Appraisal of Artificial Intelligence for fall prevention & fall risk assessment

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Abstract

The current article highlights the specific challenges and issues of the healthcare system in Europe. In addition, the particular factors towards the digitalization of the domain are highlighted, and the emerging technologies contribute to this process because many things are becoming more feasible. Thus, information and communication technologies (ICTs), such as new sensors, machine learning, big data, and analytics, provide new opportunities and challenges in their implementation and use. Therefore, it has become crucial to understand the different kinds of ICTs, such as artificial intelligence (A.I) techniques, especially machine learning algorithms and their use in the domain of interest. Thus, the paper aims to understand the mentioned technologies and their implementation in the area of interest to comprehend their current status, their suitability, and what needs to be considered for their successful development and implementation. While at the same time taking into account several key aspects that need to be well-thought-out in the domain. Consequently, the author performs a conceptual literature review of relevant scientific articles where sensors, machine learning, data mining, statistical learning, etc., have been tested and utilized in the eHealth area, especially for fall prevention and fall risk assessment. Finally, the literature findings are discussed, and the factors to consider when applying machine learning for fall prevention and fall risk assessment are underscored.

Keywords 1

Fall prevention, fall risk assessment, artificial intelligence, A.I, Machine learning, sensors, eHealth.

1. Introduction

Lately, there has been an increase in the use of both artificial intelligence (A.I.) and machine learning in both academia and industry, where machine learning is essentially an application of A.I. It is used where it can be applied to learn by comparison and correlation of numerous similar patterns from various data sources with the aim to develop models with the objective to understand and foresee different features of interest [1]. Consequently, there has been an increase in, for instance, assisted living technologies owing to a growing ageing society, among others [2]. Thus, in this case, the change in demography, which results in an increased cost and workload of health care, as well as the significance of people, puts on independently living, results in an increased motivation in technologies that support independent living in healthcare, such as innovative-assisted living technologies, etc. In addition, as people become older, their probability of fall risk increases, among other factors. Therefore, fall occurrences lead to substantial public health issues among older adults. The alternatives that are suggested to minimize falls are, for instance, physical training, stability training, and adapting the context, i.e., specific home environments, to diminish the probability of falling, etc. The authors also mention that the number of falls can be reduced by, for instance, medication and the intake of nutritional complements like Vitamin D [3].In addition, there are several

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treatments, medications, and customs of living, i.e. lifestyle changes that might affect the chances of falling.

Furthermore, computerization has been applied in several areas where it either supports processes and activities or automates them. This is currently named digitalization in academia and industry. It has even reached the health sector with a vast speed with the objective to provide alternative solutions to issues part of the domain. Supporting factors to these trends are emerging technologies, such as sensor technology, the Internet of Things (IoT), cloud computing, and big data and analytics, which have contributed to this process since many things are more feasible than before.

Keeping a level of activity is crucial for everyone; However, the older the person becomes, the more important it is to continue with various activities, such as taking walks, which health professionals highly recommend. However, for this to result in something positive, one should avoid people being harmed, especially the elderly, due to the consequences of an injury. Therefore, fall prevention and fall risk assessment are crucial so that the activities do not end with people being injured.

The technology-based application efforts for fall prevention have been increasing, and its development objectives have served to support the delivery of more effective and capable fall prevention interventions [4]. The authors mention that the different kinds of fall prevention interventions are education, home assessment/assistive equipment, fall risk assessment, exercise, and technology-based interventions. Improvement in the ability to use intelligent ICTs, such as sensors, machine learning, artificial intelligence, etc., to track falls and even prevent them provides huge benefits for the elderly and society. Furthermore, the possibilities with the emergent technologies provide academia and industry with an opportunity to develop more handy and practical devices to diminish injuries from falls, as mentioned in [5]. Therefore, it is crucial to understand the potential impact it would have on the possibilities to perform analytics and, in this case, develop software modules for fall and risk prevention. Continuously, big data analytics, artificial intelligence and machine learning technologies have the potential to transform the health sector. However, for it to become a successful application, there is a need to understand how to harness and use its capabilities, which can provide persuasive benefits. Besides, to motivate the users to use the sensors, in this case, the elderly is an issue since they should understand the benefits as well as be motivated/willing to use them. The acceptance of the technology might be for different reasons; however, motivation also seems to be a crucial factor in this case.

Thus, the increased development and implementation efforts of machine learning have brought the focus of the A.I. approach into the light. Therefore, the increased interest in A.I. and its applications in several domains, including the health area, needs to be evaluated before its implementation in real-world scenarios, i.e. their proposed solutions need to be assessed. So, there is a need to understand how they should judge and assess, i.e., how the machine learning applications should be evaluated. The matter that arises is how these A.I. should be considered so the probability of them bringing harm into its context is diminished or removed in the best-case scenario. In this case, harm is considered people being injured because of bias in the A.I. process, i.e. data gathering, processing, and recommendations provided by the A.I.

