¿Cómo puede la tecnología ayudar en l a predicción del riesgo de caídas?

EQUIPO 4:

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ALMA, RIO DE JANEIRO 2019.

Objetivos

- Recordar generalidades sobre caídas
- Comprender ¿Cómo funcionan las nuevas tecnologías?
- Conocer las herramientas actuales para predicción del riesgo de caídas (sensores ambientales y wearables, apps)
- Conclusiones y propuestas.

Síndrome de caídas

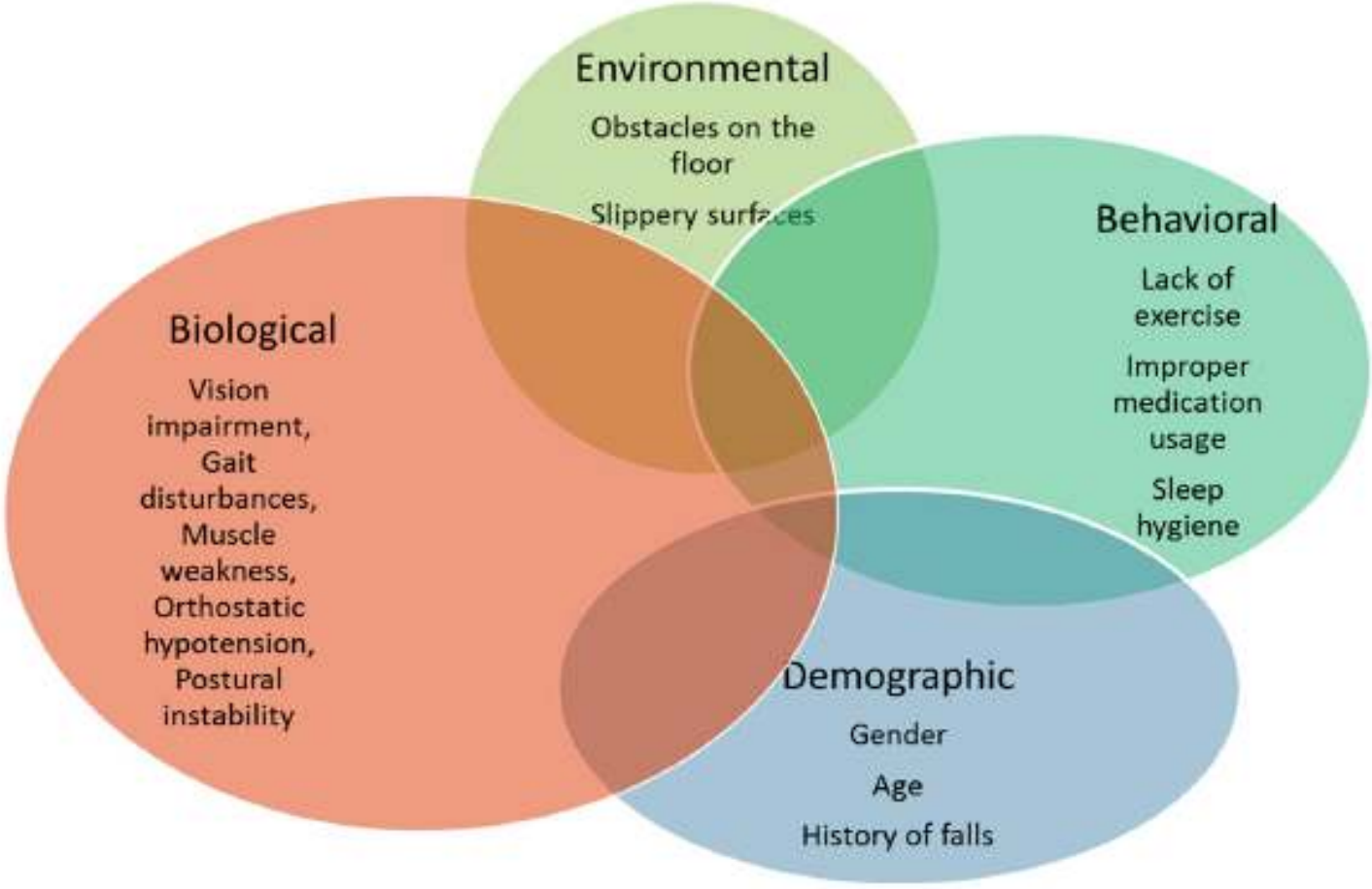


Figure 1. Interaction between various fall risk factors.

Sensors 2017, 17, 2509; doi:10.3390/s17112509

¿Cómo funcionan las nuevas tecnologías?

