5-2019

Current Challenges and Barriers to the Wider Adoption of Wearable Sensor Applications and Internet-of-Things in Health and Well-being

Mirza Mansoor Baig
Auckland University of Technology, mirza.baig@aut.ac.nz

Hamid Gholam Hosseini
Auckland University of Technology, hamid.gholamhosseini@aut.ac.nz

Shereen Afifi
Auckland University of Technology, shereen.afifi@aut.ac.nz

Farhaan Mirza
Auckland University of Technology, New Zealand, farhaan.mirza@aut.ac.nz

Current Challenges and Barriers to the Wider Adoption of Wearable Sensor Applications and Internet-of-Things in Health and Well-being

Mirza Mansoor Baig
Auckland University of Technology
mirza.baig@aut.ac.nz

Shereen Afifi
Auckland University of Technology
shereen.afifi@aut.ac.nz

Hamid GholamHosseini
Auckland University of Technology
hamid.gholamhosseini@aut.ac.nz

Farhaan Mirza
Auckland University of Technology
farhaan.mirza@aut.ac.nz

Abstract

The aim of this review is to investigate barriers and challenges of Wearable Sensors (WS) and Internet-of-Things (IoT) solutions in healthcare. This work specifically focuses on falls and Activity of Daily Life (ADLs) for ageing population and independent living for older adults. The majority of the studies focussed on the system aspects of WS and IoT solutions including advanced sensors, wireless data collection, communication platforms and usability. The current studies are focused on a single use-case/health area using non-scalable and 'silo' solutions. Moderate to low usability/ user-friendly approach is reported in most of the current studies. Other issues found were, inaccurate sensors, battery/power issues, restricting the users within the monitoring area/space and lack of interoperability. The advancement of wearable technology and possibilities of using advanced technology to support ageing population is a concept that has been investigated by many studies. We believe, WS and IoT monitoring plays a critical role towards support of a world-wide goal of tackling ageing population and efficient independent living. Consequently, in this study we focus on identifying three main challenges regarding data collection and processing, techniques for risk assessment, usability and acceptability of WS and IoT in wider healthcare settings.

Keywords: Wearable monitoring systems; Ageing population; Independent living; IoT; Wearable devices; Independent living; Acceptability and Usability.

1. Introduction

In recent years, there has been an ever-growing need for a sustainable solution/system to support ageing population and independent living, particularly for supporting activities of daily life and falls. Falls and related injuries in older adults are common worldwide and ageing could further contribute to escalating the number of falls. Therefore, false-related injuries represent one of the most common causes of long-lasting pain, functional impairment, disability and death in older adults (Tinetti & Kumar, 2010). The rate of hospital admission due to falls for people aged 60 and older in Australia, Canada and the United Kingdom ranges from 1.6 to 3.0 per 10000 population per annum (Baig, Gholamhosseini, & Connolly, 2016; GholamHosseini, Baig, Meintjes, Mirza, & Lindén, 2017; Nguyen, Mirza, Naeem, & Baig, 2017, 2018). One out of ten falls in older adults results in injuries such as hip fractures, subdural hematomas, serious soft tissue injuries and head injuries (Baig et al., 2016). In addition to physical injury, falls can also have psychological and social consequences. Fear of falling and post-fall anxiety syndrome are well-recognized as negative consequences of falls. The loss of self-confidence that leads to an inability to ambulate safely can result in self-imposed functional limitations. Moreover, Wearable Sensors (WS) systems are emerging as an effective tool for prevention, early detection and management of Activity of Daily Life (ADLs) and falls among older adults. As wearable sensors, smart textiles and body-worn garments become smaller, cheaper and more consumer-accessible, it is expected that they will be used more extensively across a wide variety of contexts. The expansion of wearable/IoT systems for data collection offers the potential for user-engagement and self-management of age-related illness and diseases (Sabesan & Sankar, 2015).

The aim of this review is to investigate how current technological barriers and challenges limiting the wider adoption among the older adults in supporting their activities of daily life and falls (falls detection and prevention). In addition, this review highlights challenges, barriers and opportunities for a sustainable adoption of WS and IoT in wider healthcare settings. This review is the continuation of previous literature reviews conducted on WS and IoT systems (Baig & Gholamhosseini, 2013; Baig, Gholamhosseini, & Connolly, 2013; Baig et al., 2016; Banaee, Ahmed, & Loutfi, 2013; GholamHosseini et al., 2017; Nguyen et al., 2017, 2018).