There are several advances in such areas as computer science, among others. However, we have a lot to learn about how humans judge or evaluate machines and A.I. in this case and how our insights mark how we handle, receive, and accept them [6]. Accordingly, some researchers highlight that people tend to see the actions of machines and A.I. as more damaging and immoral in situations that involve physical harm. On the contrary, it was found that people have a tendency to judge humans more strictly in cases involving an absence of fair-mindedness [6]. Thereupon, they express that "people judge machine actions primarily by their perceived harm." Thus, machines or A.I. solutions, in this case, the more harmful their results might be in, for instance, involving physical harm, the more harshly they are judged.

In other words, people judge humans by their intentions and machines by their outcomes, e.g. their results and consequences. The results of the study about how humans judge machines are based on a study that involved approximately 5900 people who were randomly assigned to some treatment by a machine (A.I. solution) or a human. The authors use a methodology that comprehensively considers several aspects of an A.I. solution. In general, it is evaluated/assessed by the harm they might cause to people by their use. After that, the algorithms bias is considered. Other factors also involved in the judgement of the A.I. solution are the privacy aspects and the labour displacement. However, the factors necessary for aspects of the current paper are the harm they might cause and algorithm bias, among other relevant aspects. It is, however, possible to bring interesting aspects based on fundamental concepts from moral psychology and philosophy [6]. These concepts are harm, fairness, authority, loyalty, and purity, which are essential to consider when developing A.I. solutions for the health and other sectors, i.e. whenever A.I. is considered part of a solution. Other work highlights the variety of A.I. and its potential harmfulness and argues that putting human values at the core of A.I. requires answering many questions and is still open for further research [7]. Certain organizations emphasize the importance of the development, administration, and usage of not dangerous and effective health technology. The Association for the Advancement of Medical Instrumentation (AAMI) and BSI Initiative on Artificial Intelligence (A.I.) in medical technology are making efforts that aim to understand the different alternatives that A.I. and, especially, machine learning brings, namely, its distinctive challenges to the existing standards and principles governing health devices and associated technologies [8]. They promote the use of a framework that pinpoints the importance of assurance of A.I. solutions, i.e., it should evaluate patients' risk, assurance of safety, effectiveness, and performance of the A.I. solution. Its main aspects are that the A.I. solution should have a valid clinical association that solves a real issue in the domain, a valid analytical model, and a clinical validation that its existence is meaningful. The A.I. and machine learning solutions are continuously evaluated by solely algorithmic bias; however, that does not bring justice into the picture since other essential aspects are neglected, as mentioned above. However, evaluating the algorithms is critical but does not highlight the whole picture.

The following example emphasizes the steps on how the algorithmic bias can be evaluated. For instance, it is possible to use three factors to understand the utility of an A.I. tool for the diagnostic or predictive analysis of medical images, i.e. radiology [9]. Thus, first of all, the statistical methods are applied to evaluate the assessment judgment and calibration performances of the model results, e.g. a diagnostic or predictive model, which is summarized. Consequently, the importance of using a well-presented dataset is emphasized, i.e. to avoid issues with overfitting or overestimating a classification model. This is crucial to be able to achieve a robust solution. Lastly, it's important to test the solution in a real environment to be able to verify its impact. It means its verification of the A.I. tool for diagnostic or predictive analytics through the users' outcomes, i.e. beyond performance metrics.

In conclusion, it is essential to have a model and/or framework that proves the positive adoption of the specific A.I. solutions and tools since it requires a careful confirmation of its utility that is not harmful to the people using it in the particular domain. The combination to judge and assess an A.I. solution in combination with the algorithm bias is crucial to develop a robust system that would neither harm the user nor provide incorrect information. The current paper uses the case of fall prevention and fall risk assessment to assess its suitability and value, among other aspects they bring into the context.

A fall is defined as an accidental event where a person falls when the center of gravity is lost, and the attempts to return to balance fail or no attempts are made for any reason to get into a stable position [10, 11]. The cause for a fall could be several. Though, for elderly adults, this is a typical case since falls are one of the most significant causes of injuries which usually lead to death because of the damage they have received from the fall. Thus, elderly people are exposed to the risk of falling for several reasons independently of their geographical living. Fall prevention supported by ICTs (especially the sensors, machine-learning algorithms, data mining, etc.), in this case in real-time, tries to prevent a fall before it happens by the elderly carrying sensors that collect data when performing their daily activities and signalling with the support of A.I., e.g. machine learning algorithms' when a fall might occur, more details about this approach are presented in section 4.1 and discussed in section 5. On the other hand, the fall risk prevention/assessment evaluates the probability of a fall occurring, not in real-time, but in controlled environments. In this case, the elderly people are assessed with the support of ICTs about their likelihood of falling. This provides the medical doctors with decision information so they can provide recommended instructions and, in some cases, medication. More details about this case are highlighted in section 4.2 and discussed in section 5. Thus, the current paper first performs a conceptual review in the area of fall prevention and fall risk assessment, mainly where it has been applied and hightails important current aspects of the technologies and their implementation. The paper focuses on fall prevention and fall risk assessment; however, fall detection is a closely related area where a vast amount of research has been conducted. Fall prevention goes a step further with the objective of avoiding any falls [12]. However, it is crucial to understand its similarities and differences, i.e. the technology and how they are used. Fall detection provides an understanding of fall prevention and its further developments. However, the objective is not to present a comprehensive literature review but to provide an understanding of underlying assumptions, concepts, and technologies, which goes in hand with accepted conceptual literature review approaches, as mentioned in [13]. This is in more detail explained in section 2, i.e. the Methods section. Thus, the current article carries out a conceptual literature review of relevant scientific articles where sensors, machine learning, data mining, statistical learning, etc., have been developed and tested in the eHealth area, especially for fall prevention and fall risk assessment. In addition, the article also discusses the findings concerning other features, namely: how humans judge A.I., i.e., to highlight and understand different ethical aspects than just the technologically related in the domain of interest, i.e., the specific requirements of A.I. for the health sector and what needs to be accomplished for its acceptance in the health domain. Thus, the paper is structured in the following way. First, the methods are presented. Thereafter, the related work is emphasized. The findings of the literature review are next presented. The findings are presented in two sections, i.e., fall prevention and fall risk assessment. Finally, there are discussion and conclusions sections.