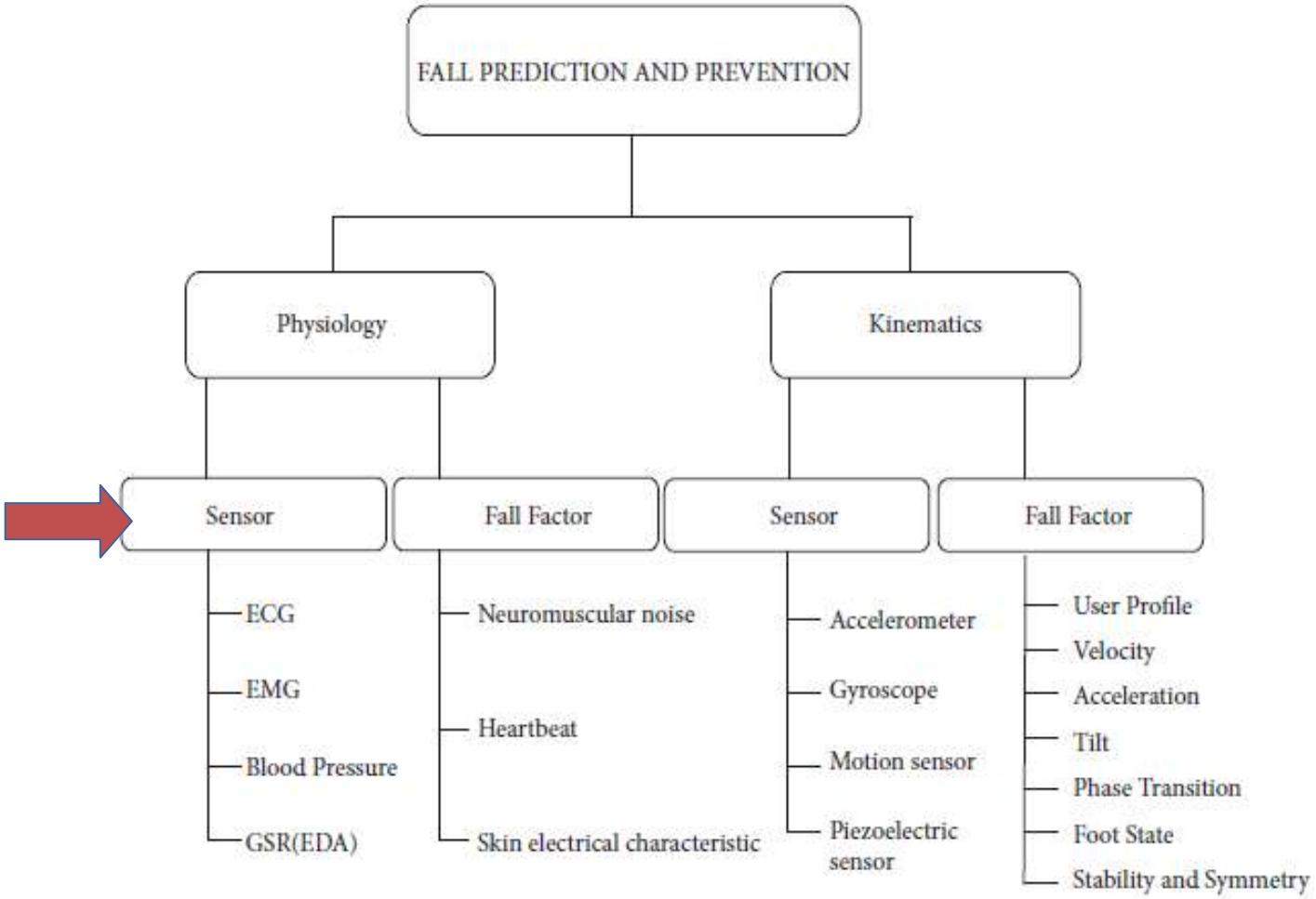


FIGURE 1: Fall prediction and prevention taxonomy.

Masoud Hemmatpour, et al. "A Review on Fall Prediction and Prevention System for Personal Devices: Evaluation and Experimental Results," Advances in Human-Computer Interaction, vol. 2019, Article ID 9610567, 12 pages, 2019.

¿Cómo funcionan las nuevas tecnologías? Herramientas predictoras de riesgo de caídas

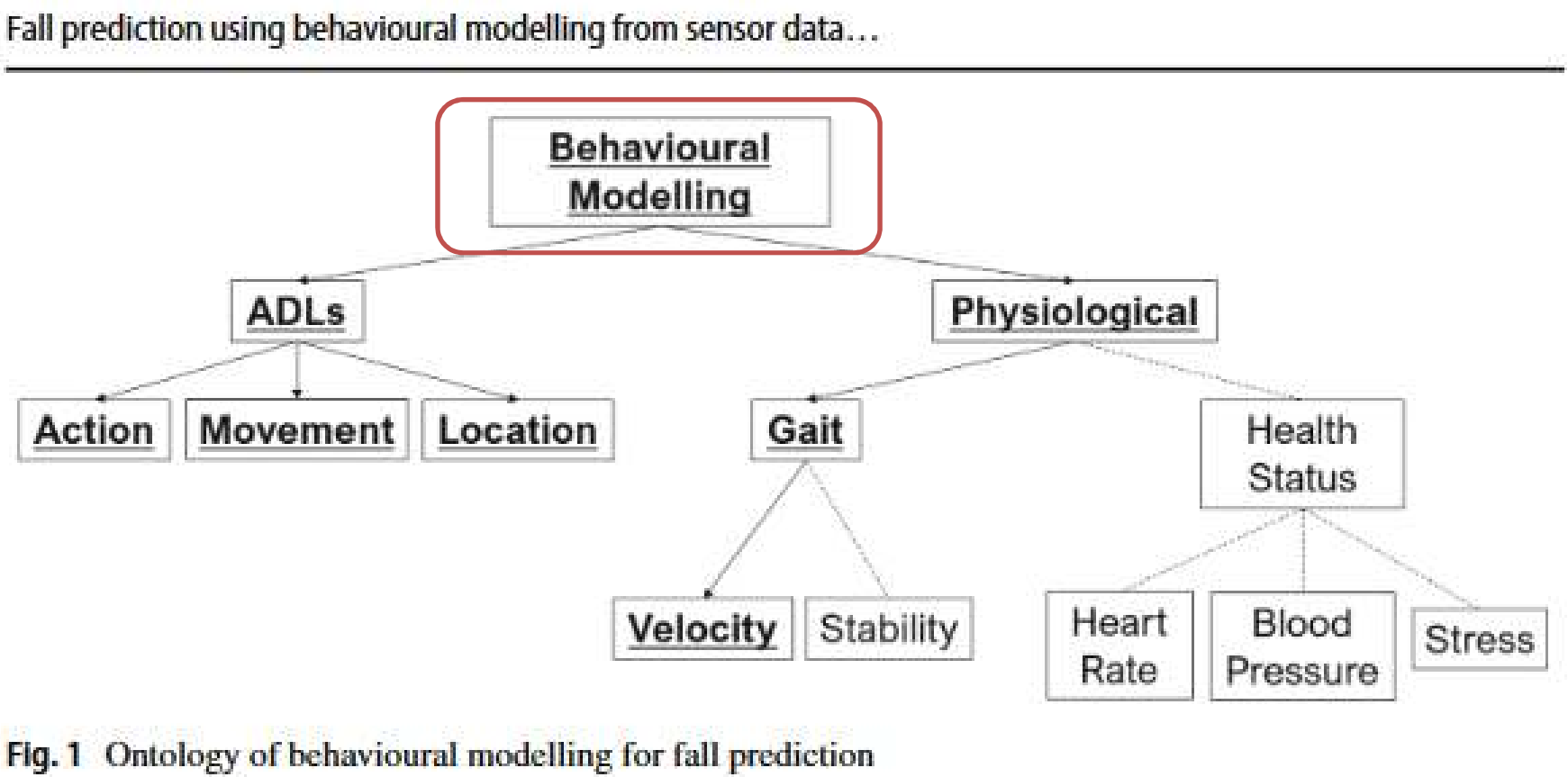


Fig. 1 Ontology of behavioural modelling for fall prediction

Masoud Hemmatpour, et al. "A Review on Fall Prediction and Prevention System for Personal Devices: Evaluation and Experimental Results," Advances in Human-Computer Interaction, vol. 2019, Article ID 9610567, 12 pages, 2019.

