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Abstract

There is an exponential increase in the range of digital products and devices promoting aging in place in particular devices aiming at preventing or detecting falls. However, their deployment is still limited and few studies have been carried out in population-based settings. Such a matter of fact is due to the technological challenges that remain to overcome but also to the barriers that are specific to the users themselves such as the generational digital divide and acceptability factors specific to the elderly population. To date, scarce studies take into account these factors. In order to capitalize technological progress, the further step should be to better take into account these factors and to deploy, in a broader and more ecological way, these technologies designed for home care seniors, in order to assess their effectiveness in real life.

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Fall detection and prevention systems of homecare for the elderly: myth or reality?

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Abstract: There is an exponential increase in the range of digital products and devices promoting aging in place in particular devices aiming at preventing or detecting falls. However, their deployment is still limited and few studies have been carried out in population-based settings. Such a matter of fact is due to the technological challenges that remain to overcome but also to the barriers that are specific to the users themselves such as the generational digital divide and acceptability factors specific to the elderly population. To date, scarce studies take into account these factors. In order to capitalize technological progress, the further step should be to better take into account these factors and to deploy, in a broader and more ecological way, these technologies designed for home care seniors, in order to assess their effectiveness in real life.

Keywords: elderly people, new technologies, fall, acceptability, digital divide.

The era of fall detection and prevention devices for elders living at home

These recent years have witnessed a considerable evolution of new technologies such as wearable sensors and connected applications aimed at promoting home life for the elderly by providing them support in their daily activities. A frequent purpose is the detection of falls, as falls are one of the main causes of institutionalization and functional decline [1,2]. Indeed, it has been shown that falls without severe injury multiply the risk of institutionalization by three while fall with severe injury multiply this risk by ten [3]. Different types of sensors and systems for the prevention and detection of falls are currently being developed. This progress is made possible by the development of remote data collection techniques with more or less distant communication technologies such as Bluetooth or Zigbee and the integration of these sensors in different contexts in research and at home as they become smaller, less expensive and thus more accessible to users [4].

Indeed, many wearable sensors in the Internet of Things' paradigm have been developed with the aim of preventing and/or detecting falls at home [5,6,7]. These technologies are mostly based on monitoring and alarm systems which are used to prevent, detect and alert caregivers in case of fall [7]. Some provide reactive assistance to the person when a fall occurs, limiting the complications when the elderly person is lying on the floor for a long time because he/she is unable to get up without help. This is typically the case of devices designed to activate an alarm when a fall occurs [8]. Other technologies such as *exergames*, *Wii-fit*, or the *Kinect* devices [9,10] act proactively, by proposing preventive actions for the elderly such as home exercise programs of muscular strength and balance training. According to several studies, such home based exercise programs could significantly reduce the risk of falls [11,12]. As a consequence, these technologies could reduce the costs and consequences of falls and increase user acceptance by providing regular information and notifications on the evolution of the user's performance and health status, encouraging the elderly to use them [7].

Most tools aiming at preventing or detecting falls are based on monitoring of individual's motor activity using one or several sensors [13,14,15]. Sensors play an essential role as they are the basic elements of data acquisition systems. These electronic devices make it possible to transform the nature of an observed physical value into an exploitable digital one. There is a huge variety of sensors: those allowing collecting data on the physiological state of a person (temperature, heart and respiratory rate, blood pressure, electrocardiogram, glycemia...), those to measuring movements (accelerometers, gyroscopes, magnetometers...), or those detecting the geolocation of the person (*global positioning system* (GPS)). There are also ambient measurement sensors (audio and video) providing information on the environment in which the individual is. For fall detection specifically, the most frequently used measures are acceleration, angular velocity, and magnetic fields to identify body movements [13].

Basically there are two types of sensors allowing detecting and prevention of falls: wearable and non-wearable ones. Wearable systems require placing sensors on the person, it may be a watch, a pendant, a wearable camera, usually attached to clothes or around the wrist [16,17]. Non-wearable systems involve sensors positioned in the person's usual environment and use a variety of measurements such as pressure sensors [18] and ambient sensors including visual (fixed cameras, *Kinect* sensors) [19], and acoustic (microphones) [20,21] sensors.

Even though they may be perceived as more constraining for the user, wearable sensors are more effective than non-wearable ones in detecting falls. Firstly, because they can detect changes in acceleration, planes of motion or impact with high accuracy [22], and secondly, because they are not limited to a specific monitoring area in the individual's environment [23]. To date, the most technologically and ergonomic advanced technologies are those combining several types of sensors. The data collected are multimodal (physiological, actimetric, mechanical) and thus allow more thorough analysis for both prevention and detection of falls [9,10,23,24,25,26,27,28,29,30,31,32].