2. Challenges and Barriers to the Wider Adoption of Wearable Sensors and IoT Applications

The next generation of WS and IoT systems is likely to improve the quality of human life by assuring high comfort while increasing the intelligent use of limited resources. Further improvements in textile sensors design, signal quality, miniaturization and data acquisition techniques are required to fulfil these expectations. Figure 1 shows the overview model of WS/IoT systems and lists three key areas which are currently limiting the wider clinical adoption of wearable technology, especially among the older adults. The following sections elaborate the issues pertaining to these three key areas.

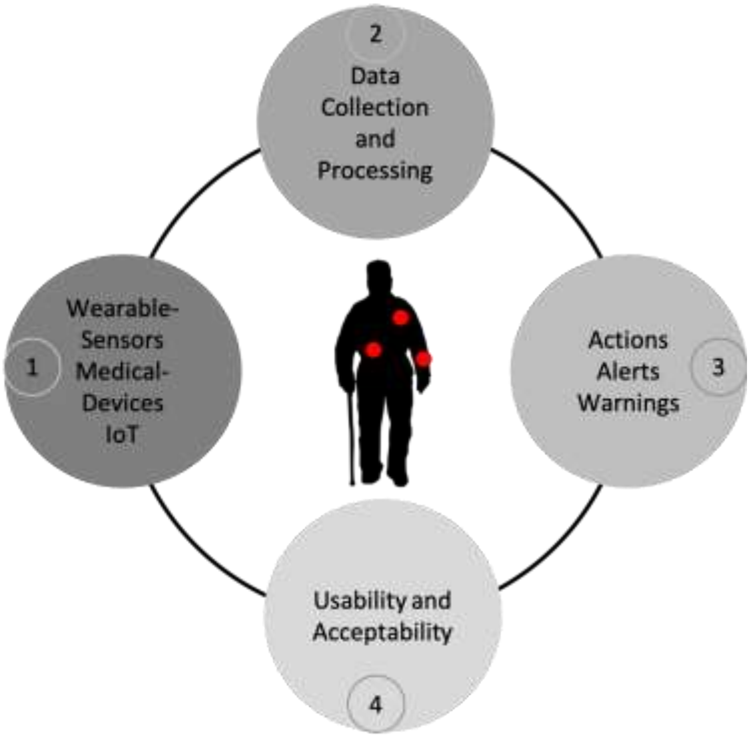

Figure 1. Overview of wearable sensors and IoT-based systems

2.1. Wearable sensors and IoT Devices

A large number of biosensors are currently being used in WS systems, which needs specific on-body placement or body postures to provide reliable readings and measurements (E. T. Chen, 2017; Rajput & Gour, 2016). One of the technical barriers for using WS and IoT applications is the feature extraction process because of motion artefacts, body movement or respiration, which should be resolved for high quality data collection (M. Chen, Ma, Song, Lai, & Hu, 2016). Advanced signal processing was exploited by Etemadi et. al (Etemadi et al., 2016) for collecting reliable Seismo-Cardio-Graphy (SCG). Some techniques were implemented for increasing the accuracy of the SCG. Linear filtering was applied, while the R-wave peak timings was detected from the ECG to be used as a fiduciary for ensemble averaging. Biofeedback training was investigated in a similar study for patient monitoring (W. Wu, Zhang, Pirbhulal, Mukhopadhyay, & Zhang, 2015), where unreliable signals were reported that were affected by various noises. Accordingly, different noises should be filtered using efficient algorithms running on speedy software platforms or powerful hardware accelerators/processors. A wearable T-shirt was proposed for monitoring postures of patients through rehabilitation exercise (M. Chen et al., 2016). Good outcome was achieved in a small setting, where different factors affected the impedance value of the sensor like skin conductivity and relaxation of the proposed T-shirt. Table 1 summaries significant issues and challenges related to wearable sensors and internet-of-thing devices.

2.2. Data Collection and Processing

The delay in generating results and alerts is considered the most common issue in WS systems (Rault, Bouabdallah, Challal, & Marin, 2017; Thomas et al., 2016; J. Wu, Li, Cheng, & Lin, 2016b). Data collection, monitoring and processing are key challenges that were addressed in some of the developed systems for meeting patients needs. A waist-worn detector was presented for fall detection of older adults, which utilized an Attitude and Heading Reference System (AHRS) combining a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer (Pierleoni et al., 2015). A barometer sensor was integrated into the targeting device to improve the efficiency and performance of the system by measuring the altitude variation in a fall (Pierleoni et al., 2016). The results demonstrated better performance compared to existing conventional fall detection systems exist in the literature through using the four combined sensors with the data fusion algorithms efficiently.