2. Methods

The author has tried to draw aspects of interest from different literature findings for the current research, i.e., related areas of fall prevention, its use, and value for stakeholders. The search for relevant literature was done with the relevant keywords in different combinations. The study was done to understand the essential aspects that need to be considered and understood to implement those technologies in the domain of interest successfully. The literature search was done in different databases, such as the University search database engine, which includes such databases as ACM digital library, Google Scholar, IEEE Xplore, and Inspec, where the most relevant papers for the study were selected. The theoretical objective of the review was to get an understanding of underlying assumptions, concepts as well as technologies which fulfil the aim of the current work. Hence, it is essential to highlight that the goal was not to cover all the work done in the area as one of the approaches for a review [13]. Thus, in this specific case, the objective of the current work is to understand fall prevention and the ICTs, especially the sensors, machine-learning algorithms, data mining, etc., as well as their use and implementation aspects. Thus, the keywords used in the literature search are fall prevention, fall risk prevention, elderly people, e-healthcare, sensors, wearable sensors, accelerometer, machine learning, statistical learning, artificial intelligence, ambient assisted living (AAL) in different combinations in the above-mentioned databases between the years 2015-2020. The search procedure gave a total of 186 published articles. They were selected with the following criteria: fall prevention, use of sensors, i.e., especially accelerometers, machine learning, statistical learning for elderly people, and the domain of eHealth care with a focus on areas like ambient assisted living (AAL). Irrelevant papers outside the current paper's focus were excluded after the title and abstract screening. The remaining 31 articles were full-text read. A total of 16 articles were excluded for the following reasons: some of the findings were too general, emphasized more other technologies than those in the focus of the current study, and highlighted more the strategical approaches and technology acceptance. In addition, several of the papers were about fall detection and not prevention. The remaining articles were part of the current paper. Therefore, there were 15 relevant papers selected for the analysis of the conceptual literature review. Among the selected articles in the current literature review were also survey and review articles in the area of interest to gain a deeper understanding of what has been done in the area and the issues involved, i.e., to be able to conclude the findings. An essential aspect of the literature findings showed two directions for using the mentioned ICTs, i.e., one was the real-time monitoring of elderly people for fall prevention. At the same time, the other was the assessment of a risk of falling, e.g., fall risk prevention/assessment, i.e., to assess the elderly people probability of falling based on ML, accelerometers, etc.)

3. Related work

E-healthcare encompasses the usage of ICTs in various activities related to the health sector. Thus, activities connected with the use of digital applications impact both the patient and the professional to diagnose, prevent and treat diseases. Further, research into ambient assisted living (AAL) attempts to facilitate the daily activities of the elderly as well as people with disabilities or chronic medical conditions [14, 2].

The AAL systems normally involve several sensors and embedded applications which generate a huge amount of data. Literature reviews that reveal the aspects of ambient assisted living can be found in [15, 16, 17]. Thus, in the AAL application, we can find heart rate, blood pressure, position detection, and fall detection, and lately, there have been efforts made regarding fall risk and fall prevention solutions. Hence, the AAL applications are sustained by various algorithms and computational approaches, such as activity recognition and anomaly detection, which are nowadays even called machine learning algorithms [2]. Consequently, fall prevention is an essential strategy to tackle and to be able to handle the issue of falls among the elderly. These issues have been studied for over a decade with the help of different approaches, as mentioned above, where fall detection is paid particular attention [18]. Thus, the various alternatives proposed to diminish falls are physical training, stability training, and adaption to the elderly, in this case, contextual environment, i.e. their home environment to reduce the probability of falling, etc. Currently, with the emergence of new intelligent I.S. technologies, the interest in the computerized approach has significantly increased, i.e. with the entrance of new sensor technology, Internet of things (IoT), the big data approach, better computer performance for data processing, more significant amount of data that are transferred continuously in different forms, i.e. big data usually presented as part of the three V's, namely volume, velocity and variety of data, which later are processed for purposes of analytics. Accordingly, IoT, big data and analytics, A.I., and machine learning have resulted in expectations and promises in the health sector, as in this case, for fall prevention. Thus, the literature findings on fall prevention are presented next, which aims to conceptualize the results/discoveries.