Different types of connections are possible, such as wearable sensors connected to an app via a smartphone. The “SmartStep” system for instance uses sensors integrated into the shoe sole which record the users' motion. “SmartStep” is a connected electronic device which includes a 3D accelerometer, a 3D gyroscope, pressure sensors, and Bluetooth connectivity. The system is wirelessly connected to an Android phone app allowing both recording and visualization of data. This device has shown excellent accuracy in recognizing several daily living actions (such as walking, running...) and has shown higher efficiency than wrist-worn devices [24,25]. Similarly, a fall detector worn in a waist belt, based on an Attitude and Heading Reference system and a barometric sensor has been developed. This system has shown maximum sensitivity (100%) for fall detection in several studies [23,27]. Another fall detection system has been developed in an indoor environment, consisting of a belt with an accelerometer connected to a data concentrator with a wireless connection based on machine learning Ensemble-Random Forest algorithm. This device has shown a rate of success of more than 94% for accuracy, sensitivity, and specificity in the detection of three types of falls (forward, backward, and sideways fall) and several actions of daily life such as walking, climbing stairs, and sitting [29]. In this line of devices integrating data from different sensors worn directly on the individual, Bio Immersive Risk Detection System (BIRDS) is currently being developed. It is a particularly innovative system as, in addition to ambient, physiological and motor sensors, the system includes a wearable camera with real-time transfer via an Android app and automatic analysis of the images in order to detect several risk situations including falls and the risk of falling [30,31].

Other detection systems combine both wearable and non-wearable sensors based on the Internet of Things. For instance, there is a smart and connected home health monitoring system [26] comprising several sensors placed on household objects, and sensors worn directly on the individual (on the belt, on a key ring, or on a pendant) with an alarm button, an interface and software for data collection. Sensors can be attached to strategic household objects to provide information on the user's activity or health status; for example, the pillbox (indicating adequate/inadequate medication intake), the refrigerator door (indicating food consumption), etc. The sensor worn by the user is used to record different movements, such as walking and more especially falling. The data processing is based on deep learning methods and hidden Markov models. The alarm button can be activated at any time by the user to alert an emergency response team. Finally, the physiological data from the different sensors are gathered on the same software platform. This system showed a sensitivity of 99% and a specificity of 98% for fall detection. Another study reported a prototype monitoring system for fall detection called “Tagcare” based on Doppler frequency recorded from a sensor worn on the person and sensors placed in the environment. The “Tagcare” system has shown high accuracy (98%) in detecting sudden movements and falls [32].

Regarding devices specifically designed for fall prevention, most are based on ambient and contextual sensors, connected to the Internet of Things, and rely on the analysis of the user's gait and balance measures collected through different tests and physical exercises [9,10]. In a pilot study, Williams et al. (2010) proposed a game console (Wii) consisting of a balance tray (like a bathroom weigh scale) in which pressure sensors are integrated to monitor changes in the person's balance, weight and gravity while performing a recreational activity [10]. Another study reports a *Kinect* device allowing detecting the posture of a person with a combined system comprising a color camera coupled with an infrared emitter and its detector [28]. Although still in progress, this type of device highlights the relevance of using gait and specifically cadence variability while walking as predictors of falls and functional decline [28].

As may be seen, a large variety of technological solutions aiming at supporting older adults’ home life is now available and the recent results regarding fall prevention are particularly promising. Nevertheless, important challenges and barriers to a wider adoption of these devices remain [5].

The technological challenges

Falls refer to “the act of falling to the ground independently of one's will. It is associated with sensory, neuromuscular and/or osteoarticular deficiencies” [33]. Although falls in the elderly are widely studied in the scientific literature, from a technical point of view, the act of falling is complex to analyze and model [34]. Falls encompass three types of falls: the “soft” fall, when the person holds on to a piece of furniture; the “heavy” fall, corresponding to a rapid loss of verticality associated with an impact; and the “syncopal” fall, when the person slips after losing consciousness. In addition, a distinction should be made between an effective accidental fall situation and a risk of fall. The accidental fall situation has been widely studied and its occurrence can be determined with an accuracy of 200 to 600 ms before the onset of the fall whereas the risk of falling depends on individual-specific data (physiological or environmental) and requires more sophisticated analyses.

An additional difficulty in the study of falls is that occurrence depends on the clinical context. Although falls are far less frequent in healthy individuals than in a population of frail elders with pathological conditions, it is more difficult to detect falls in these populations. Indeed, a study from the Cambridge City over-75s Cohort (CC75C) on 110 oldest old participants (over 90 years of age) considered at risk of falls equipped with an emergency call system has shown that 80% of them forgot to press the alarm button after a fall [35]. Therefore, with aging, monitoring technology solutions based on a “passive” interaction, i.e., which do not require any intervention of the user, are more adapted for falls and risk of falls detection [6].