Herramientas actuales para predicción del riesgo de caídas

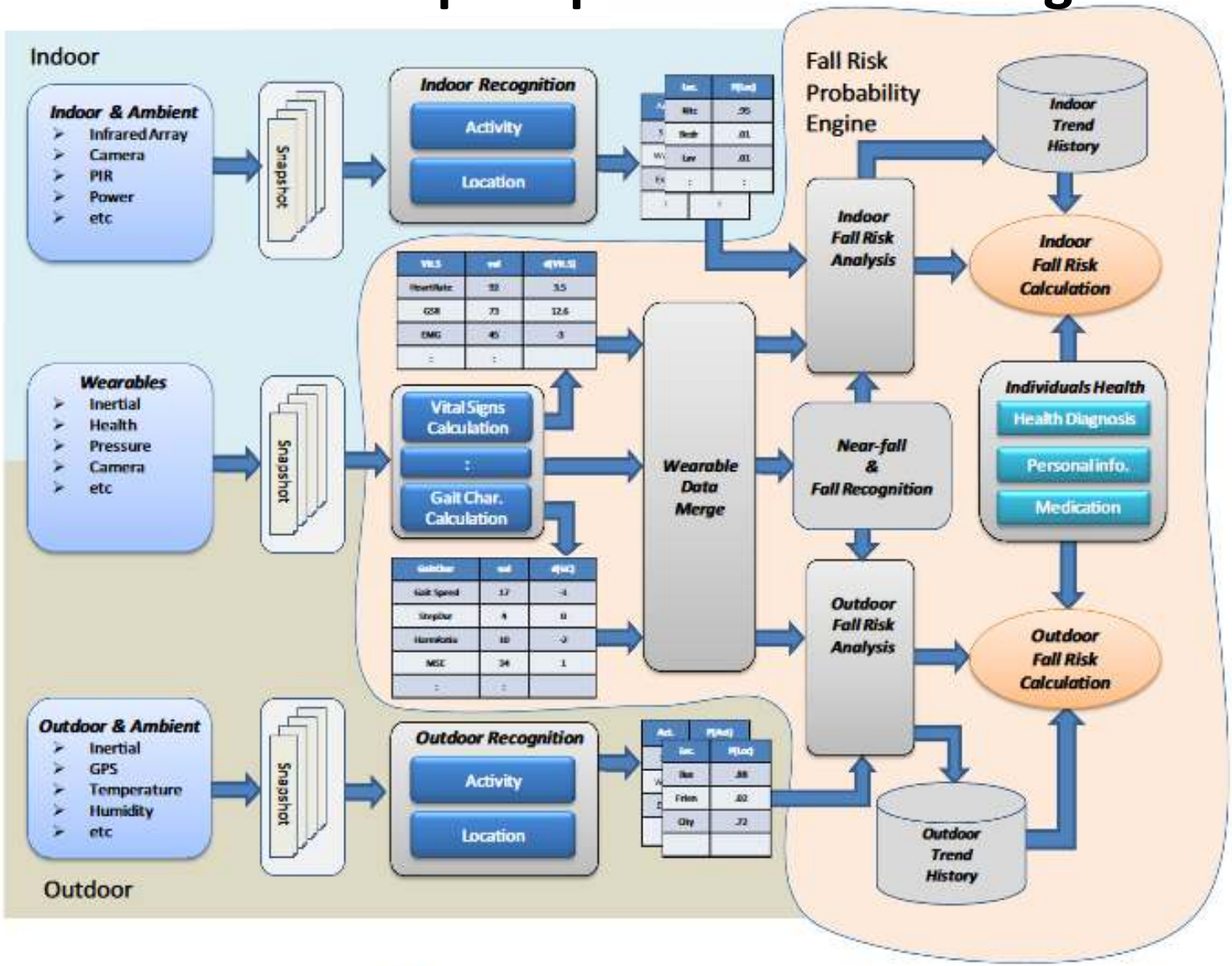
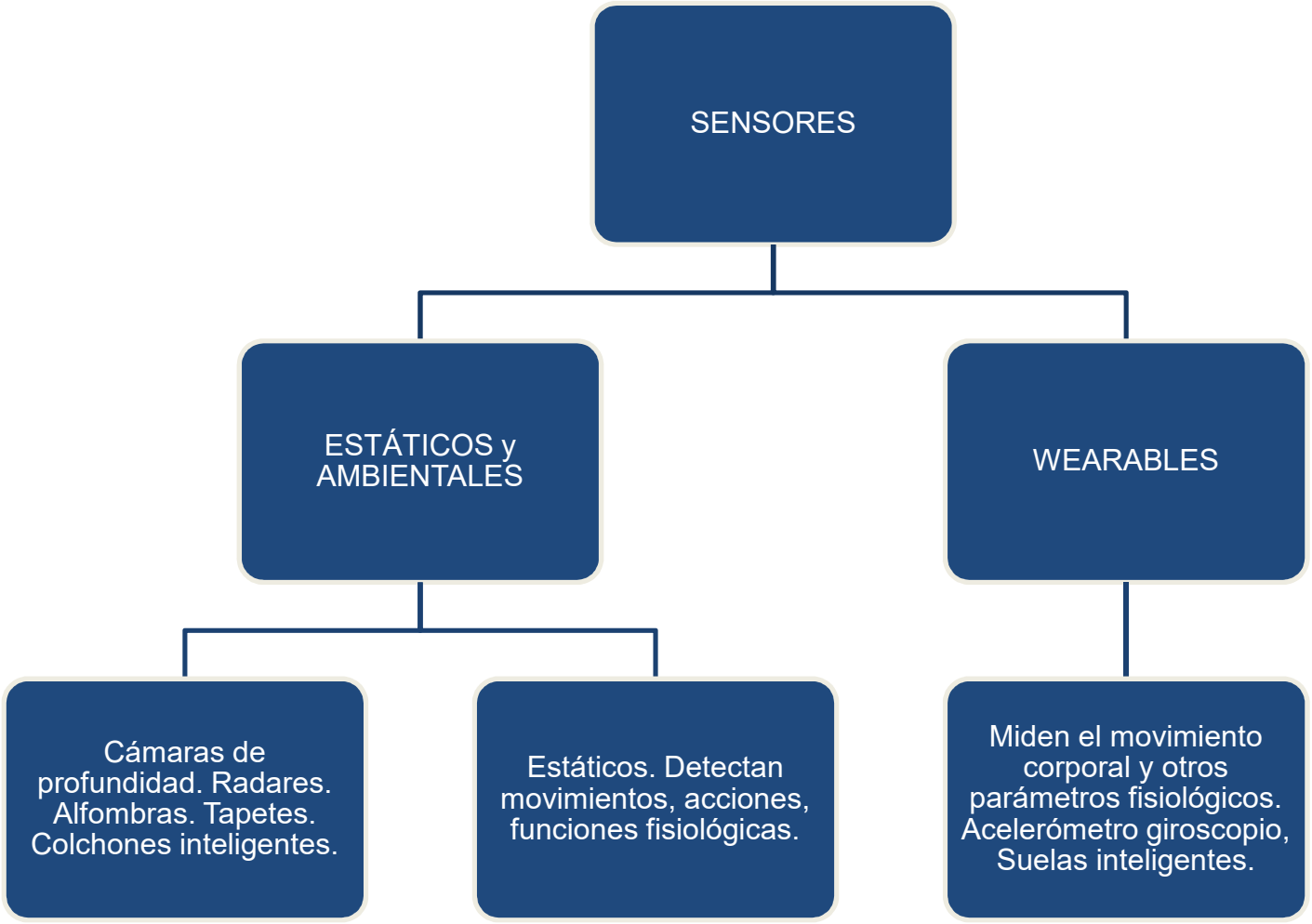


Fig. 2. Calculating fall risk using the fall risk probability engine.