4. Machine learning in fall prevention & fall risk assessment

The current section is divided into fall prevention and fall risk assessment. The findings characterize that fall prevention uses technologies such as accelerometers, gyroscopes, and machine learning for fall prevention purposes in real-time monitoring. While in the findings for fall risk assessment/prevention, the same technologies are used in different combinations, except for the gyroscope, to assess if there exist any risk (factors) for falls.

4.1. Fall prevention

Fall risk prediction and prevention go one step further than the detection of a fall. They try to predict and prevent a fall before it happens, which makes things more complicated. There have been various efforts to try to prevent falls in people, such as surveys, checklists, subjective movement-based assessments, namely the time the person wakes up and starts walking called "Timed Up & Go" as well as measurable assessments of their movements, which are based on data from wearable-sensor [19, 20]. The area of wearable-sensor for fall risk offers a wide variation regarding such sensors as accelerometers, gyroscopes, magnetometers, force sensors, pressure-sensing insoles, etc. In addition, feature extraction and various models in diverse research efforts have been investigated with the outcome of various models with different results in their predictive accuracy, i.e., 60% to 100% (62–100%) [19, 20].

Another work investigated prospective elderly fall prediction based on a twenty-five-foot walk test [21]. Fall risk modelling was done with feature selection, which was later compared with the retrospective fall results, i.e., the classification outcomes [21]. The aim was to conclude how prospective and retrospective methods for purposes of fall prediction diverge after suitable feature selection approaches are applied. The results showed that feature selection enhanced the predictive models' performance with a twenty-five-foot walk test. It was shown that the accuracy increased by 9% higher than the models without feature selection through the use of the feature selection method. Consequently, in this case, the Relief-F, feature selections are essential to apply for prospective and retrospective fall classification. The classifiers Naïve Bayesian, multi-layer perceptron neural network and support vector machine (SVM) classifiers were applied for fall prediction. Further, the retrospective fall data approach is more common than the prospective one for the evaluation of predictive precision. The drawbacks of the first-mentioned approach might be inaccurate fall recall because of gait pattern variations. Therefore, the authors supported and recommended that fall prediction should be performed by the prospective method [21]. The feature-space- size reduction should as well be utilized when a massive amount of data is gathered to evade high computational costs since redundant and unsuitable features can be removed as part of the analytics process.

A further, systematic review of the area of interest highlights essential aspects of fall prevention and detection based on four themes: low-power fall detector fall-related systems, fall detection/prevention, and sensor placements for fall-related approaches [22]. Regarding fall-related systems, the authors highlight fall detection/prevention characteristics based on diverse technologies, for instance, accelerometer-based, smartphone-based, vision-based, and multisensory fusion-based methods. It includes as well as categorization factors, such as data availability perspective, low-power implementation technologies, etc. The authors mention that the sensor technologies used by both fall detection and prevention are somewhat similar; however, what is essential to consider is the placement and the number of wearable sensors. The placement of the sensors is vital since they provide a difference in precision. Thus, for fall detection, the placing on the hips gave the best results to detect a fall conversely for fall prevention; the ones placed on the waist and the thigh gave the best results for fall prevention. Thereafter, when it comes to the process, i.e. the process conducted before analytics takes place is that the data needs first to be collected and pre-processed. After that, feature extraction and analysis is done. Subsequently, the classification algorithms are implemented, and evaluation occurs. When it comes to the sensors, they collect data, which directly or indirectly reveals the body motions. Then, a crucial part might be done, i.e. with different methods, namely the pre-processing. These approaches are made with, for instance, the Kalman filters, mean filters as well as integration methods to eliminate noise and external influences on the signal. -It is crucial in fall-related systems to identify and extract distinctive features from the raw data to understand if a fall or a non-fall situation is or will occur. The former mentioned plays a vital role in the analytics algorithm that is applied later for fall detection and/or prevention. Relevant features are, for instance, magnitude and acceleration, as well as angular velocity. After the feature, extraction and analysis are done, the classification algorithms are applied, i.e. trained with the extracted features to identify or prevent a fall.

Howcroft et al. [23] applied feature-selection methods for fall risk prediction of elderly people. They used feature extraction was diminished with the use of Relief-, a correlation-based feature selection and fast correlation-based filter algorithms. The approaches implemented in fall detection and prevention can be divided into three methods depending on the algorithms used, i.e. threshold, non-threshold, and fusion-based analytical algorithms. The threshold is the most popular for detection and prevention; however, the threshold level affects the application's performance. Further, its level can be fixed or adaptive. Sivaranjani et al. [24] predicted falls based on sensor data from the gyroscope and triaxial accelerometers. Analysis and association were performed regarding a fixed threshold, i.e. from the gathered sensor signals of acceleration and angular velocity. The issue with a fixed threshold is that it should be different for different people based on their characteristics, i.e. age, sex, body location, and its composure.