The detection systems approach suffers from some limitations. Since falls generally follow a specific pattern (pre-fall, fall, and post-fall) and are characterized by significant variations in movement, most approaches take into account this sequence by using temporal models and by calculating the person's movement. Many detection systems have been based on a thresholding technic which uses a fixed threshold to detect movement variations (via wearable sensors) to distinguish falls from non-fall situations [13,22]. One of the limits of this method is that a fixed threshold value cannot be representative of the different types of falls. Moreover, in most cases the threshold is determined by the lowest peaks of simulated falls assessed in healthy individuals. Thus, the thresholding is quite empirical, generating numerous false positives, particularly in ecological contexts. A solution has been to turn to machine learning methods applied to measurements collected from various sensors (motion and ambient), and thus using multi-sensor and multimodal fusions. Using data from multiple sources ensures greater device reliability, increased robustness towards environmental interference and improved measurement accuracy.

In addition to the difficulties inherent to fall analysis, other difficulties are related to the sensors and the Internet of Things. The first concerns the extraction of high quality and reliable data depending on both the sensors used and their sensitivities. For example, a non-optimal placement of the sensors on the individual or on a household object would directly alter the quality of the recording or leads to errors during the reception of the signal. Connected objects are also subject to artifacts and may be interfered by the individual's movements when they are worn on the body [36].

The second challenge concerns the collection and processing of remote data. Indeed, quality Internet bandwidth cannot be ensured continuously, and the greater or lesser speed of data transmission can lead to misinterpretations and/or data loss [5]. Therefore, it is necessary to use backup systems and more reliable networks such as *Sigfox* to retrieve data stored in a device (e.g., a smartphone) and transfer it to another device [37]. However, few information can be transmitted because there are specific conditions of security and protection of personal data. Connected devices are also limited by storage capacities and battery issues of the objects used [38,39].

Also, most technologies aiming at promoting home support are based on artificial intelligence techniques such as deep learning to proactively detect events. Deep machine learning requires a very big data volume to ensure model accuracy. Collecting such an amount of data requires a lot of time and is very costly.

Finally, another potential limitation is that the data extracted from the sensors cannot be directly used by the elderly person, a family caregiver, or by the clinician [5].

Taken together, these limitations explain the scarce deployment of such devices in the general population or in clinical routine. Advances in digital science progressively allow finding alternatives or solutions addressing each of the technical issues previously mentioned [5]. Yet, if such technical improvements are undeniably necessary, they may not be sufficient. More research in the field of new technologies should be dedicated to social and human factors since real needs, representations, knowledge and skills of the elderly population actually play a critical role in the effective use of the device.

Barriers to adopting new technologies among the elderly related to the users themselves: between the digital divide and levers of acceptability

Despite technological advances, there are many barriers that make connected objects poorly operational for the majority of the elderly population. One of these obstacles is related to the intergenerational digital divide, which refers to an inequality in the use of and access to technology between generations who highlights the exclusion of certain people or social groups, because of their physical, social, psychological or economic characteristics which make them unable to access the digital world and the resources that it makes available [40]. In France, one out of two people over 75 years old does not have an Internet connection at home, compared to only 2% for the 15-29 age group [41]. This technological divide between the different generations may increase in the next decades due to the exponential advance of a digitally oriented world and the non-meeting of real needs, skills and attitudes of older users with the opportunities provided by the current digital offer. This situation generates often stereotyped conceptions of ageism in terms of interfaces, contents and functionalities, often proving unsuitable to cover the heterogeneity of the needs and capacities of older people [42].

Another potential barrier is the social stigma generated by the exponential offer of innovative technologies (home automation, fall detectors, robotics…) called “gerontechnologies” [43]. Paradoxically, the use of these new technologies to help elderly people stay at home can be perceived by the general population as a new form of dependency. Indeed, in our modern societies, old age is often associated with dependence and illness. These age-related stereotypes are manifestations of "ageism" with negative consequences on the mental and physical health of our seniors, and as a consequence, on their access to new technologies. Biased and often stereotypical views of aging lead designers to produce solutions which are not very accessible or inclusive for older users and contribute to the perception of older people as incompetent and unable to understand and use new technologies [44]. Several qualitative studies using focus group methodology reveal that older adults have limited knowledge of technologies which could be offered to them and experience a negative stigma towards them by the simple fact that they use technological tools in their daily lives [42,45,46]. Thus, the use of technologies for home life may contribute to create a new stereotype in the elderly who become "technologically assisted persons", the use of assistive technologies nourishing the stigma of aging and dependence [47,48]. In turn, this vision can lead the elderly to reject new technologies and thus accentuate the digital divide already prevalent in our societies [40].

Regarding "human factors" more specifically, a systematic review conducted by Hawley-Hague et al. (2014) report specific intrinsic and extrinsic acceptability factors for the adoption of fall prevention and detection systems.