A. Danielsen et al. / Journal of Biomedical Informatics 63 (2016) 184–194

Tecnologías disponibles: SENSORES



Sensores ambientales ¨estáticos¨

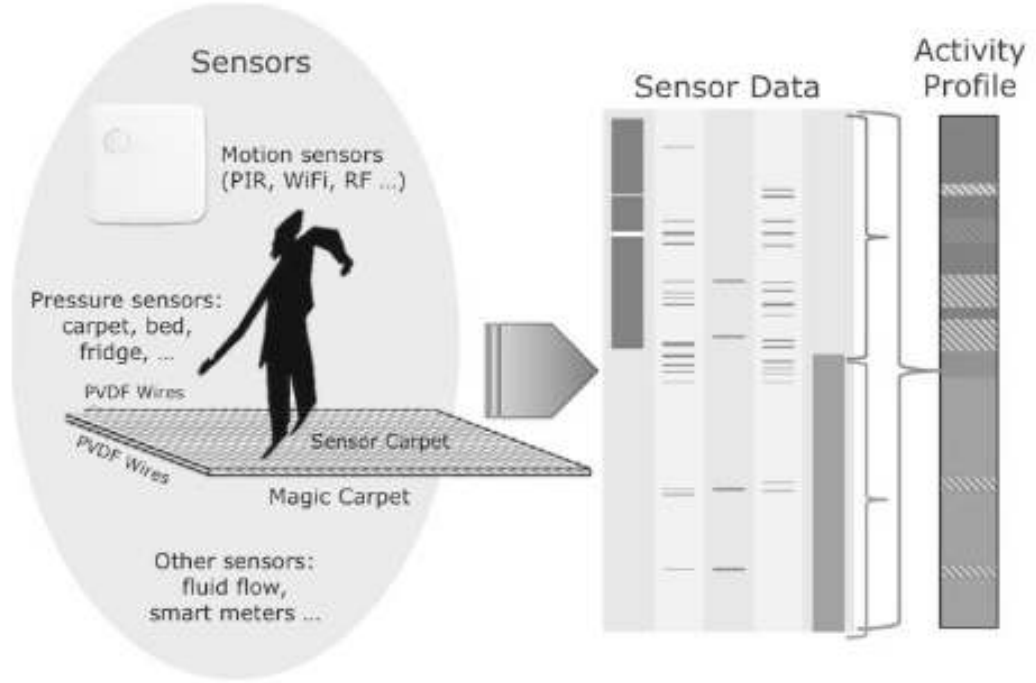


Fig. 2 A passive monitoring system for time-series-based behavioural interpretation



Fig. 3 A wearable system for constant activity profile generation, using motion measured with an accelerometer and gyroscope

Sensores de movimiento (detectan cambios en la posición corporal)

Sensores de presión (posición, simetría)

Recopilación de Datos

Perfil de actividad ¨FAP¨ (functional ambulation profile) / velocidad marcha

Forbes, G., Massie, S. & Craw, S. Artif Intell Rev (2019). https://doi.org/10.1007/s10462-019-09687-7

Sensores portables ¨Wearables¨

Miden el movimiento corporal.
Análisis de marcha y movimiento Vs sujeto sano o estado previo

ACELERÓMETRO	GIROSCOPIO	VARIOS
• Masa en relación a movimiento o gravedad. • Tres dimensiones • Orientación postural • Actividad física, sueño, ejercicio, podómetro, gasto energético.	• Vibración • Desplazamiento proporcional al ángulo de rotación.	• Smartwatch (pasos, FC y variabilidad, gasto energético) • Suelas inteligentes (velocidad marcha, número pasos, cambios pisada, estilo caminata)

Localización sensores

Table 2
Inertial sensor location and focus.

Location	Gait study focus
Lower back	[1]: Harmonic Ratio (HR), index of harmonicity (IH), Multiscale Entropy (MSE), Recurrence quantification analysis [4]: Balance Shifting in turns, Yaw Amplitude during turns, Gait Speed, and Gait Consistency [15]: Harmonic Ratio [17]: Gait Speed, Step Duration, Gait Variability [20]: Gait Speed, Activity Level [23]: Gait Variability [43]: Kinetic Energy, Gait Speed, Step Duration, Gait Variability
Upper back	[3]: Local Dynamic Stability, Gait Variability [15]: Harmonic Ratio
Insole	[5]: Ground Reaction Force, Ankle Moment, Balance [25]: Gait Variability [39]: Abnormal Gait Pattern
Smartphone	[39]: Abnormal Gait Pattern
Hip	[14]: Local Dynamic Stability

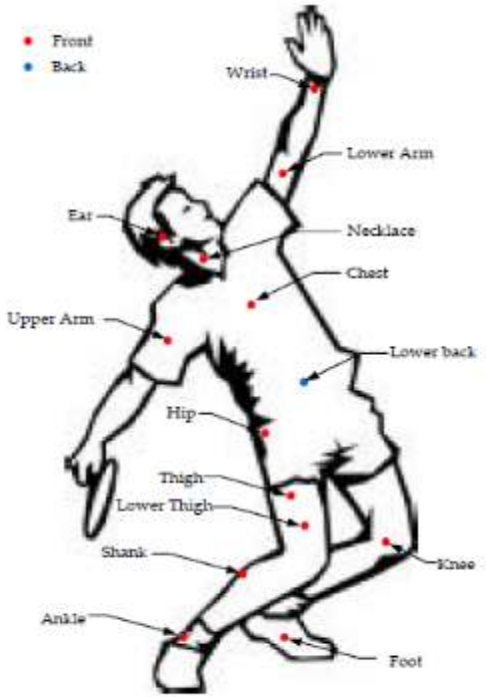


Figure 5. Graphical demonstration of sensor placement.

Table 3
Non-inertial sensor locations and focus.

Location	Sensor	Sensing focus	Study focus
Chest	ECG	Heart Rate Variability	[83] Identifying future fallers prospectively [83] Fall prediction from sitting to standing position
Chest	ECG	ST interval length R peak amplitude	[83] Fall recognition
Lower Leg	EMG	Co-Contraction Indices Integrated EMG	[84] Pre-impact fall detection
Head	EEG	Brainwave	[82] Fall prevention, recognizing onset of Freezing of Gait (FOG) in Parkinson's patients

Sensors 2017, 17, 341; Doi:10.3390/s17020341

A. Danielsen et al./Journal of Biomedical Informatics 63 (2016) 184–194



Table 3. Summary of research on sensor placement for HAR.