Consequently, it makes it tricky since it might not perform well for all, i.e., the elderly people in this case [25]. Thus, it makes it unreliable and may cause a high probability of, for instance, false alarms. However, the adaptive threshold performs better since it is based on the persons' historical data [26]. The adaptive threshold is relevant for both fall detection and prevention. Ren and Peng [22] highlight the suitability of the adaptive threshold-based fall detection and prevention approaches and that their use will increase in real applications. Non-threshold fall detection and prevention applies cutting-edge machine learning algorithms to differentiate or forecast a fall based on the activities of daily living (ADL). Also, advanced statistics approaches have been used for both fall detection and prevention. In addition, the fusion-based fall detection and prevention approaches are divided into homogenous and heterogeneous methods. The approach that provides the best performance, i.e., the threshold, non-threshold, is the fusion approach, followed by the non-threshold one.

Hemmatpour et al. [27, 28] successfully tested different algorithms for fall prevention. The emphasis of their study is mainly technical and focuses on machine learning algorithms. In addition, Hemmatpour et al. [29] conducted a literature review within the area of fall prediction and prevention based on embedded sensors in a smartphone, i.e., accelerometer and gyroscope. The gathered data characteristics are Kinematic features, i.e., from the accelerometer and gyroscope. The data is evaluated through machine learning algorithms. In an experimental analysis, the authors assessed the different approaches, e.g., accuracy and their capability to predict and prevent a fall. The best results were obtained with tilt features when they were combined with decision trees. They give a wide-ranging outline of several fall issues and connected features. The authors' main focus was the study of machine learning algorithms and their suitability for fall prediction and prevention.

4.2. Fall risk assessment

Immonen [30] highlights a population-based survey by the collection of data from older people aged 65-98, and a total of 918 were studied via their participation in filling out a questionnaire. The included parts of the questionnaire highlighted aspects, such as health status, lifestyle, and falls. The study's purpose was to understand if specific characteristics of chronic illnesses are related to an increased risk of falling. In addition to comprehend how intelligent I.S. technologies, data, and the particular case on the use of accelerometers can be implemented to measure the real risk factors for older adults falls. In the phase where intelligent I.S. technologies were tested, 42 of the participants were part of the study by their own choice (voluntary) in a fall risk measurement where accelerometers were worn to the lumbar spine and front hip of the elderly. In conclusion, the result showed that chronic illnesses as well as multiple diseases have an association with a higher risk of falls. As the research community shows, several technologies are being used to assess the risk of a fall. In the current study, the author mentions that a mobile application with a separate sensor is able to detect if a higher risk of falling exists. A sensor attached at the front of the hip provides information to judge if a fall risk is present, i.e., with the support of gait features connected with fall risk. It could; therefore, we concluded that accelerometer technologies provide acceptable results for fall risk assessment.

Sun & Sosnoff [31] performed a systematic review connected with sensor technology in fall risk evaluation in older adults. The authors highlight that recent sensor technologies provide objective, economical, and easy-to-implement fall risk assessment, as not existent before the latest digital developments. The different modelling technologies, i.e. machine-learning algorithms, used to predict fall risk in the different findings were, for instance, logistic regression, linear regression, different classifiers, cluster, and discriminant analysis techniques. It was found that the most frequently used was the logistic regression modelling technique. The authors report the effectiveness of the modelling techniques, such as their accuracy, sensitivity, specificity, and area under the curve for the ROC curve. The classification techniques were found to achieve an accuracy of 80%; however, the authors highlight that a comparison cannot be made owing to the different tasks, parameters, and end-users of the population. Nevertheless, the authors emphasize the importance of future work to understand the clinical significance of evaluating fall risk diagnosis using sensor technologies. Furthermore, it is highlighted that there is a need for functional assessment and user experience of the technology to understand its acceptance and its expected impact.

Rescio, et al. [32] mention that several wearable sensor types have been tested for automatic fall and pre-fall detection purposes. However, the authors emphasize that they have been tested in controlled conditions. These test results always show high prediction accuracy for unbalance detection, i.e., equal to 100% of specificity and sensitivity. There is also a need to increase the time of an "alarm" that a fall is occurring, even if, at the moment, it is enough time to activate an impact reduction system to diminish the risk of an injury. However, the authors highlight that the alarm time needs to be improved so that the system's efficiency and reliability are augmented. Continuously, the authors propose a cost-efficient expert system able to detect a fall in real-time, i.e., an automatic fall risk detection system. The system is based on muscle behaviour analysis, which permits a fast evaluation and appreciation of an imbalance event. The assessment of an imbalance is made through the monitoring of the lower limb muscles. The system is based on machine learning algorithms and schema, which by so avoids the well-known drawbacks of the threshold methods that have been extensively used in pre-fall detection systems. Thus, they implicate a wearable surface EMG-based unbalanced detection system supported by a machine learning approach. The system is able to detect a fall during its initial phases, which leads to increased margins for decision-making time. It results in the proper decision of when to activate the protection systems. Hence, the system indicates high performance in sensitivity and specificity of 90% (in the controlled tests) with an average lead time in advance of an impact of 775 ms.