The first intrinsic factor concerns privacy, more particularly for the systems involving automatic activation of video after a fall. To ensure the acceptability of such technologies using video recording, one solution is to use image blurring, especially in the most private areas of the home like the bedroom or the bathroom [49,50]. Another question is whether it is appropriate to ask the elderly person to set the thresholds for the activation of the video monitoring system or to turn off the video recording in the case of false alarms. At least, it should be clearly specified to the elderly person what situations are likely to activate the video recording [49,51,52].

Autonomy and feeling of control may also be determining factors in the use of fall-specific technologies. To a certain extent, these technologies allow users suffering from loss of autonomy recovering a feeling of independence for some actions (e.g., using stairs, mopping the floor in slippery areas, etc.) which are considered to be risky with advancing age, and thus regaining confidence in their functional abilities while being secured by the connected system [51,53,54].

The third factor is the perceived need by the user him/herself for fall prevention and detection systems. This factor is influenced by the older person's self-perceived physical, cognitive, and emotional condition, and self-esteem [47,49,50,52,53,55,56]. Faced with a society increasingly turned towards the use of new technologies, some elderly people feel excluded. They fear being “overtaken”, being “out of the game” or “unable” of appropriating and using new technology. This feeling may lead elderly persons to develop “technophobia”, which is an exacerbated fear of using technology and a concern about its effects on society [57,58]. In this respect, the image of one's own aging will be an essential issue [47]. Aging persons with a positive view of themselves will be more enthusiastic about using new technology because they will perceive an opportunity to develop new skills and new experiences in their life. On the contrary, a person who has a negative image of the way his/her ages will tend to feel “incapable” of acquiring the skills to use new technologies and will be reluctant to it, even if their use is simplified. The life trajectory of the individual can also be a factor influencing the use of technologies and the level of anxiety associated to their use [35,47,57]. This factor refers to the experience the person has developed throughout his/her life, both personally and professionally, which will contribute to the representations of his/her own general skills acquired in this field. For example, a person who has used in his/her former occupation tools considered as “technical” may feel more armed to apprehend new technologies and may see an opportunity to capitalize his/her previous experience. This experiential factor can be favorable or unfavorable to the discovery and use of connected devices. Other factors such as anticipation of difficulties in one's home life, the physical environment, the type of technology may play a role in the perceived need and requirements of the technology [55]. Finally, it is important to highlight the elderly user's entourage, which is often intergenerational, and often plays the role of mediator between the technology and the elderly person. In some cases, the entourage not only facilitates, but also encourages, valorizes, gives meaning to the use of new technology, and provides a form of positive "social pressure" whereas in some families where digital devices are less present and enhanced, the entourage may rather be an impeding factor [55].

Among the extrinsic factors, usability, feedback, and cost are the most important to consider in the use of fall-specific technologies [7]. Usability and usage factors refer to the individual's perception of the object utility. This principle applies at any age of life when it is a question of appropriating a new tool of any kind [59]. The notion of utility is generally linked to a value judgment since there is no "universal" or "intrinsic" utility to an object. Similarly, the appreciation of the usefulness (or uselessness) of the object tap into individual representations which depend on the relationship that the person has with his/her physical and social environment [60]. In the elderly population, the notion of usefulness can be linked to a specific need, for example fighting against social isolation [61], but it is also often associated with the notion of immediacy. Indeed, the utility representation of an object depends on its capacity to address a specific and immediate need. Unfortunately, to date, very few studies take into account the usefulness of technologies appreciated from the point of view of the user, in particular when it comes to older adults' users [62].

Once the tool is acquired, abandonment and poor adherence remain one of the major pitfalls [63,64]. Motivational and commitment factors depend on the ease of use of the technology which underlines the importance giving feedback to the user [5,60,64,65,66]. If the object is perceived as useful and easy to use, the person will be motivated to repeat the experience. An experience of "success" will enhance the person's image as well as the acquired skills [65]. The connected object will not be perceived as a simple data collection system but rather as a motivational and self-engagement system [5].

Lastly, from the perspective of the older adult user, cost is an important consideration. Therefore, in order to guarantee a wide and egalitarian application for the whole elderly population, cost issues are very important to consider, as there is an increasing impoverishment of the 65 and over [50].

In order to promote active and independent aging at home, it is important to encourage the use of certain assistive and preventive technologies, conveying positive messages about their benefits and ensuring that these technologies are easy-to-use, reliable, effective and adapted to the older adults needs to motivate their adoption [7].

Conclusion

The use of new technologies for the prevention and detection of falls among the elderly encompasses a complexity which goes far beyond the technological challenges. Even though there is a growing interest in optimizing the accessibility of seniors to new technologies, scarce research takes into account the diversity of factors participating directly or indirectly in the digital divide and the factors of acceptability specific to the elderly population which are decisive in the adoption of these tools.

Both technological and human barriers appeal for more multidisciplinary and collaborative work between the different actors and stakeholders, i.e., users, family caregivers, clinicians, researchers from digital science, clinical sciences and humanities, may be a key to accelerating research.