Sensor	Location	Activities	Reference
Gyroscope Accelerometer	Wrist, hip, neck, knee cap	Wing Tsun movements	Heinz et al. [13]
Accelerometer	Ankle, thigh, hip, wrist, chest	Typing, talking, riding, walking, arm movement, etc. (20 activities)	Bao et al. [74]
Accelerometer	Thigh, Necklace, Wrists.	Falling backward, falling forward, chest pain, headache, vomiting, and fainting and a normal activity walking	Pirttikangas et al. [59]
Accelerometer	Waist.	Walking, running, scrubbing, standing, working at a PC, vacuuming, brushing teeth, sitting.	Yang et al. [71]
Accelerometer, Gyroscope	Lower arm, Hip, Thigh, Wrist	Walking downstairs, walking upstairs, walking, jogging, biking, sitting and standing.	Shoaib et al. [66]
Accelerometer	Thigh	Walking, jogging, ascending stairs, descending stairs, sitting, standing.	Kwapisz et al. [75]
Accelerometer	Lower Back.	Lying, sitting, standing, working. on a computer, walking, running, cycling.	Bonomi et al. [72]
Accelerometer	Hip, wrist, arm, ankle, thigh	Lying, sitting, standing, walking, stair climbing, running, cycling.	Mannini et al. [58]
Accelerometer; gyroscope	Upper arm, thigh	Slow walking, normal walking, brisk walking, jogging, sitting, ascending and descending stairs normally or briskly	Wu et al. [60]
Accelerometer	Chest, thigh, ankle.	Stairs ascent and descent, walking, sitting, standing up, sitting on the ground	Chamroukhi et al. [69]
Accelerometer	Chest, thigh, ankle.	16 daily living activities.	Moncada-Torres, et al. [68]
Accelerometer gyroscope	Thigh	Walking, walking upstairs, walking downstairs, sitting, standing, and lying down	Ronao et al. [76]
Accelerometer; Gyroscope; Barometric pressure sensors.	Wrist; ankle; chest	Walking, running, stair descending and ascending, standing, sitting, lying down, brushing teeth, drinking, cutting food, writing, peeling carrot, eating butter bread, etc.	Moncada-Torres, et al. [68]



Figure 5. Graphical demonstration of sensor placement.

IDEALMENTE PARA PREDICCION DE CAÍDAS DEBE UTILIZARSE TECNOLOGÍAS MULTISENSORES (cefálico, pelvis posterior, gemelo izquierdo).

Sensors 2017, 17, 341; Doi:10.3390/s17020341

Predictores de caídas al evaluar la marcha con sensores

Table 1
Gait parameters separating fallers from non-fallers.

¨FALLERS¨	¨FALLERS¨
• Asimetría en pasos • Mayor angulación del tronco y pelvis • Menor abducción y flexión de cadera • Menor variación de la altura del tobillo	• Menor velocidad de la marcha • Menor cadencia • Menor zancada • Menor duración del paso • Mayor tiempo de doble soporte

Fortina and gravina [23] developed a novel real-time non-invasive fall detection and alarm notification system using a wearable accelerometer an d a smart phone. their system is able to trigger fall events using
different alerting modalities enabling prompt emergency interventions. the experimental results on 20 subjects demonstrated a 97% sensitivity, 83% specificity, and 90% precision.

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¿FUNCIONAN EN LA PREDICCIÓN DE CAÍDAS?

Table 1. Qualitative comparison of various fall detection and prediction systems.

Article	Sensor	Subjects	Obtrusive	Comments
Bourke et al. [18]	Waist mounted accelerometer	10 young healthy subjects and 10 elderly heathy subjects	medium	Threshold based algorithm achieves 100% specificity and sensitivity with a false-positive rate of less than 1 false-positive (0.6 false-positives) per day of waking hours.
Binachi et al. [19]	Waist-mounted wearable sensor system composed of an accelerometer and a barometric pressure sensor.	20 young healthy volunteers	medium	The proposed system demonstrated an accuracy, sensitivity and specificity of 96.9%, 97.5%, and 96.5%, respectively, in the indoor environment, with no false positives generated during extended testing during activities of daily living.
Howcraft et al. [21]	Accelerometers and pressure sensing insoles	75 individuals who reported six month prospective fall occurrence	Low	The best performing fall prediction system used a neural network, dual-task gait data, and input parameters from head, pelvis, and left shank accelerometers.
Sannino et al. [22]	A tag placed on subjects' chest	real-world database containing a set of fall and non-fall actions	Low	Their method achieves better accuracy than four state of the art machine learning algorithms.
Hirata et al. [26]	Proximity sensors attached to walking aid device	unspecified	Low	Their method uses a passive intelligent walker to prevent the user's fall according to the support polygon and the walking characteristic of the user.
Bian et al. [27]	Infrared camera	Four healthy subjects	Medium	The proposed approach uses the infra-red based depth camera that can operate in dark environments. Experimental results show that the accuracy of the proposed algorithm is improved by 11.8% compared with a state-of-the-art fall detection algorithm.
Hilbi et al. [28]	Pressure sensors	Older adults in a hospital	Low	The results show that sensitivity and the specificity of the proposed approach are 96% and 99% respectively indicating a satisfactory performance. Further consistently designed studies such as randomized controlled trails are required to show the effect of bed-exit alarm systems on fall risk.
Pisan et al. [29]	Microsoft Kinect camera	57 elderly patients	Medium	Their results show that for users who are at risk of falling, the slowing down in reaction time due to cognitive load is much larger than for users who are not at risk of falling.

ISSUES: Falsa detección de caídas. Comodidad de uso. Privacidad.

Otras tecnologías

CUESTIONARIOS DIGITALES y APPS

- Síndrome poscaídas
- Historial de caídas
- Situación global de salud
- Edad, género, comorbilidades, cognición, sensorial, fármacos…