A real-time online assessment and mobility monitoring framework based on a smartwatch was proposed, incorporating a smartwatch application and a remotely-connected server (Kheirkhahan et al., 2019). An infrastructure was designed for sensor and user-reported data collection, transmission, visualization, and analysis for the targeted framework. The smartwatch application collects sensor and user-reported data for processing and transmitting to the remote server, where data is collected and retrieved for remote monitoring as well as data visualization and analysis in real-time. The framework is promising for the next generation of IoT-based mHealth, offering an interactive interface and remote application configuration in addition to server features for flexible online customization. Moreover, the smartwatch accelerometer sensor achieved highly correlated results with a validated and research-grade accelerometer.

A smartphone-based solution was presented for remote and non-invasive monitoring of older adults in smart cities that is based on smartwatch usage (Bellagente et al., 2018). The proposed architecture includes a wearable smartwatch, home sensors and three Android smartphones. The user smartphone handles WS, while the home smartphone/tablet manages home sensors and ambient assisted living's devices. The caregiver smartphone receives data and alerts to allow user monitoring. A framework was adopted for simplifying data collection and management of different external connected devices and sensors in Android applications. The proposed smartphone-based approach (ambient assisted living application) is feasible to achieve non-invasive monitoring and improve the independent living of older adults.

2.3. Techniques for Risk Assessment, Actions and Warnings

Machine learning techniques and classification algorithms have been widely used in healthcare applications for enhancing diagnosis and decision support systems. An ADL classification algorithm alog with a fall detection algorithm were proposed based on a wrist-worn wearable device to be implemented on microcontrollers units (MCUs) (Yuan, Tan, Lee, & Koh, 2015). The proposed algorithms are power-efficient that are capable of implementing on 8-bit MCUs with limited clock speed and memory. Both algorithms employed an interrupt-driven method based on a recent digital Micro-Electro-Mechanical Systems (MEMS) accelerometer that supports interrupts and data buffering. The used approach is more power-efficient and different from conventional algorithms by decreasing time dependency on the host MCU. The proposed classifier achieved 94.97% accuracy as well as saving power and bandwidth.

A novel fall detection system was implemented based on simple passive Radio Frequency Identification (RFID) tags and exploiting the Doppler frequency value for fall detection (Zhu, Wang, Wang, & Yang, 2017). The RSS was used to detect a static state and the Doppler effect value was used for identifying a fall action of the older adults. A Wavelet Transform (WT) was applied for pre-processing the RF signal, while a support vector machine classifier was used for fall detection. In addition, a monitoring system's prototype called "TagCare" was introduced and evaluated using extensive experiments, showing a high accuracy for efficient movement and fall detection in real life.

Another fall detection system was presented for older adults in indoor environments, which is based on IoT and a Big Data model "Ensemble-Random Forest (RF)", exploiting the machine learning processing algorithms (Yacchirema, de Puga, Palau, & Esteve, 2019). The proposed system utilized a 3D-axis accelerometer embedded into a 6LowPAN wearable device for capturing data in real time, to be processed and analysed by the employed ensemble-RF model. For achieving high performance and efficient system, the ensemble-RF classifier was selected based on a comparative study based on testing and analysing other three machine learning algorithms for fall and ADL detection. The proposed system was evaluated for detecting three types of both falls and ADLs, where a high success rate of above 94% was achieved for accuracy, precision, sensitivity, as well as specificity.

A smart and connected home health monitoring system was presented for senior care at home (Maimoon et al., 2016) that exploited the advanced deep learning model. The proposed system has both hardware and software components. The hardware components consist of four object sensors, a wearable human sensor with an alarm button and a gateway, while the software components include data collection API, a database, an analytics engine and a web portal. A fall detection system using the WS was proposed, which is based on hidden Markov models with sensor orientation calibration methods. The developed model achieved 0.990 and 0.984 for sensitivity and specificity respectively. In addition, a deep learning-based model (CNN+ RNN) was proposed to process accelerometer readings from the wearable and object sensors for recognizing ADLs, showing 99.5% accuracy from the used CNN model.