Finally, although efforts are being made to improve the feasibility and acceptability of digital devices outside of a laboratory setting, few studies have assessed their efficacy in “real life” of older adults selected from general population. After a first step which resulted in the development of a wide range of devices relatively accessible in terms of use and cost, evaluating such devices in large samples of older adults assessed in ecological contexts is the second necessary step to take if we want these tools to be not just technological prototypes, but operational allies really effective in promoting active aging and improving the quality of life of older adults suffering from frailty or loss of autonomy.

References

1. Gill, T. M., Desai, M. M., Gahbauer, E. A., Holford, T. R., & Williams, C. S. (2001). Restricted activity among community-living older persons: Incidence, precipitants, and health care utilization. *Annals of Internal Medicine*, *135*(5), 313–321. https://doi.org/10.7326/0003-4819-135-5-200109040-00007
2. Tinetti, M. E., & Williams, C. S. (1998). The effect of falls and fall injuries on functioning in community-dwelling older persons. *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences*, *53*(2), M112-119. https://doi.org/10.1093/gerona/53a.2.m112
3. Tinetti, M. E., & Williams, C. S. (1997). Falls, injuries due to falls, and the risk of admission to a nursing home. *The New England Journal of Medicine*, *337*(18), 1279–1284. https://doi.org/10.1056/NEJM199710303371806
4. U.Farooq, M., Waseem, M., Mazhar, S., Khairi, A., & Kamal, T. (2015). A Review on Internet of Things (IoT). *International Journal of Computer Applications*, *113*(1), 1–7. https://doi.org/10.5120/19787-1571
5. Baig, M. M., Afifi, S., GholamHosseini, H., & Mirza, F. (2019). A Systematic Review of Wearable Sensors and IoT-Based Monitoring Applications for Older Adults—A Focus on Ageing Population and Independent Living. *Journal of Medical Systems*, *43*(8), 233. https://doi.org/10.1007/s10916-019-1365-7
6. Chaudhuri, S., Thompson, H., & Demiris, G. (2014). Fall Detection Devices and Their Use With Older Adults: A Systematic Review. *Journal of Geriatric Physical Therapy*, *37*(4), 178–196. https://doi.org/10.1519/JPT.0b013e3182abe779
7. Hawley-Hague, H. (2014). Older adults' perceptions of technologies aimed at falls prevention, detection or monitoring: A systematic review. *I n t e r n a t i o n a l j o u r n a l o f m e d i c a l i n f o r m a t i c s*, 11.
8. Porter, E. J. (2005). Wearing and using personal emergency respone system buttons. *Journal of Gerontological Nursing*, *31*(10), 26–33. https://doi.org/10.3928/0098-9134-20051001-07

9. Miller, C. A., Hayes, D. M., Dye, K., Johnson, C., & Meyers, J. (2012). Using the Nintendo Wii Fit and body weight support to improve aerobic capacity, balance, gait ability, and fear of falling: Two case reports. *Journal of Geriatric Physical Therapy (2001)*, *35*(2), 95–104. https://doi.org/10.1519/JPT.0b013e318224aa38

10. Williams, M. A., Soiza, R. L., Jenkinson, A. M., & Stewart, A. (2010). Exercising with Computers in Later Life (EXCELL)—Pilot and feasibility study of the acceptability of the Nintendo® WiiFit in community-dwelling fallers. *BMC Research Notes*, *3*, 238. https://doi.org/10.1186/1756-0500-3-238

11. Gillespie, L. D., Robertson, M. C., Gillespie, W. J., Sherrington, C., Gates, S., Clemson, L. M., & Lamb, S. E. (2012). Interventions for preventing falls in older people living in the community. *The Cochrane Database of Systematic Reviews*, *9*, CD007146. https://doi.org/10.1002/14651858.CD007146.pub3

12. Sherrington, C., Tiedemann, A., Fairhall, N., Close, J. C. T., & Lord, S. R. (2011). Exercise to prevent falls in older adults: An updated meta-analysis and best practice recommendations. *New South Wales Public Health Bulletin*, *22*(3–4), 78–83. https://doi.org/10.1071/NB10056

13. Bourke, A. K., & Lyons, G. M. (2008). A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor. *Medical Engineering & Physics*, *30*(1), 84–90. https://doi.org/10.1016/j.medengphy.2006.12.001

14. Tong, L., Song, Q., Ge, Y., & Liu, M. (2013). HMM-Based Human Fall Detection and Prediction Method Using Tri-Axial Accelerometer. *IEEE Sensors Journal*, *13*(5), 1849–1856. https://doi.org/10.1109/JSEN.2013.2245231

15. Tong, Lina, Chen, W., Song, Q., & Ge, Y. (2009). A research on automatic human fall detection method based on wearable inertial force information acquisition system. *2009 IEEE International Conference on Robotics and Biomimetics (ROBIO)*. https://doi.org/10.1109/ROBIO.2009.5420725

