding of the 3 key concepts that will be used in the design activity later: falls among seniors, mobile devices, and wearable technologies. The discussion is facilitated, as to help participants with unfamiliar concepts.

The second part introduces the design problem, through the use of scenarios (narrative storytelling). These are relevant to the participants, and progress from non-technology to technology-focused, e.g. from visiting a doctor that has the participant's fall risk information, to using mobile or wearable devices presenting such information.

Once the participant is comfortable with the idea of using new technology for monitoring the risk of falling, we then present mock-ups of the information display interface, from simple/emotional to more technical and numerical (Figure 2). The mock-ups serve as an artifact to provoke responses

Figure 2: Design mock-ups used in the Phase I scenarios.



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from the participants and engage them into producing their own sketches. We purposefully omit other details about the interfaces, and instead solicit ideas from the participants.

The third scenario is a discussion about risk alerts, where we describe the case of receiving alerts on a mobile device once the fall risk is estimated to be high. Participants are asked how they would like to have the alerts delivered to them, and what these would look or behave like.

With the design problem and their preferences in mind, the participants then move on to the final component of this study: designing their own prototype. We provide guidance in this process, and help them reflect and summarize their ideas and preferences using paper-and-pencil prototyping.

Results: Fall Risk Display Features

PD data is analyzed by clustering features suggested by participants (Table 2). Three categories emerged: interface design, notifications, and feature suggestions.

	P1	P2	P3	P4	P5
Interface Design Features					
Numerical display (*)	•	•	•	•	•
Emotional display			•	•	•
Use graphs (*)	•	•	•	•	•
Adding notes to data (*)	•		•	•	•
Qualitative information overlay (*)		•	•	•	•
Overall estimation (*)			•	•	•
Detailed daily estimation (*)	•	•			•
Goal setting		•	•		•
User avatar			•		
Record fall risk estimation by user	•				
High Fall Risk Notifications Features					
Reminder or alert for high risk (*)	•		•		•
Daily use reminder				•	
Dismiss reminder	•		•		•
User can set high risk level (*)	•		•	•	•
Additional Suggestions					
Actionable suggestions (*)	•	•	•		
Session estimation mode	•	•			

Table 2: Features suggested by Phase I participants. Items marked (*) were requested by more than one participant and implemented in Phase II. Most of the other requests would have required changes to the underlying algorithm.

For fall risk information display design, all participants suggested or agreed with using graphs to display the risk of falling, with numerical values to quantify the risk. Most participants also suggested there should be some qualitative information overlay for additional clarity. Participants also gave examples of using colours, lines or other visual elements to create a "high risk zone" on the graph, to aid interpreting the information in the graph. Most participants indicated that they would like to see an overall daily estimation, as well as detailed breakdown of this estimation. They would like to have the ability to "zoom in" on the data and see their fall risk information during certain periods of time and activities. Some participants suggested using emoticons to display the risk of falling, e.g. a stick figure animation of walking steadily to denote low risk. Participants explained that using such emotional elements can engage the user better than only using graphs; however, they would still prioritize the display of accurate information. As our target demographic is the "younger seniors", this may explain why participants have produced designs suitable for longer-term trends (graphs), instead of simple indicators (smileys) or auditory or haptic warnings.

For notification, participants suggested a reminder received the day after the risk of falling reaches high. It is especially important for individuals with declining memory. Most participants also wanted the ability to dismiss or mute the reminders, and custom-setting the high risk level.

Two other features were suggested by multiple participants. First, they believe the fall risk estimation should be coupled with instructions on what to do regarding the current risk of falling. For example, it would be meaningful to include instructions for fall prevention practices, when high risk of falling is detected. A second feature suggested was session estimation mode. Instead of having the wearable device recording data autonomously, users would have better control over the system by recording sessions of their walking, and viewing results for each session they initiate. A subset of these suggested features was implemented in the mobile UI of the SFRA system deployed in the field study in Phase II (Figure 3, and marked with (*) in Table 2).

For fall risk information display, we implemented numerical graphical displays for both current estimation as well as daily history. These included a customizable high risk line to overlay qualitative information and create a clear indication of high risk. Daily estimations are also divided into time periods (morning/evening). Other features include tips based on current fall estimation (including advice to see a specialist), note taking (attached to daily estimations and viewable from the history screen), and reminders if the risk was estimated to be high for the previous day (alerting users to be attentive while walking).