Horta et al. [33] use biofeedback to monitor fall detection, which is a way to augment the information of bio-signals, i.e. when a fall is occurring as well as before and after. The authors also mention that the approach has a specific potential to provide a more detailed diagnosis to be able to identify the cases when a fall occurs and, by so, increase patient safety. Thus, the authors mention that more detailed data can be accessed from body sensors attached to the body, like an electrocardiogram, electromyography, blood volume pressure, electrodermal activity, or galvanic skin response, with the purpose of patient monitoring. This is done to avoid the use of accelerometer data for the purpose of fall detection. The development of a prototype has validated the suggested system.

Castaldo et al. [34], the authors of this paper, use a different approach for fall prediction purposes. Their approach is not based on accelerometers and gyroscopes, a common method for fall prevention. They instead use an approach that considers the short-term Heart Rate Variability analysis, which is attained at the baseline. It is used to identify first-time fallers that are, according to the authors, challenging to distinguish. In the test, 170 hypertensive patients comprising 56 females and 114 males between the ages of 64 and 80 were studied. Three months after the baseline statement, 34 of them fell once. The data was gathered when they had their regular visits, which involved Electrocardiogram, which was recorded. Each patient had eleven extracts of data of five minutes, respectively, gathered for the analysis. The analysis involved linear and nonlinear Heart Rate Variability feature extraction and later averaged amid the eleven data results. Next, the results were used for further analysis with different methods, and the one that provided the best results was Multinomial Naıve Bayes. It was able to predict first-time fallers by a sensitivity of 72% and specificity of 61%, and accuracy of 68%. The authors mention that the used approach is convenient since patients usually need to perform an Electrocardiogram and can, by so, detect early fallers who need to be part of a fall prevention program.

5. Discussion

The literature review provides us with an apprehension of the issues that we are currently facing with the available technologies, such as the aspects of the sensors and their battery life. It also gives us a comprehension of the machine learning algorithms and their possibilities to understand the data and provides us with information and knowledge of the situation so that we can avoid and evaluate, for instance, fall risk and by so prevent it. In addition, it is also discussed how the A.I. solutions should be assessed, i.e., based on the concepts of how humans judge machines, i.e., A.I., machine learning solutions in connection with aspects of fall and risk prevention.

5.1. Fall prevention

The current section discusses fall prevention findings when sensors, accelerometers, machine learning, etc., are utilized for real-time monitoring. The findings show that the placement of sensors is essential to consider when applying both fall detection as well as prevention when monitoring is the main objective [22]. It makes a considerable difference in the sensors' placement, depending on fall detection or prevention. Thus, for fall prevention, the optimal placement is being attached to the waist and thigh. It was concluded from a test of several classification algorithms.

However, a drawback of the sensor technologies is the high battery power consumption, especially when they are frequently gathering data and when analytics is performed at the sensors level. Besides, it also depends on the sensors' quality, which will surely improve as we get new sensor technologies. Therefore, it is essential to keep updated on the sensors that enter the market to be able to choose the most optimal ones. In addition, it has been highlighted that previous research enables one to understand that wearing small sensors, such as accelerometer devices, is well accepted by the elderly even when they are worn for several weeks [35].

When it comes to fall prevention, the technological factors that might impede their successful use are the lack of real data since a fall happens seldom. It has been shown that the existing data are simulated data leading to perfect results in the datasets, i.e., training and testing. The reason is that the algorithms perform very well in a simulated environment, but they fail to deliver as expected when moving into a real-world scenario. It means that later when the machine learning algorithms are applied to real data, they might, for instance, create either false alarms or even don't send any kind of alarm signal at all, i.e., for the case of fall prevention. Another issue with the wearable sensors, for fall prevention is the implemented threshold, which might vary depending on the person wearing these sensors, i.e., the elderly person's health condition, degree of activity, etc. All this leads to difficulties in setting an exact threshold for the person in question.

In addition, the person's health can change, and then the issue that emerges is how this threshold should be changed, etc. All of the former mentioned brings questions about the technology suitability for fall prevention and real-time monitoring of the elderly. Therefore, real data must be gathered over a long period to learn from different studies and understand how to use the sensors and machine learning approaches for real-time monitoring. Moreover, special attention should be paid to such real data aspects as missing or incomplete data, which is of the utmost importance to keep in mind in the case of fall prevention so that a proper strategy is applied which does not affect its main objective, i.e., to avoid elderly people to fall and provide them with the appropriate recommendations for their daily activities. Furthermore, it was shown that mostly supervised machine learning algorithms are used for fall prevention and not unsupervised since the classification algorithms try to give the prognosis of a future event. In contrast, the unsupervised algorithms are more suitable for understanding the reason/s a fall occurs.