16. Fleming, J., & Brayne, C. (2008). Inability to get up after falling, subsequent time on floor, and summoning help: Prospective cohort study in people over 90. *BMJ*, *337*, a2227. https://doi.org/10.1136/bmj.a2227

17. GANYO, M., Dunn, M., & HOPE, T. (2011). Ethical issues in the use of fall detectors. *Ageing and Society*, *31*, 1350–1367. https://doi.org/10.1017/S0144686X10001443

18. Alwan, M., Rajendran, P. J., Kell, S., Mack, D., Dalal, S., Wolfe, M., & Felder, R. (2006). A Smart and Passive Floor-Vibration Based Fall Detector for Elderly. *2006 2nd International Conference on Information Communication Technologies*, *1*, 1003–1007. https://doi.org/10.1109/ICTTA.2006.1684511

19. Sixsmith, A., & Johnson, N. (2004). A smart sensor to detect the falls of the elderly. *IEEE Pervasive Computing*, *3*(2), 42–47. https://doi.org/10.1109/MPRV.2004.1316817

20. Li, Y., Zeng, Z., Popescu, M., & Ho, K. C. (2010). Acoustic fall detection using a circular microphone array. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, *2010*, 2242–2245. https://doi.org/10.1109/IEMBS.2010.5627368

21. Popescu, M., Li, Y., Skubic, M., & Rantz, M. (2008). An acoustic fall detector system that uses sound height information to reduce the false alarm rate. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, *2008*, 4628–4631. https://doi.org/10.1109/IEMBS.2008.4650244

22. Bourke, A. K., O'Brien, J. V., & Lyons, G. M. (2007). Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. *Gait & Posture*, *26*(2), 194–199. https://doi.org/10.1016/j.gaitpost.2006.09.012

23. Pierleoni, P., Belli, A., Maurizi, L., Palma, L., Pernini, L., Paniccia, M., & Valenti, S. (2016). A Wearable Fall Detector for Elderly People Based on AHRS and Barometric Sensor. *IEEE*

Sensors Journal, *16*, 6733–6744. https://doi.org/10.1109/JSEN.2016.2585667

24. Hegde, N., Bries, M., Swibas, T., Melanson, E., & Sazonov, E. (2018). Automatic Recognition of Activities of Daily Living Utilizing Insole-Based and Wrist-Worn Wearable Sensors. *IEEE Journal of Biomedical and Health Informatics*, *22*(4), 979–988. https://doi.org/10.1109/JBHI.2017.2734803

25. Hegde, N., & Sazonov, E. (2014). SmartStep: A Fully Integrated, Low-Power Insole Monitor. *Electronics*, *3*(2), 381–397. https://doi.org/10.3390/electronics3020381

26. Maimoon, L., Chuang, J., Zhu, H., Yu, S., Peng, K.-S., Prayakarao, R., Bai, J., Zeng, D. D., Li, S.-H., Lu, H.-M., & others. (2016). *SilverLink: Developing an International Smart and Connected Home Monitoring System for Senior Care*. 65–77. https://doi.org/10.1007/978-3-319-59858-1_7

27. Pierleoni, P., Belli, A., Palma, L., Pellegrini, M., Pernini, L., & Valenti, S. (2015). A High Reliability Wearable Device for Elderly Fall Detection. *IEEE Sensors Journal*, *15*, 4544–4553. https://doi.org/10.1109/JSEN.2015.2423562

28. Stone, E. E., & Skubic, M. (2011). Evaluation of an inexpensive depth camera for passive in-home fall risk assessment. *2011 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*, 71–77. https://doi.org/10.4108/icst.pervasivehealth.2011.246034

29. Yacchirema, D., Puga, J., Palau, C., & Esteve, M. (2019). Fall detection system for elderly people using IoT and ensemble machine learning algorithm. *Personal and Ubiquitous Computing*, *23*. https://doi.org/10.1007/s00779-018-01196-8

30. Yebda, T., Benois-Pineau, J., Amieva, H., & Frolicher, B. (2019, September). Multi-sensing of fragile persons for risk situation detection: devices, methods, challenges. In 2019 International Conference on Content-Based Multimedia Indexing (CBMI) (pp. 1-6). IEEE.

31. Yebda T., Benois-Pineau J., Pech M., Amieva H., Middleton L., Bergelt M. (2021).

Multimodal Sensor Data Analysis for Detection of Risk Situations of Fragile People in @home Environments. In: Lokoč J. et al. (eds) MultiMedia Modeling. MMM 2021. Lecture Notes in Computer Science, vol 12573. Springer, Cham. https://doi.org/10.1007/978-3-030-67835-7_29

32. Zhu, L., Wang, R., Wang, Z., & Yang, H. (2017). TagCare: Using RFIDs to Monitor the Status of the Elderly Living Alone. *IEEE Access*, *5*, 11364–11373. https://doi.org/10.1109/ACCESS.2017.2716359

33. Dargent-Molina, P., Dargent-Molina, P., & Breat, G. (1995). Epidémiologie des chutes et des traumatismes liés aux chutes chez les personnes âgées. *Epidémiologie Des Chutes et Des Traumatismes Liés Aux Chutes Chez Les Personnes Âgées.*

34. Bobillier-Chaumon, M. E., Cros, F., Cuvillier, B., Hem, C., & Codreanu, E. (2013). *Concevoir une technologie pervasive pour le maintien à domicile des personnes âgées: La détection de chutes dans les activités quotidiennes*. 189–199.