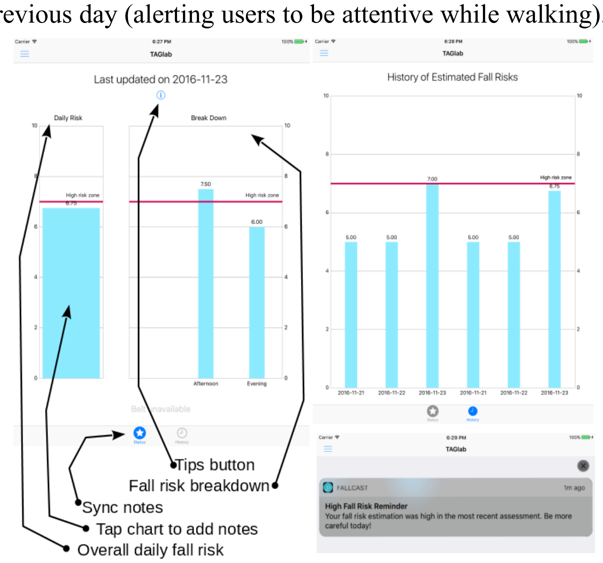

Figure 3: Current fall risk estimation (left) and history (right), both implemented in the main app. The high risk notification (bottom) is delivered through the iPad's built-in notification system, the day after the estimated fall risk exceeds the default or user-set threshold.

PHASE II: FIELD EVALUATION

Phase II focuses on evaluating the recommendations from the participatory design sessions. Older adults were invited to become the user of the system in a short-term deployment study. Similar to Phase I, this study is in the form of fieldwork gathering qualitative data – methodologically this has been employed in the past as an effective mechanism for informing the design of assistive technologies such as those used by older adults [36,53].

Participants

Participants were recruited for this phase following the same process as in Phase I. There was no overlap between participants in the two phases, to avoid any bias. Inclusion criteria were older than 55, familiar with using mobile touchscreen devices, and comfortable wearing a belt while walking. Table 3 shows details about participants.. All participants are living independently, and are engaging in various levels of daily physical activity, including walking.

ID	Age	Gender	Belt User	Adopts Fall Prevention	Familiar with Mobile Device	User of Mobile Device	Familiar with Wearable	Uses Wearable Devices	Fall History
A	74	M	Yes	Yes	Yes	Yes	Yes	No	Yes
B	73	M	Yes	No	Yes	No	No	No	No
C	64	F	No	Yes	Yes	Yes	No	No	No
D	69	F	No	Yes	Low	Yes	No	No	No

Table 3: Demographics of participants in the Phase II field study.

Protocol and Instruments

Instances of the SFRA system (belt, laptop as server, and tablet) were set up in the participant's home. Researchers visited the participants at the end the deployment. Qualitative data was collected through interviews and surveys, which reflected the indicators in the TAM [51] for assessing technology acceptance.

Experimental Protocol

Each deployment took between 5 to 10 days, depending on the participant's availability. The trial involves participants using the device in real-world settings, as well as a simulated high fall risk event during deployment. Participants are aware of the simulation. Two surveys are used to collect data: survey S1 during deployment and before the simulated high risk event, and survey S2 after the deployment. S1 and S2 are designed to evaluate the general acceptance of the technology and the effect of the simulated high risk event. Interviews are conducted after the trial, collecting users' responses on usability and acceptance, with more depth in the discussion with the researcher.

During the first visit, we set up the system at the participant's home, and walk through the features of the system with the participant. The mobile UI of the SFRA system was deployed on an iPad Mini 2 tablet. A belt paired with a tablet running the SFRA UI were left with each participant for the deployment. The UI as deployed during the trial implemented the features emerging from the earlier collaborative design sessions. We also ask the participant to wear the belt and walk briefly, and perform their first fall risk assessment to familiarize them with the SFRA system.