CONSOLAS VIDEOJUEGOS

- Microsoft Kinnect (cámara)
- Nintendo Wii Fit

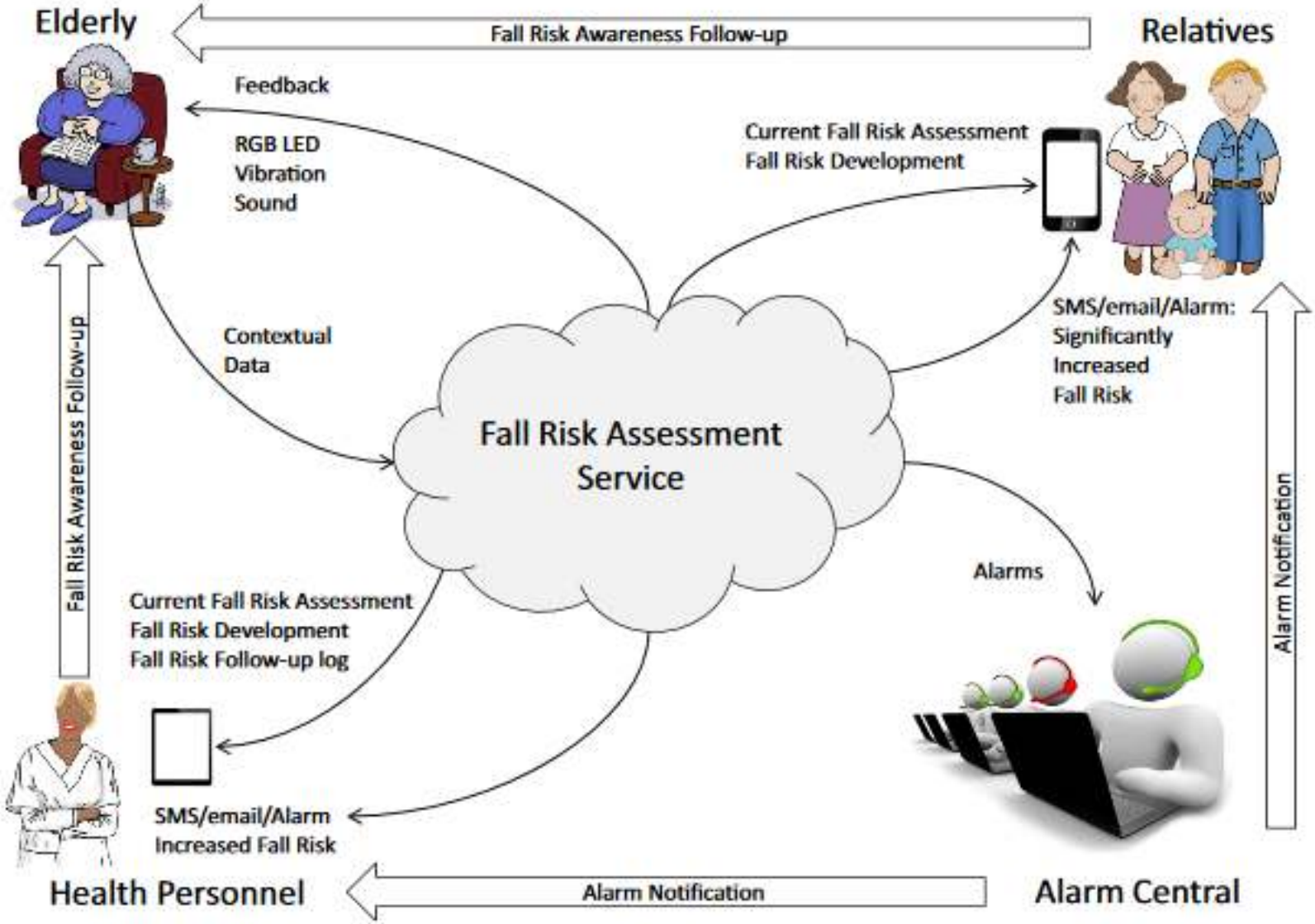


Fig. 3. Fall risk awareness protocol overview.

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¿Qué hay disponible en la actualidad?

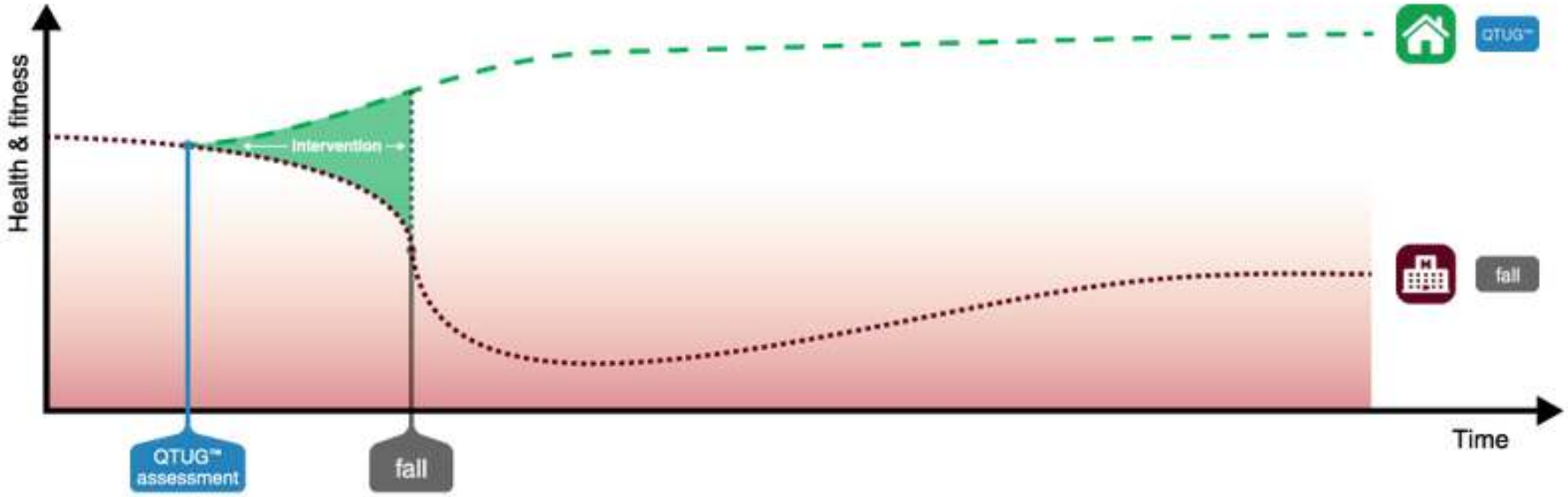


How can Kinesis QTUG™ drive falls prevention?

Falls occur as a result of a decline in health and fitness in older adults, which is part of the normal ageing process. By using QTUG™ to screen for gait and mobility impairment, and identify those at risk, QTUG™ uses the Timed Up and Go (TUG) test and body-worn sensors to produce a simple falls risk score and identify gait and mobility problems. This can facilitate early intervention, as a result setting patients on a different path by reducing a patients' risk of a fall, with the added goal of maintaining independence and allowing the patient to stay in their home and community. Studies have shown that early and targeted intervention can reduce the incidence of falls by 30% - 40% (6-9). The challenge then becomes identifying those patients at risk of falls.

Recently, NICE, The National Institute of Health and Care Excellence have issued a briefing note on QTUG™ (16).

Click here to read the briefing note.



https://www.kinesis.ie/qtug/

What Is FallSkip?

FallSkip is a biomechanical application, which allows clinicians to evaluate older adults´ fall risk, attributed to their functional state. The system uses an Inertial Measurement Unit integrated in an Android device, which analyses the biomechanical response when performing a modified protocol of the Timed up and Go Test (TGU).