35. Fleming, J., & Brayne, C. (2008). Inability to get up after falling, subsequent time on floor, and summoning help: Prospective cohort study in people over 90. *BMJ*, *337*, a2227. https://doi.org/10.1136/bmj.a2227

36. Chen, M., Ma, Y., Song, J., Lai, C. F., & Hu, B. (2016). Smart Clothing: Connecting Human with Clouds and Big Data for Sustainable Health Monitoring. *Mobile Networks and Applications*, *21*(5), 825–845. https://doi.org/10.1007/s11036-016-0745-1

37. Gomez, C., Veras, J. C., Vidal, R., Casals, L., & Paradells, J. (2019). A Sigfox Energy Consumption Model. *Sensors*, *19*(3), 681. https://doi.org/10.3390/s19030681

38. Rault, T., Bouabdallah, A., Challal, Y., & Marin, F. (2017). A survey of energy-efficient context recognition systems using wearable sensors for healthcare applications. *Pervasive and Mobile Computing*, *37*, 23–44. https://doi.org/10.1016/j.pmcj.2016.08.003

39. Thomas, S. S., Nathan, V., Zong, C., Soundarapandian, K., Shi, X., & Jafari, R. (2016).

BioWatch: A Noninvasive Wrist-Based Blood Pressure Monitor That Incorporates Training Techniques for Posture and Subject Variability. *IEEE Journal of Biomedical and Health Informatics*, *20*(5), 1291–1300. https://doi.org/10.1109/JBHI.2015.2458779

40. Bigot, R., Alibert, D., & Foucaud, D. (2005, November 1). *La dynamique des inégalités en matière de nouvelles technologies*. https://www.credoc.fr/publications/la-dynamique-des-inegalites-en-matiere-de-nouvelles-technologies

41. *L'usage des technologies de l'information et de la communication par les ménages entre 2009 et 2019 | Insee*. (2020). https://www.insee.fr/fr/statistiques/4466247

42. Durick, J., Robertson, T., Brereton, M., Vetere, F., & Nansen, B. (2013, November). Dispelling ageing myths in technology design. In *Proceedings of the 25th Australian Computer-Human Interaction Conference: Augmentation, Application, Innovation, Collaboration* (pp. 467-476).

43. Wu, Y.-H., Damnée, S., Kerhervé, H., Ware, C., & Rigaud, A.-S. (2015). Bridging the digital divide in older adults: A study from an initiative to inform older adults about new technologies. *Clinical Interventions in Aging*, *10*, 193. https://doi.org/10.2147/CIA.S72399

44. Adam, S., Missotten, P., Flamion, A., Marquet, M., Clesse, A., Piccard, S., Crutzen, C., & Schroyen, S. (2017). Vieillir en bonne santé dans une société âgiste…. *NPG Neurologie - Psychiatrie - Gériatrie*, *17*(102), 389–398. https://doi.org/10.1016/j.npg.2017.05.001

45. Chen, K., & Chan, A. H.-S. (2013). Use or non-use of gerontechnology—A qualitative study. *International Journal of Environmental Research and Public Health*, *10*(10), 4645–4666. https://doi.org/10.3390/ijerph10104645

46. Mitzner, T. L., Boron, J. B., Fausset, C. B., Adams, A. E., Charness, N., Czaja, S. J., Dijkstra, K., Fisk, A. D., Rogers, W. A., & Sharit, J. (2010). Older adults talk technology: Technology usage and attitudes. *Computers in Human Behavior*, *26*(6), 1710–1721. https://doi.org/10.1016/j.chb.2010.06.020

47. Bobillier Chaumon, M.-E., & Oprea Ciobanu, R. (2009). Les nouvelles technologies au service

des personnes âgées: Entre promesses et interrogations – Une revue de questions. *Psychologie Française*, *54*(3), 271–285. https://doi.org/10.1016/j.psfr.2009.07.001

48. Caradec, V. (1999). Vieillissement et usage des technologies. Une perspective identitaire et relationnelle. *Réseaux. Communication - Technologie - Société*, *17*(96), 45–95. https://doi.org/10.3406/reso.1999.1059

49. Londei, S. T., Rousseau, J., Ducharme, F., St-Arnaud, A., Meunier, J., Saint-Arnaud, J., & Giroux, F. (2009). An intelligent videomonitoring system for fall detection at home: Perceptions of elderly people. *Journal of Telemedicine and Telecare*, *15*(8), 383–390. https://doi.org/10.1258/jtt.2009.090107