2.4. Usability and Acceptability

We believe that one of the core advantages of WS systems is the patient's (user's) self-engagement with the treatment – which is often missing. There is a shift in wider thinking of WS and IoT systems as ‘only data collectors’ to viewing them as being self-engaging and motivating systems which allow rich interactions between patients and clinicians (Davis, Roudsari, Raworth, Courtney, & MacKay, 2017; Milani & Franklin, 2017; Price-Haywood, Harden-Barrios, Ulep, & Luo, 2017). Due to WS systems being traditionally regarded as data collectors only, the majority of wearable systems lack user-engagement and user-interaction aspects. The WS and IoT systems are often focused on providing real-time health data to clinicians for timely treatment and actions but are missing user-acceptance and engagement. User-engagement and user-interaction are some of the key uptake factors among consumers (non-clinical care settings) for wearable technologies (Park et al., 2016; Rupp, Michaelis, McConnell, & Smither, 2016; J. Wu, Li, Cheng, & Lin, 2016a).

There are very few existing studies that address usability and acceptability challenges for health monitoring. Usability and acceptability performance are evaluated based on different measurements of willingness to use and keep, simplicity, reliability, wearable time, satisfaction level and ADL interference (Klaassen, van Beijnum, & Hermens, 2016). The existing WS and IoT devices need modifications in terms of manufacturing and technical capabilities to address critical issues such as, battery/power consumption, restricting the user’s movements within a confined area/space and high cost. Interoperability is required for IoT applications in order to support the electronic health record of the user and also to maintain the large health data, specially related to long-term condition or chronic care conditions (Kovacs et al., 2016; Ullah et al., 2017).

User-engagement should be addressed as one of the system design constraints, aiming to support real-life demands of users/patients. A behavioural change of older users is reported with incorporating related information of estimated fall risk to the wearable system, as well as improving level of user acceptability and awareness (A. Y. Wu & Munteanu, 2018). Different processes are identified for facilitating the user-engagement with remote measuring technology. A feedback loop model is proposed to work on identified barriers and facilitators, aiming to moderate a point of disengagement towards a sustainable engagement through a reengagement process (Simblett et al., 2018). However, specifically designed experimental studies are required for further evaluation of usability and acceptability.

Accepting current wearable technology is considered a critical issue especially for older people. Many factors are affecting the acceptance level of adoption of such smart systems, including technology awareness, user attitude, privacy concerns, lifestyle and hardware compatibility. User feedback is one of the essential components for developing an acceptable system that developers should carefully consider. In addition, incorporating behavioural and emotional change models should be considered in requirements engineering phase, as well as in development, evaluation and deployment phases. The usability and acceptability challenge for older patients is analysed with a comparative study of using four selected wearable/mobile devices. The study concluded that both hardware/device designers and system developers should cooperate towards ease-of-use and comfort WS and other special needs of older people. Consequently, usability and acceptability of wearable devices should meet the challenging demands and concerns of the older adults, while achieving an efficient and reliable monitoring system (Ahmadi et al., 2018; Malwade et al., 2018; Spanakis, Psaraki, & Sakkalis, 2018).

Study Name/ Reference	Aim and Objective	Challenges and Gaps
(E. T. Chen, 2017)	Review of the IoT applications	Size of the device and accuracy of the collected data
(M. Chen et al., 2016)	Interoperability of the wearable devices	Poor feature extraction from the signal due to motion artefacts, body movement or respiration
(Etemadi et al., 2016)	Advanced signal processing to collect accurate and reliable seismocardiography (SCG)	Accuracy and reliability of the sensor data
(W. Wu et al., 2015)	Wearable sensor system for ECG monitoring	Signals collected were unreliable and disturbed by a variety of noises.
(M. Chen et al., 2016)	User's posture during rehabilitation exercise	Usability and accuracy
(Rault et al., 2017; Thomas et al., 2016; J. Wu et al., 2016b).	Data collection and data processing techniques	Data loss, buffering delay, network/ communication errors, and outcome delays due to complex processing
(Balamurugan, Madhukanth, Prabhakaran, & Shanker, 2016; Ghosh, Halder, & Hossain, 2016)	Connected network and data security for hospital settings	Privacy, security and safety of the transmitted data
(Lee, Yoon, & Park, 2016)	ECG monitoring	Poor signal quality, disturbances and noise in the signal
(Kyriazakos et al., 2016; Lee et al., 2016).	sensor-based WS and IoT applications	Delays in processing, noise/ signal processing and quality of the collected data
(Araújo, Santana, & Neto, 2016)	Machine learning for big data in healthcare	Saleability and big data processing
(Klaassen et al., 2016)	Usability and acceptability performance measurements	Low user acceptability and low usability in other use-cases

Table 1 summaries the issues and challenges related data collection, data processing, usability and acceptability related to wearable sensors and internet-of-thing devices.