The second visit takes place midway in the deployment, and involves a simulated event of elevated fall risk. This probes the participant's response to how the event is reported by the system. loaded on the device. Participants are informed that the data they are viewing is simulated. The use of a simulated high risk event ensures that participants' feedback will not be limited by their own data, which is likely to reflect low fall risk. Hence we are able to investigate acceptance of this technology and the effect of the fall risk information in depth, by gathering participants' opinions on both real and simulated data. After the scenarios are presented, we conduct an interview about how the participant would perceive and react to the risk of falling.

During the last visit participants complete survey S2, which includes the questions in S1 ("S2 part 1"), to detect any change in their opinions, as well as additional questions on user experience, value of information, and features of the system ("S2 part 2"). An interview is then conducted to research the user's experience, opinions of features, value of information and behaviour change, acceptance of the wearable device, and change in usage over time.

Instrument Design

Surveys are designed to assess the general level of acceptance and usability. We use the Likert scale to obtain most responses from participants, with occasional short answer questions for clarification. Survey S1 is conducted before the simulated high risk event during deployment, and covers the following aspects:

- General User Experience: perceived usefulness and overall experience
- Information Reception: clarity of fall risk information and whether it can motivate fall prevention practices
- Usage: frequency of using the system to monitor fall risk and synchronizing data

Besides surveys, we used interviews for in-depth responses:

- General User Experience: user's interaction with the system, integration with daily routine, willingness to continue using the system beyond the trial
- Fall Risk Display: clarity of information
- Motivation and Behavioural Change: usefulness of fall risk information, trust, complacence, fall prevention awareness
- Acceptance of Wearable Device: usability, form factor, usage pattern, data recording mode
- Adoption Over Time: change in usage pattern, expected long-term usage.

Usage

During the field evaluation participants mostly used the tablet interface to monitor progression (over time) of their fall risks, interact with the notifications, and adjust the risk threshold. While participants had various preferences on how frequent or how long they would like to use the system (as detailed later in this Section), their interactions shared the same pattern: ensuring they wear the belt before taking a walk outside, and upon return synchronizing the data from the belt to the iPad device to obtain the fall risk estimation. While the belt was designed to allow wear at any time, participants felt they gained the most by wearing it during walks. The iPad was not carried during walks but typically used to check the visualizations upon their return from the outside walks (after synchronization).

Results: Survey Responses

Participants indicated an overall positive user experience with this system. All participants agree or strongly agree that the wearable system is easy to wear and maintain, and it is useful for motivating physical activities. Regarding behaviour modification, all participants believe the fall risk information provided by the system creates motivation for adopting fall prevention practices. They also indicated they are more willing to adopt fall prevention practices after using this device. Survey answers are tabulated in Figure 4.

In terms of fall risk awareness, all participants except Mr. B agree that the system made them more aware of the risk of falling. Furthermore, regarding the main feature (fall risk information display) all participants suggested it is clear to read and easy to understand. However, regarding other features, the opinions are mixed. Due to the simulated high fall risk event, all participants have interacted with the reminder and tips features. Overall participants believe theses features are useful, while Ms. C is neutral towards the high risk reminder feature and disagrees that the tips feature is helpful. Most participants also agree that to be able to set the high risk zone is useful. However, interaction logs suggest only one of the participants interacted with this feature as the high risk zone was left at the default level by other participants. In addition, the none of the participants used the notes feature to annotate their data, and most of them are neutral towards this feature.

In addition, the questions in S1 are reused in S2 (part 1) to reveal the changes in participants' opinions after the simulated high fall risk event. Although participants' opinions did not change significantly regarding user experience and the usefulness of the system, it appears that there are more participants in agreement with the statement that this system creates motivation for adopting fall prevention practices: Ms. C and Ms. D changed their opinions from neutral to agree, and Mr. A changed from agree to strongly agree. This indicates the simulated high risk event did improve the participants' understanding of this technology by providing an example they would otherwise not experience during this brief field trial.