50. Mihailidis, A., Cockburn, A., Longley, C., & Boger, J. (2008). The Acceptability of Home Monitoring Technology Among Community-Dwelling Older Adults and Baby Boomers. *Assistive Technology : The Official Journal of RESNA*. https://doi.org/10.1080/10400435.2008.10131927

51. Blythe, M., Monk, A., & Doughty, K. (2005). Socially dependable design: The challenge of ageing populations for HCI. *Interacting with Computers, 17*, 672–689. https://doi.org/10.1016/j.intcom.2005.09.005

52. Heinbüchner, B., Hautzinger, M., Becker, C., & Pfeiffer, K. (2010). Satisfaction and use of personal emergency response systems. *Zeitschrift Fur Gerontologie Und Geriatrie*, *43*(4), 219–223. https://doi.org/10.1007/s00391-010-0127-4

53. Brownsell, S., & Hawley, M. S. (2004). Automatic fall detectors and the fear of falling. *Journal of Telemedicine and Telecare*, *10*(5), 262–266. https://doi.org/10.1258/1357633042026251

54. Van Hoof, J., Kort, H. S. M., Rutten, P. G. S., & Duijnstee, M. S. H. (2011). Ageing-in-place with the use of ambient intelligence technology: Perspectives of older users. *International Journal of Medical Informatics*, *80*(5), 310–331. https://doi.org/10.1016/j.ijmedinf.2011.02.010

55. Courtney, K. L., Demiris, G., Rantz, M., & Skubic, M. (2008). Needing smart home

technologies: The perspectives of older adults in continuing care retirement communities. *Informatics in Primary Care*, *16*(3), 195–201. https://doi.org/10.14236/jhi.v16i3.694

56. Holzinger, A., Searle, G., Prückner, S., Steinbach-Nordmann, S., Kleinberger, T., Hirt, E., & Temnitzer, J. (2010). Perceived Usefulness among Elderly People: Experiences and Lessons Learned during the Evaluation of a Wrist Device. *Proceedings of the International Conference on Pervasive Computing Technologies for Healthcare*, 1–5. https://doi.org/10.4108/ICST.PERVASIVEHEALTH2010.8912
57. Dyck, J. L., & Smither, J. A.-A. (1994). Age Differences in Computer Anxiety: The Role of Computer Experience, Gender and Education. *Journal of Educational Computing Research*, *10*(3), 239–248. https://doi.org/10.2190/E79U-VCRC-EL4E-HRYV
58. Osiceanu, M.-E. (2015). Psychological Implications of Modern Technologies: “Technofobia” versus “Technophilia”. *Procedia - Social and Behavioral Sciences*, *180*, 1137–1144. https://doi.org/10.1016/j.sbspro.2015.02.229
59. Bouchayer, F., Flichy, P., & Rosenkier, A. (Eds.). (1999). *Communication et personnes âgées. Réseaux: Vol. n°96*. Hermès Science Publications.
60. Eve, M., & Smoreda, Z. (2001). L’utilité: Un concept complexe. *Retraite & Société*, *33*, 22–51.
61. White, H., McConnell, E., Clipp, E., Branch, L. G., Sloane, R., Pieper, C., & Box, T. L. (2002). A randomized controlled trial of the psychosocial impact of providing internet training and access to older adults. *Aging & Mental Health*, *6*(3), 213–221. https://doi.org/10.1080/13607860220142422
62. Klaassen, B., van Beijnum, B. J. F., & Hermens, H. J. (2016). Usability in telemedicine systems-A literature survey. *International Journal of Medical Informatics*, *93*, 57–69. https://doi.org/10.1016/j.ijmedinf.2016.06.004
63. Eysenbach, G. (2005). The Law of Attrition. *Journal of Medical Internet Research*, *7*(1), e11. https://doi.org/10.2196/jmir.7.1.e11

64. Malwade, S., Abdul, S. S., Uddin, M., Nursetyo, A. A., Fernandez-Luque, L., Zhu, X. (Katie), Cilliers, L., Wong, C.-P., Bamidis, P., & Li, Y.-C. (Jack). (2018). Mobile and wearable technologies in healthcare for the ageing population. *Computer Methods and Programs in Biomedicine*, *161*, 233–237. https://doi.org/10.1016/j.cmpb.2018.04.026

65. Dupuy, L., Consel, C., & Sauzéon, H. (2016). Self-determination-based design to achieve acceptance of assisted living technologies for older adults. Computers in Human Behavior, 65, 508-521.

66. Uzor, S., Baillie, L., & Skelton, D. (2012). Senior designers: Empowering seniors to design enjoyable falls rehabilitation tools. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1179–1188. https://doi.org/10.1145/2207676.2208568