3. Discussion and Conclusions

Our focus is to highlight the current challenges and barriers limiting wider adoption of WS and IoT systems in healthcare monitoring, aiming for efficient falls monitoring and independent ADL for older population. Three key areas have been addressed in this review study that limit wider adoption of existing wearable systems in aging population. The three main areas include data collection and processing, techniques for risk assessment, actions and alerts, usability and acceptability.

In conclusion, this review indicates the heavy dependency of WS and IoT on communication technology and some studies have reported cost problems when using mobile data (3G/4G) for data communication for longer time and multiple data collection. Data connectivity is one of the main drawbacks of deployed WS systems where patients are 'constrained' within fixed spaces fitted with monitoring devices with small Bluetooth range (Davis et al., 2017; Iqbal, Aydin, Brunckhorst, Dasgupta, & Ahmed, 2016; Kumari, Mathew, & Syal, 2017; Kurien, Trott, & Sanders, 2016; Raja, Saravanan, Anitha, Priya, & Subhashini, 2017). A marked change in healthcare delivery is occurring which has been made possible by the technological revolution in WS systems, IoT, and the potential of employing machine learning and artificial intelligence. The treatment of many medical conditions are guaranteed to benefit from the use of wearable technology (Ribeiro, 2016). With the ever growing use of WS and IoT systems, end-user acceptability is becoming an important aspect of the design of such systems. The acceptance of any system in the healthcare domain depends on user-awareness, as well as clinician and patient acceptance.

The use of Bluetooth Low Energy (BLE) and on-demand data collection is helping and supporting the real-world clinical use of WS and IoT applications. Regarding usability and acceptability, an iterative design process including co-design with usability and acceptability evaluation/feedback is required in the future for developing the user-engagement process. Also, considering contextual information of estimated results of fall risk in the designed system could improve the user acceptability and awareness. In addition, limited awareness of older people to adopt WS and IoT systems should be addressed for future developments and improving acceptability. Finally, the level of usability and acceptability could be improved by incorporating the wearable device design issues into the development and deployment process, meeting critical needs and comfort ADL of aging population. Overall, WS and IoT applications are showing some potential for low cost remote monitoring, supporting independent living, reducing falls among older adults, early detection of various long-term conditions and more.

References

Ahmadi, H., Arji, G., Shahmoradi, L., Safdari, R., Nilashi, M., & Alizadeh, M. (2018). The application of internet of things in healthcare: a systematic literature review and classification. *Universal Access in the Information Society*, 1-33.

Araújo, F. H., Santana, A. M., & Neto, P. d. A. S. (2016). Using machine learning to support healthcare professionals in making preauthorisation decisions. *International Journal of Medical Informatics, 94*, 1-7.

Baig, M. M., & Gholamhosseini, H. (2013). Smart health monitoring systems: an overview of design and modeling. *Journal of medical systems*, *37*(2), 9898.

Baig, M. M., Gholamhosseini, H., & Connolly, M. J. (2013). A comprehensive survey of wearable and wireless ECG monitoring systems for older adults. *Medical & Biological Engineering & Computing, 51*(5), 485-495.

Baig, M. M., Gholamhosseini, H., & Connolly, M. J. (2016). Falls risk assessment for hospitalised older adults: a combination of motion data and vital signs. *Aging clinical and experimental research, 28*(6), 1159-1168.

Balamurugan, S., Madhukanth, R., Prabhakaran, V., & Shanker, R. G. K. (2016). Internet of Health: Applying IoT and Big Data to Manage Healthcare Systems. *International Research Journal of Engineering and Technology*, *310*, 732-735.

Banaee, H., Ahmed, M. U., & Loutfi, A. (2013). Data mining for wearable sensors in health monitoring systems: a review of recent trends and challenges. *Sensors, 13*(12), 17472-17500.