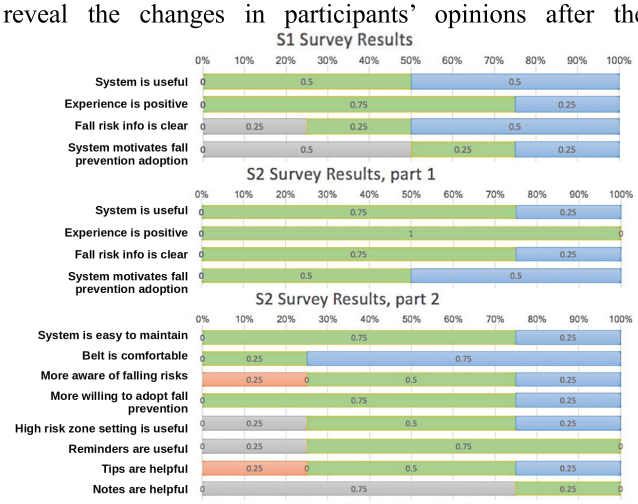

Figure 4: The results of the early- and post-deployment surveys.

Results: Analysis of Interview Responses

We interview each participant twice: once during the simulated high fall risk event, and once after completing the field trial. The first probes the participants' reaction to simulated high fall risk information and the interactions with the reminder features. The second probes usability, interaction, perception, and behaviour modification.

Inductive thematic analysis (following guidelines from [7]) was used to reveal patterns in order to answer the research questions. Seed codes were generated following the two TAM indicators and the structured topics in the interviews, and further codes were bootstrapped iteratively, producing the thematic map shown in Figure 5, with the middle rectangles indicating how the codes converged to the five key themes. The overarching themes (Table 4) were identified using both initial and secondary codes. This was guided by the research questions, and we focused our analysis on the usability of the SFRA system and how older adults interact with and react to the fall risk information.

Themes	***Description***
Perceived Ease-of-Use	*The degree to which a person believes that using a particular system would be free from effort*
Perceived Usefulness	*The degree to which a person believes that using a system would enhance their performance*
Information Reception	*The ways the users react or respond to information delivered by the system regarding their estimated risk of falling*
Potential for Behaviour Modification	*The tendency or promise that the users are willing to subject themselves to regarding adopting fall prevention practices*
Awareness Conformation	*The user's construction of awareness and conceptualization of falls, technologies, one's physical abilities and how these factors interplay*

Table 4: Themes identified in Phase II interview data and descriptions.

Analytic Memo

The findings from the interviews are further discussed in this section as we apply the identified themes to capture qualitative feedback from the users. To address the research questions and validate the hypotheses, we will first investigate the acceptance of the SFRA system using usability factors and perception factors, then we consider the effect of the fall risk information in terms of how users respond and react to it. Figure 6 shows how these topics relate to the themes – as the design of our measurements

Authors' Pre-print Copy. The official published paper is available at: https://doi.org/10.1145/3173574.3173693

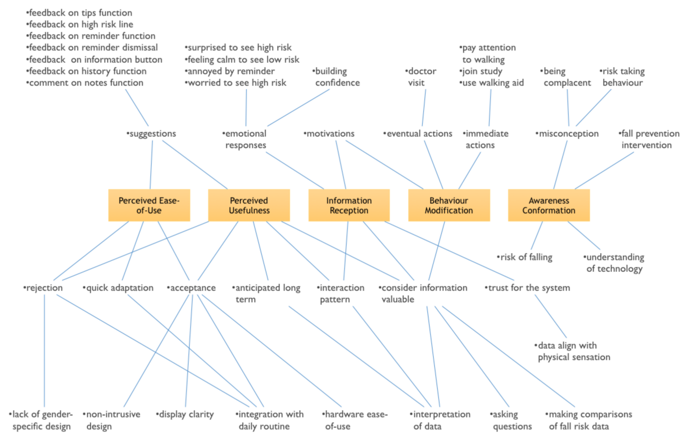

Figure 5: Identified codes and themes from Phase II interview data.

was guided by the TAM, the themes that emerged from the collected data are aligned with TAM indicators such as perception of usefulness, utility, and ease of use. We structure the following (sub)sections along these themes. In addition, we also summarize users' feedback on features of the SFRA system as an evaluation of the design guidelines for fall risk information display.

User Acceptance of the SFRA System

Overall, the participants reported good adoption of this system in the interview data: 3 out of 4 participants stated that they have integrated this system with their daily routines, and they indicated willingness to continue using the system outside of the trial. To evaluate the acceptance of the SFRA system with more depth, we identify two groups of factors that affect the acceptance of this technology: usability factors, which directly correspond to the theme "Perceived Ease-of-Use"; and perception factors, which cover themes "Perceived Usefulness" and "Information Reception". These are based on the Technology Acceptance Model, where usefulness and ease-of-use are treated distinctively, as are also in fundamental texts such as [16].