FEATURES

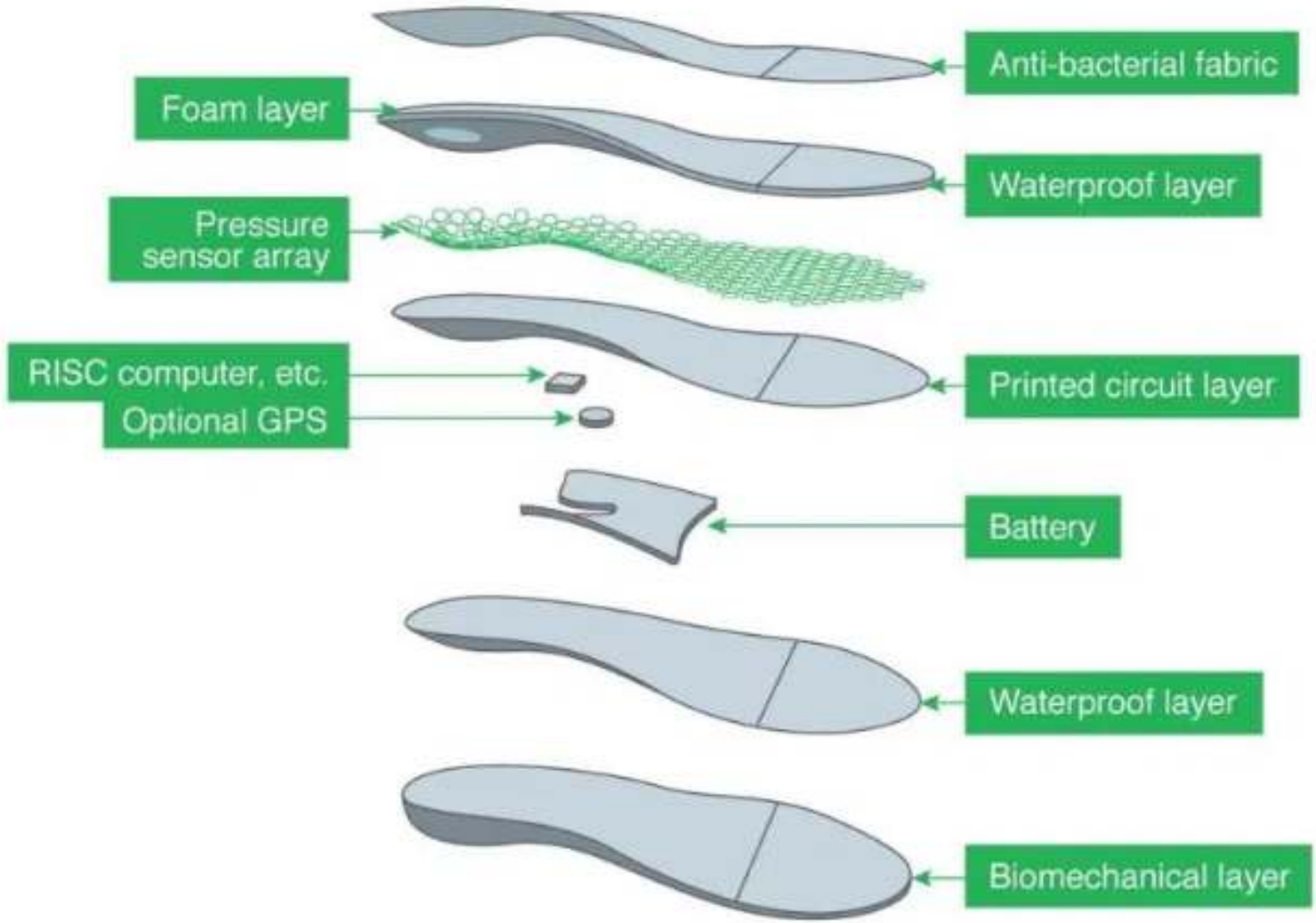
- Non invasive Plug&Play system
- Can be applied by non specialized staff.
- Less tan 2 minutes test.
- **Fall Risk valuation** depending on age and gender.
- Indexes and plots for diagnosis and decision making
- Storage and data visualization without any external devic
- Lifespan is more than 4 years.

ANALYZED PARAMETERS

- Balance pattern.
- Gait pattern.
- Coordination ability.
- Reaction time.
- Muscular strength.
- Total time.



http://fallskip.com/en/what-is-fallskip/



Autonomous ID is a company working on insole technology that could help prevent seniors from falling. graphic handout from the Autnonmous ID to go with 0211 obs falls side/ Liz Payne

ocuvera

Just The Camera

There is nothing in the bed or on the patient.

Multiple Alert Levels

To help reduce alarm fatigue, there are multiple options available to make the system more or less sensitive.

Flexible Alerting

Let's work with you to determine how best to integrate Ocuvera into your existing workflow.

No Sitter

No need for a sitter or monitoring tech to watch video feeds. Ocuvera does it automatically without need to be hired, trained, or use the bathroom.

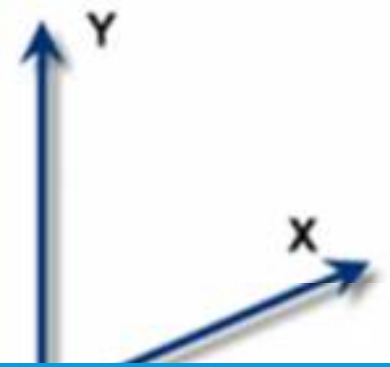
Privacy

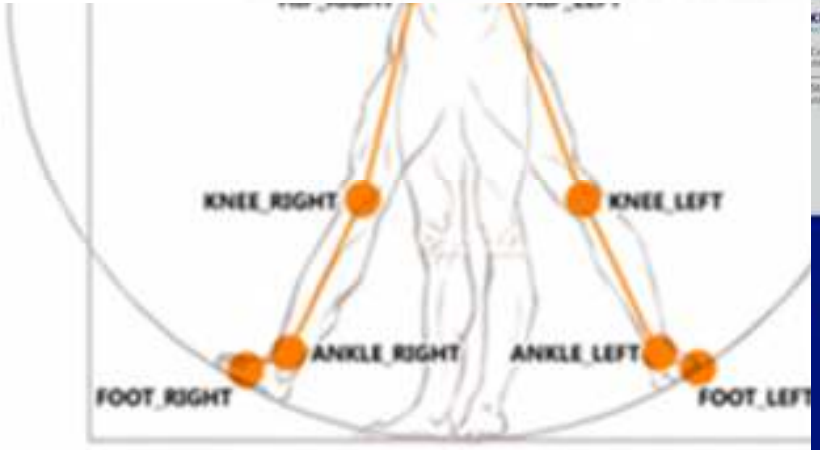
Our depth images aren't able to detect any personally identifiable data (age, gender, skin tone, facial structure).