5.2. Fall risk assessment

In this section are the findings related to fall risk assessment/prevention discussed where similar technologies are used in different combinations, i.e. sensors and/or machine learning, etc., to evaluate possible risk of falling. Some findings use sensors, accelerometers, and machine learning to evaluate a person's risk of falling. Thus, the study also showed different approaches where the accelerometers were not continuously used to monitor a person and prevent a fall. Instead, the accelerometers were used to understand the balance of the elderly person [30]. It could then assess if the person were at risk of falling. The result was successful, and the approach used can be used in real scenarios. It shows reliable results compared to situations when the accelerometer is used to monitor in real-time to avoid a fall, as mentioned above, which works well with simulated data, but is less efficient in real scenarios. In addition, Rescio et al. [32], present other findings that used the sensor to monitor limb muscles based on machine learning and schema. By so, avoid the use of threshold values used extensively in fall prevention, which has its obvious drawbacks. The suggested approach makes it possible to detect a fall during its primary stages resulting in good margins to activate protection systems. The study gives as well good results in controlled environments; however, it's the same as mentioned in former projects that the risk of this kind of system with simulated data performs well in the test but is less reliable in real scenarios. Horta et al. [33] avoid the use of an accelerometer. Instead, it uses body sensors attached to the body that provide alternatives like electrocardiogram, electromyography, blood volume pressure, electrodermal activity, or galvanic skin response to monitor a patient. The study has validated results from a prototype. Another research results were accelerometers and gyroscopes were not used, as usual, are instead used to sense short-term Heart

Rate Variability analysis [34]. This approach provides a high probability of evaluating and identifying early fallers using machine learning algorithms based on the heart Rate Variability analysis data. To sum up, the above findings vary in the sense that they either don't use an accelerometer and gyroscope, but use it in a different form, i.e. senses heart variability and imbalance, which are done by evaluating the person's state, namely, they don't need real-time monitoring but are more reliable since they avoid the issues with simulated data and the threshold approach which might bring complications when trying to set the suitable threshold in patients.

5.3. Assessment of the A.I. approach

There is a high amount of research in academia and industry regarding related technologies. For instance, several products are available in the industry, such as smartwatches that track activities, i.e. steps counting, which depends on the watch on many occasions and the steps taken differ. However, in real-time fall prevention, there are nonexistent products that can match the requirements needed to function as a preventive tool to avoid a fall.

Thus, a lot of investment is taking place in related technologies, such as IoT, big data, and analytics, especially artificial intelligence, and machine learning. Still, there is less knowledge concerning how much the investment has contributed to increased effectiveness and efficiency in its various processes and activities, i.e., its value creation. It is also a fact that only a small proportion of organizations can apprehend their full potential [36]. Thus, Ross [37] highlights those aspects in her article "the fundamental flaw in A.I. implementation." Nevertheless, what is expected for the technologies part of the study to be able to implement them successfully in real-time monitoring for fall prevention applications is that first real data needs to be used to evaluate them. It is vital to comprehend that data is essential in this case and for any machine learning algorithm that learns from their respective data and/or datasets.

Thus, the technology should be tested, including sensors, accelerometers, gyroscope, connectivity to the platform (Bluetooth or other), machine learning algorithms, etc., so their suitability and potential can be tested and verified before real-time monitoring in real scenarios can be suggested as an option for fall prevention, i.e., to avoid the risk of physical harm of the user when the technology is not working in an optimal manner. Other essential aspects that can only be concluded from real scenarios are its validity, thus, the user acceptance of these technologies, which is vital for its successful implementation.

Nevertheless, when it comes to the case of fall prevention, the data used are simulated, bringing issues of generalization. Thus, it results in so-called algorithm bias because the algorithm provides recommendations based on simulated data. It is a complex task to get representative data because a fall rarely occurs. Due to this, models are developed during the experimental phases, which in the end, will not work optimally. Hence, in real-time monitoring, it has been shown that a fall seldom occurs and that the models are based on simulated data.

Consequently, the models are expected to not perform well in a real-case scenario since it learns from data that is not representative. The users do not benefit from a model that does not provide them with a good prognostic, in this case, a fall. In addition, as mentioned earlier, we have issues with the proper threshold, as it is challenging to choose an exact threshold level. The algorithm bias might bring other aspects, such as the acceptance and ethical aspects of their use for fall prevention, since their wrong warning/signal of a fall can harm the user if a fall is not detected in time or too late at all. This is especially the case of real-time monitoring because there are so many factors involved in such a solution that could go wrong, i.e., sensors, loss of connectivity (Bluetooth technology), proper threshold and algorithm bias, etc.

Thus, if an A.I. solution for fall prevention and fall risk assessment/prevention purposes is evaluated based on how humans judge machines, it can be said that the alternative that involves a higher probability of harm to the user would be for sure perceived as not acceptable. Consequently, it was shown that in situations including physical harm machines and A.I., in this case, they are judged more harshly [6]. Given that, the A.I. algorithms are judged based on a methodology that highlights aspects of how people judge machines, in this case, applied with machine learning for fall and risk prevention purposes. In the work of Hidalgo et al. [6], it has been found that at high levels of harm, especially when perceived as intentional, human actions were judged additionally strictly. It was then concluded that, typically, individuals judge humans in connection with their intentions and A.I. by their outcomes. They mention that the result is an oversimplification; however, it is supported by several observations in their study. Though in the case of fall prevention and fall risk assessment/prevention, an A.I. solution is developed to solve a situation of a fall to provide the users with additional risk and responsibility is not a suitable option, i.e. where a wrong fall prevention signal is given or not given at all, or it occurs too late, etc., which would then entails the ethical aspects of such a solution.