Perceived Ease-of-Use

While the survey and interview data suggested varying degrees of acceptance of the overall system, all participants agreed that the device is comfortable to wear. Ms. D reports: "*Absolutely (easy-to-wear), it was fine. You didn't even notice that you were wearing a belt*." Participants also pointed out their interactions with the belt as "very easy". Mr. A described his daily routine: *"It was very easy actually. I just put the belt on, and I immediately started moving, walking. I walked in my home, in the hallway, and in my building, downstairs, outside, depending on the day.*

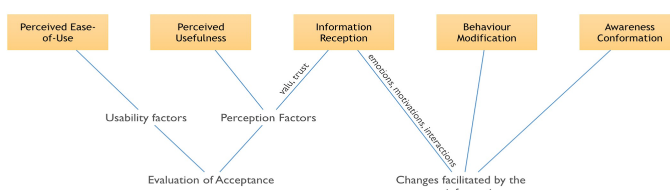

Figure 6: Themes and their relationships to the topics in Analytic Memo.

That was it. Came back, took it off, placed the belt on the table, synced it in with the tablet. It worked every time."

Other participants shared similar experiences to Mr. A. In addition, despite none of the participants having previous experience with wearable technologies, they did not report having any problems with the wearable device, and they could all recall and describe clearly how they interacted with the belt and system on a daily basis. This indicates the device has been adopted successfully and the users have learned how to use this new technology. Another benefit of designing the wearable device as a belt is to avoid any form of intrusion, which was confirmed by Mr. A: "*I like the idea that it's a belt, easy to wear, easy to maintain. It's hidden, you can wear it almost anytime. That makes it very useful.*"

We also found that participants want the device they interact with to integrate with familiar objects as much as possible. This preference may directly affect how well OAs will adopt the wearable device. Mr. B reported that he likes the belt, but suggested he "*wouldn't wear it everyday*" over a longer period of time, unless the device can be "*easily integrated into a regular belt, rather than being a special belt*". In fact, all participants expressed interest in a design where the sensors inconspicuously attach to the belt.

We did not notice gender differences, despite our prototype being of a single colour and size – "*Women also wear belts*" (Mr. A), and a more fashionable design "*wouldn't make a difference*" (Ms. D). However, all participants suggested manufacturing the belt to appeal to a wider range of tastes.

Clarity and Simplicity in Fall Risk Information Display

Both the survey and the interview data suggested that participants consider the information display – namely the charts of risk of falling – easy to read and understand. Rather surprisingly, participants indicated a preference for graph visualizations. Ms. D said: "*It was very clear. The bar charts are great. The history was very easy, going back and forth, and also between morning and evening, yeah.*" Mr. A concurs: "*A graph is worth a thousand words: here is the risk line, here is where you are, it's clear.*"

While clarity of information is necessary for adoption, it is not sufficient. Three participants found themselves using the system voluntarily (while going out for walks and even wearing it all day): "*I just made a routine of putting it on every morning, and syncing it every night.*" (Mr. B). However, Ms. C showed lowest level of acceptance of the system, due to this altering her daily routine by having to remember to put on the belt before going out. Designing the SFRA system for integration into daily routines may increase adoption, as users then interact with it more often.

Perceived Usefulness

As per the TAM framework, perceived usefulness is "the degree to which a person believes that using a particular system would enhance their job performance" [51]. In our study, all participants agreed that having access to the estimated risk of falling is useful. In particular, they find this valuable when compared to conventional clinical assessments, which in their experience is often time-consuming. However, this is only a shallow benefit offered by the system, and our data showed participants would like the system to be able to provide them with more useful information beyond simple risk estimations.