Bellagente, P., Crema, C., Depari, A., Ferrari, P., Flammini, A., Lanfranchi, G., . . . Sisinni, E. (2018). Remote and non-invasive monitoring of elderly in a smart city context*IEEE*. Symposium conducted at the meeting of the Sensors Applications Symposium (SAS), 2018 IEEE

Chen, E. T. (2017). The Internet of Things: Opportunities, Issues, and Challenges. In *The Internet of Things in the Modern Business Environment* (pp. 167-187): IGI Global.

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.

Davis, S., Roudsari, A., Raworth, R., Courtney, K. L., & MacKay, L. (2017). Shared decision-making using personal health record technology: a scoping review at the crossroads. *Journal of the American Medical Informatics Association*.

Etemadi, M., Inan, O. T., Heller, J. A., Hersek, S., Klein, L., & Roy, S. (2016). A Wearable Patch to Enable Long-Term Monitoring of Environmental, Activity and Hemodynamics Variables. *IEEE Transactions on Biomedical Circuits and Systems, 10*(2), 280-288. https://doi.org/10.1109/TBCAS.2015.2405480

GholamHosseini, H., Baig, M. M., Meintjes, A., Mirza, F., & Lindén, M. (2017). Smartphone-based blood pressure monitoring for falls risk assessment: techniques and technologies. *Human Monitoring, Smart Health and Assisted Living: Techniques and Technologies, 9*, 203.

Ghosh, A. M., Halder, D., & Hossain, S. A. (2016). Remote health monitoring system through IoT*IEEE*. Symposium conducted at the meeting of the 2016 International Conference on Informatics, Electronics and Vision (ICIEV)

Iqbal, M. H., Aydin, A., Brunckhorst, O., Dasgupta, P., & Ahmed, K. (2016). A review of wearable technology in medicine. *Journal of the Royal Society of Medicine, 109*(10), 372-380.

Kheirkhahan, M., Nair, S., Davoudi, A., Rashidi, P., Wanigatunga, A. A., Corbett, D. B., . . . Ranka, S. (2019). A smartwatch-based framework for real-time and online assessment and mobility monitoring. *Journal of biomedical informatics, 89*, 29-40.

Klaassen, B., van Beijnum, B. J., & Hermens, H. J. (2016). Usability in telemedicine systems—a literature survey. *International journal of medical informatics, 93*, 57-69.

Kovacs, E., Bauer, M., Kim, J., Yun, J., Le Gall, F., & Zhao, M. (2016). Standards-based worldwide semantic interoperability for IoT. *IEEE Communications Magazine, 54*(12), 40-46.

Kumari, P., Mathew, L., & Syal, P. (2017). Increasing trend of wearables and multimodal interface for human activity monitoring: A review. *Biosensors and Bioelectronics, 90*, 298-307.

Kurien, M., Trott, N., & Sanders, D. (2016). Long-term care for patients with coeliac disease in the UK: a review of the literature and future directions. *Journal of Human Nutrition and Dietetics*.

Kyriazakos, S., Mihaylov, M., Anggorojati, B., Mihovska, A., Craciunescu, R., Fratu, O., & Prasad, R. (2016). eWALL: An Intelligent Caring Home Environment Offering Personalized Context-Aware Applications Based on Advanced Sensing. *Wireless Personal Communications, 87*(3), 1093-1111.

Lee, W., Yoon, H., & Park, K. (2016). Smart ECG Monitoring Patch with Built-in R-Peak Detection for Long-Term HRV Analysis. *Annals of Biomedical Engineering*, 1-10.

Maimoon, L., Chuang, J., Zhu, H., Yu, S., Peng, K.-S., Prayakarao, R., . . . Lu, H. (2016). SilverLink: Developing an International Smart and Connected Home Monitoring System for Senior Care*Springer*. Symposium conducted at the meeting of the International Conference on Smart Health

Malwade, S., Abdul, S. S., Uddin, M., Nursetyo, A. A., Fernandez-Luque, L., Zhu, X. K., . . . Li, Y.-C. J. (2018). Mobile and wearable technologies in healthcare for the ageing population. *Computer methods and programs in biomedicine, 161*, 233-237.

Milani, R. V., & Franklin, N. C. (2017). The Role of Technology in Healthy Living Medicine. *Progress in Cardiovascular Diseases*.