The other approach that uses a machine-learning algorithm, i.e. fall risk assessment, to evaluate the elderly is by measuring the balance and by so consider possible risk/s of falling. In this case, the accelerometers or other approaches were not used constantly to monitor the user. For instance, accelerometers were used to comprehend the balance of the elderly person. In conclusion, the scenario gathers real data, i.e. data created by the users and then the same data is used to analyze if the person's balance is normal. It means that simulated data does not create the models; on the contrary, real data is used to evaluate the person's balance, in this case, to evaluate/assess a fall risk. A medical doctor does the evaluation in conjunction with an A.I. solution that supports him/her in assessing the specific patient. It means that the A.I. solution is used as decision support and that a human is also involved in diagnosing the risk of a fall. In this case, no harm is done; the algorithm could contribute since the accelerometers are used in a controlled environment. In addition, there is no algorithm bias since the model is developed with actual/real data.

We see two directions, namely a real-time approach and a consultative (advice-giving) approach for the matters of fall and risk prevention. The characteristics of both have been highlighted in the current article; it can be concluded that fall prevention is still in the research phase and has yet not the sufficiently mature technology for its solution for real scenarios because of the complementary technologies (Bluetooth, suitable sensors, battery life, real data, etc.). In contrast, fall risk prevention is closer to a mature stage in its use and acceptance. Thus, in this case, it is essential to consider fall and risk prevention when real-time monitoring is applied versus assessing the balance of the elderly, as well as which one of the solutions diminishes the probable physical harm when using the specific technology as an outcome. In addition, it is essential not to fall into the trap of algorithm aversion since rejecting an A.I. solution that could improve a particular situation in a specific context for certain people etc., should be avoided. Though in some instances, algorithms are more accurate than humans, and this should not be neglected.

Taking into account several of the aspects mentioned above, some interesting efforts, such as the AAMI/BSI Initiative, suggest a framework that emphasizes the importance of assurance of A.I. solutions, i.e. that it should be evaluated in its context. The factors to be assessed are the potential risks a patient may face, the assurance of safety, effectiveness and performance of the A.I. solution. Thus, it is necessary that the A.I. solution should have a valid clinical association that solves a real issue in the domain, a valid analytical model, and a clinical validation that its existence is meaningful. In addition, it is highlighted that the deployments of A.I. solutions in healthcare are explored from many other standpoints beyond governing authorization. For example, it includes the organization's management, professional conduct, research and ethics, evidence-based practice, and data governance [8]. However, it is crucial that emergent A.I. solutions consider including such aspects as fairness, explainability/explicability, and transparency, as well as validate and provide trustworthiness [38, 7]. To conclude, it's essential to understand how the A.I. solution will support the issues in a specific domain and, in that process, consider the human values in focus when evaluating them, as highlighted in [6, 7]. This is a matter that requires further research, for instance, how the A.I. should be evaluated considering several aspects, including the ones highlighted in the current article.

6. Conclusions

As can be understood from the current paper, the use of A.I., by and large, provides challenges as well as opportunities. More efforts should be made to continue to make use of A.I. so that they work as a preventive tool taking into consideration facets highlighted in this paper, such as sensors, machine-learning algorithms, etc. Thus, by applying emergent technologies correctly, people can get different diagnostics depending on their constant needs. However, when it comes to real monitoring via sensors and machine-learning algorithms for purposes of fall prevention, there is still a gap until they can become reliable for their primary objective, i.e. to avoid a fall. As discussed above, the data is simulated, and the machine learning algorithms perform well in simulated scenarios. Simultaneously, as it is known, they can provide overfitting, i.e. predicting outcomes with high accuracy. Still, later when the created model is applied to new data (from a real scenario), the accuracy diminishes significantly. It means that the created model does not generalize well from simulated data to new data, for instance, from a real scenario. This is a well-known issue in machine learning and data science. When it comes to fall risk assessment/prevention, it has been found that the same technique is applied to evaluate the risk of a fall, i.e. fall risk assessment in the elderly person. However, the data used to make a decision is based on heart rate variability analysis, assessment of an imbalance through the monitoring of the lower limb muscles, etc., based on sensors and machine learning. It currently appears to be the most trusted way to use the A.I. technologies, which are part of the current study, to reduce falls. One of the reasons is, as mentioned formerly, that real data is used to evaluate the risk in the case of fall risk assessment/prevention. It results in averting the well-known issues of overfitting. In addition, the articles using A.I. technologies for fall risk assessment/prevention show reliable results. It is also concluded that human values should be involved in assessing an A.I. solution since it emphasizes crucial aspects for its acceptance. Thus, human values bring other important aspects, namely that an A.I. solution should not result in a situation that harms the user physically, i.e. give incorrect information that can lead to harm. In conclusion, it is crucial to understand how an A.I. solution will support the problems in a specific area and, in that process, consider the human values in focus, namely, when they are evaluated.

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