Ms. D believes the numerical fall risk lacks information that can help to interpret the risk: *"But I would like to know why I have a [number] point whatever. It would be interesting to know. I want it to tell me more, how it's making that determination"*. *S*he adds: *"The numbers don't mean anything unless you have context around it."* Mr. B is confident in his physical abilities, and indicates he would use the belt only for occasional sampling, as *"actual numbers are not so important"* because he would be *"more interested to look at trends instead"*. This indicates that providing contextual information may lead to increased perceived usefulness. Indeed, participants suggested contextual examples such as activities performed, surface condition, trip hazards, footwear, and comparison to data from other users. They are also interested in how the estimation is determined – this provides further evidence to our initial assumption that such assessment systems must offer transparent interpretations of data (much in the same vein of "Explainable Artificial Intelligence" [10]).

Usefulness in High Risk Situations
The simulated high risk events were used to expand participants' experience in the field trial. The screens showing simulated high risk data were previously shown in Figure 3, in the Section "Results: Fall Risk Display Features". In this case, participants have suggested this information is useful because for someone with high risk, he or she would likely want to track changes in the data, especially if fall prevention intervention is in place, and fall risk estimation would provide feedback and track progress. For example, although Ms. C sees no use for the system when fall risk is low, she would consider using it frequently if the risk is high: "*trying to compete with myself, to see the difference. It's almost the idea of giving people the power to change, or giving them the idea they can change.*"

Besides the value of fall risk estimation, it was also suggested that it would be useful to provide tips for participants on what actions to take regarding different levels of fall risk. We implemented this as a proof of concept with generic tips for high risk. The tips appear as a dismissable pop-up, invoked by tapping the (i) button of the main UI. While this was positively received, participants prefer to have the tips customized and provided by a specialist, which will make the system even more useful.

Information Reception: Trust
Three participants have confirmed that they trust the system. Participants also expressed that because of this trust, they are willing to use the estimation fall risk to make decisions regarding fall prevention practices.

Participants have suggested several reasons why they developed trust in the system. First, the explanation of technology set the basis for trust. During deployment, we explained the technology used for assessing the risk of falling with a high-level description, and the researcher also explicitly stated that the expected accuracy of fall risk is around 70% [48] to assure the participant. Moreover, the trust is reinforced when the participant sees their estimated risk of falling matching with their expectations. "*I believe the device on that point because it aligned with my own expectations*." (Mr. B), or "*I trusted it more as I saw it going down because I was focusing.*" (Ms. D).

This suggests that the algorithms and interfaces developed for the SFRA system must be able to produce results that can align with seniors' expectations (e.g. not generate false alerts), their understanding of their abilities, and physical sensations, as well as reflecting their activities.

Changes Facilitated by Using the System
Information Reception and Behaviour Modification
All participants were considered at low fall risk and none of them showed significant changes in the fall risk estimation data. This is expected, as one's gait would change little over a limited time. When asked about their experience with seeing the estimated risk of falling for the first time, all participants had similar reactions, such as calm or confident. On the other hand, they described their emotions towards the simulated high risk information as worried, scared, or surprised. Participants showed that they are more eager to know why risk of falling is high than when it was low. This also initiates the user's problem-solving process: "*My thought was, who can I talk to about this and what can I do about it? And I better do something.*" (Ms. C).

Even under the low-risk scenario, Ms. D mentioned she was paying more attention to walking. However, participants reported becoming motivated to adopt prevention strategies based on their experience with simulated high risk data. Mr. B indicated he would visit his doctor if the risk is high. All indicated other actions they would take, such as paying attention to walking, or using railings or walking aids.

This re-emphasizes the importance of providing additional information to seniors to help them understand the situation and guide their behaviours. In addition, high risk of falling also creates motivation for behavioural changes.

Awareness
Throughout the deployment of devices with participants, we observed changes in OAs' attitude and awareness. The data suggest the experience of using the SFRA system has improved users' awareness of falls and prevention, while the awareness of low risk may also lead to complacence in certain situations: "*it's normal for people to get complacent*" (Mr. A), although that depends on "*how quickly you get down to low risk*" (Ms. D). On the other hand, Mr. B, who is very confident in his physical abilities, believes he would not become complacent, because he would "*discipline*" himself while using this device

Three participants agreed that using the SFRA system has made them more aware of the risk of falling. "*When you pay more attention and ... focus on it, you are in a better position to improve the balance*." (Ms. D). This did not apply for seniors who were already confident of their very low risk of falling, but even those participants indicated they would follow suggestions and instructions from the system if their risk "*had been much higher up*" (Ms. C).