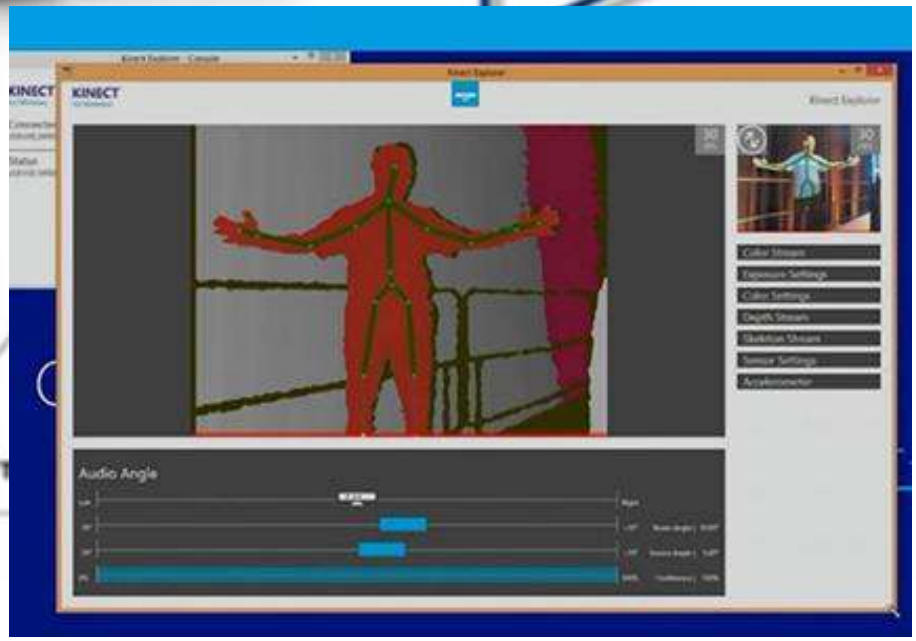


Microsoft Kinect









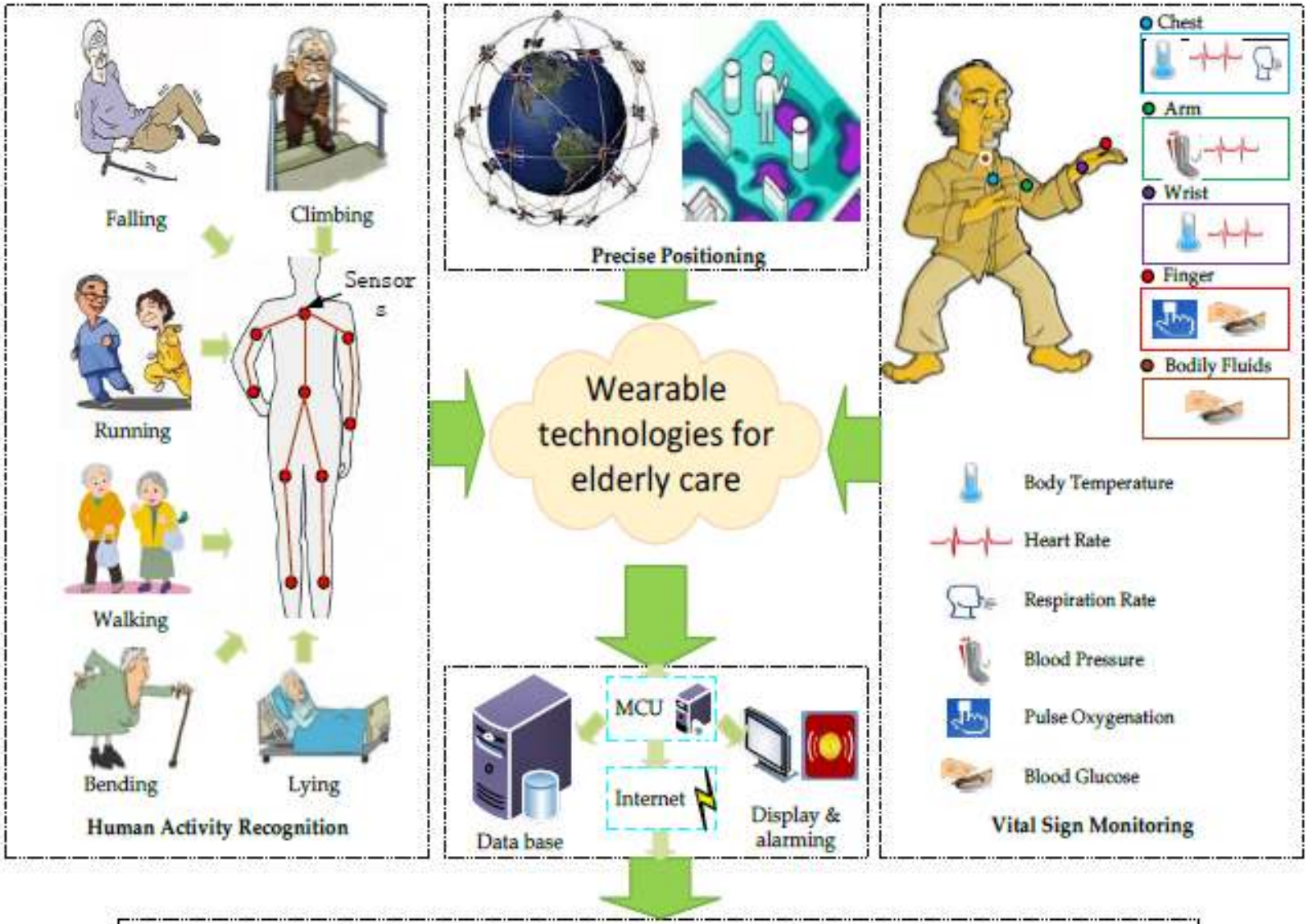


Figure 1. Schematic of functions for elderly care, including precise indoor positioning, physical activity tracking and real-time monitoring of vital signs.

Sensors 2017, 17, 341; Doi:10.3390/s17020341

Conclusiones

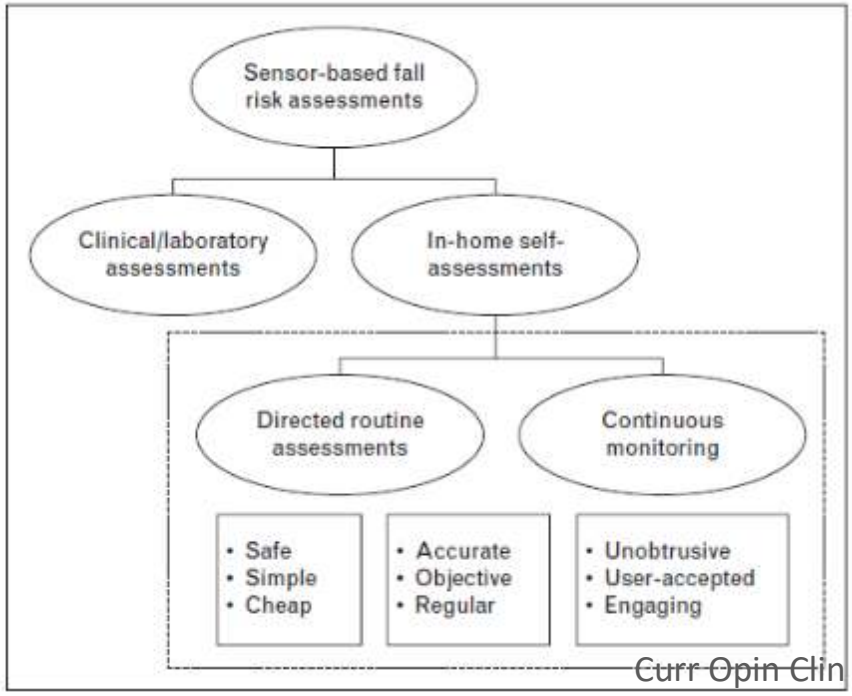
- La etiología del síndrome de caídas es multifactorial por lo que la tecnología podría permitir evaluar de una forma sencilla el riesgo de caídas y dar seguimiento.
- **Sensores** y cuestionarios son las herramientas más estudiadas.
- Herramientas actuales evalúan movimiento, características de la marcha, signos vitales, **cambios en comportamiento**
- Se deben tomar en cuenta otras variables
- La predicción del riesgo de caídas nos permite plantear intervenciones preventivas

Propuestas y desafíos.

- Múltiples herramientas novedosas que podrían permitir predecir el riesgo de caídas

Sensores son la base de dichas herramientas

- Accesibles, económicas, sencillas de utilizar.
- Involucro del paciente: wearables. En el consultorio: dispositivos que evalúan marcha.
- Es un desafío ampliar la evidencia actual



Curr Opin Clin Nutr Metab Care 2014, 17:407–411