Nguyen, H., Mirza, F., Naeem, M. A., & Baig, M. M. (2017). Detecting Falls Using a Wearable Accelerometer Motion Sensor*ACM*. Symposium conducted at the meeting of the Proceedings of the 14th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services

Nguyen, H., Mirza, F., Naeem, M. A., & Baig, M. M. (2018). Falls management framework for supporting an independent lifestyle for older adults: a systematic review. *Aging clinical and experimental research*, 1-12.

Park, E., Park, E., Kim, K. J., Kim, K. J., Kwon, S. J., & Kwon, S. J. (2016). Understanding the emergence of wearable devices as next-generation tools for health communication. *Information Technology & People, 29*(4), 717-732.

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*(17), 6733-6744.

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*(8), 4544-4553.

Price-Haywood, E. G., Harden-Barrios, J., Ulep, R., & Luo, Q. (2017). eHealth Literacy: Patient Engagement in Identifying Strategies to Encourage Use of Patient Portals Among Older Adults. *Population Health Management*.

Raja, K., Saravanan, S., Anitha, R., Priya, S. S., & Subhashini, R. (2017). Design of a low power ECG signal processor for wearable health system-review and implementation issues*IEEE.* Symposium conducted at the meeting of the Intelligent Systems and Control (ISCO), 2017 11th International Conference on

Rajput, D. S., & Gour, R. (2016). An IoT framework for healthcare monitoring systems. *International Journal of Computer Science and Information Security, 14*(5), 451.

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.

Ribeiro, J. (2016). Wearable Technology Spending: A Strategic Approach to Decision-Making. *Wearable Technology and Mobile Innovations for Next-Generation Education*, 37.

Rupp, M. A., Michaelis, J. R., McConnell, D. S., & Smither, J. A. (2016). The Impact of Technological Trust and Self-Determined Motivation on Intentions to use Wearable Fitness Technology*SAGE Publications.* Symposium conducted at the meeting of the Proceedings of the Human Factors and Ergonomics Society Annual Meeting

Sabesan, S., & Sankar, R. (2015). Improving long-term management of epilepsy using a wearable multimodal seizure detection system. *Epilepsy & Behavior, 46*, 56-57.

Simblett, S., Greer, B., Matcham, F., Curtis, H., Polhemus, A., Ferrão, J., . . . Wykes, T. (2018). Barriers to and facilitators of engagement with remote measurement technology for managing health: systematic review and content analysis of findings. *Journal of medical Internet research, 20*(7).

Spanakis, E. G., Psaraki, M., & Sakkalis, V. (2018). Congestive Heart Failure Risk Assessment Monitoring through Internet of things and mobile Personal Health Systems*IEEE.* Symposium conducted at the meeting of the 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)

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

Tinetti, M. E., & Kumar, C. (2010). The patient who falls. *JAMA: the journal of the American Medical Association, 303*(3), 258-266.

Ullah, F., Habib, M. A., Farhan, M., Khalid, S., Durrani, M. Y., & Jabbar, S. (2017). Semantic interoperability for big-data in heterogeneous IoT infrastructure for healthcare. *Sustainable Cities and Society, 34*, 90-96.

Wu, A. Y., & Munteanu, C. (2018). Understanding Older Users' Acceptance of Wearable Interfaces for Sensor-based Fall Risk Assessment*ACM.* Symposium conducted at the meeting of the Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems

Wu, J., Li, H., Cheng, S., & Lin, Z. (2016a). The promising future of healthcare services: When big data analytics meets wearable technology. *Information & Management*, *53*(8), 1020-1033.

Wu, J., Li, H., Cheng, S., & Lin, Z. (2016b). The Promising Future of Healthcare Services: When Big Data Analytics Meets Wearable Technology. *Information & Management*.

Wu, W., Zhang, H., Pirbhulal, S., Mukhopadhyay, S. C., & Zhang, Y. T. (2015). Assessment of Biofeedback Training for Emotion Management Through Wearable Textile Physiological Monitoring System. *IEEE Sensors Journal, 15*(12), 7087-7095. https://doi.org/10.1109/JSEN.2015.2470638

Yacchirema, D., de Puga, J. S., Palau, C., & Esteve, M. (2019). Fall detection system for elderly people using IoT and ensemble machine learning algorithm. *Personal and Ubiquitous Computing*, 1-17.

Yuan, J., Tan, K. K., Lee, T. H., & Koh, G. C. H. (2015). Power-efficient interrupt-driven algorithms for fall detection and classification of activities of daily living. *IEEE Sensors Journal*, *15*(3), 1377-1387.

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.