This suggests that quantifying fall risks can help those who are unsure about their risks to be more aware and help them better assess their situation. This is especially valuable for individuals who have medium to high fall risk, who are otherwise unaware of such risks without using the system.

Summary of Recommendations

The interviews and PD sessions revealed that our (healthy) OA participants wanted the ability to monitor their risks and especially changes in risks – in many ways similar to how one would use a blood pressure monitor (awareness of changes over time instead of prevention of an imminent event). Through the thematic analysis presented earlier and through participants direct input, we draw a set of design recommendations for mobile-based UIs that interface with fall risk assessment sensor devices.

- Provide quantitative visualizations of fall risk data (e.g. numerical scores), but overlay these with qualitative information (e.g. textual qualifiers or explanations of the assessment, such as "for someone your age, this means that the risk is moderate"). Our participants thought a system is "useless" without both types of information.
- Design SFRA systems to empower users and facilitate problem solving; avoid omitting information that may hinder the user's decision process. The system should not hide information, leading to perceptions of controlling users' lives; instead, it should support their risk mitigation strategies (e.g. deciding what kind of walks to engage in).
- Provide info on fine-grained changes over time instead of immediate alerts.
- Attach contextual information regarding user's fall risk estimation, as well as specific instructions for fall prevention practices, preferably from healthcare professionals. Our participants indicated that the fall prevention tips (e.g. risk mitigation advice) were very useful and suggested improvements, including bringing these up automatically when the risk exceeds a threshold, or tailoring them to their current risk assessment.
- Include a high risk reminder, prompting users to change their behaviour if warranted by data from the previous day. Combine this with providing practical advice (e.g. use railings while on stairs). Provide options to configure individual preferences on how to receive the reminders.
- Allow customization of what high risk is, based on users' own physical abilities, while providing a sensible default setting. Our study suggests that participants see as useful the ability to adjust the high risk line for their own needs.
- Allow customization of how data is collected (on-demand vs. automatic). Participants were split with respect to how this is handled (Mr. B: "*I don't want that because then I can manipulate the data. Bad.*"). Providing a choice would empower them; yet, this may have implications for the accuracy of the algorithms used to estimate fall risks.

Limitations

Due to the nature of our study not all features suggested in Phase I were evaluated, mainly the ability to attach notes to logs and using "emotional" elements to present data. The short-term deployment was limited to changes in awareness and attitudes, as this was the first study of a collaboratively-designed system that empowers OAs to visualize fall risk sensor data. We avoided other confounds such as (lack of) digital literacy which may influence ease of use, or cognitive decline, which may impact understandability, especially over longer term use.

CONCLUSION

Our survey and interview results showed that overall the SFRA system implemented in this study achieved high user acceptance (Hypothesis H1), and participants consider the fall risk estimation useful and the accessibility is appreciated. Participants have also indicated they are more aware of the risk of falling from this experience (Hypothesis H2), and they also believe this information can motivate them to adopt fall prevention interventions. With the simulated high risk data, we also found that older users consider fall risk estimation more useful when the fall risk is high, and they have also pointed out the value of estimation is limited when the fall risk is low. This highlights the importance of attaching contextual information to the estimation data to help users interpret and understand their situations better, thus providing more values in the information to keep users engaged. Furthermore, it is necessary to provide specific instructions in the case of high risk, in order to guide the older user to take most appropriate actions while they are motivated to improve their situation. In addition, any misconception of technology must be carefully addressed as it could lead to risk-taking behaviours. Lastly, feedback from field evaluation were collected regarding features suggested through participatory design, leading to recommendations on improving the design of mobile UIs for SFRA systems.

ACKNOWLEDGEMENTS

This work was supported by AGE-WELL NCE Inc., a member of the Government of Canada's Networks of Centres of Excellence. The authors also acknowledge the sacred lands on which the University of Toronto operates, which are the traditional territories of the Huron-Wendat and Petun First Nations, the Seneca, the Haudenosaunee, and most recently, the Mississaugas of the Credit River. The authors wish to thank Kimberley van Schooten for the permission to use the SFRA algorithm.

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