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Review

Is The Timed-Up and Go Test Feasible in Mobile Devices? A Systematic Review

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Abstract: The number of older adults is increasing worldwide, and it is expected that by 2050 over 2 billion individuals will be more than 60 years old. Older adults are exposed to numerous pathological problems such as Parkinson's disease, amyotrophic lateral sclerosis, post-stroke, and orthopedic disturbances. Several physiotherapy methods that involve measurement of movements, such as the Timed-Up and Go test, can be done to support efficient and effective evaluation of pathological symptoms and promotion of health and well-being. In this systematic review, the authors aim to determine how the inertial sensors embedded in mobile devices are employed for the measurement of the different parameters involved in the Timed-Up and Go test. The main contribution of this paper consists of the identification of the different studies that utilize the sensors available in mobile devices for the measurement of the results of the Timed-Up and Go test. The results show that mobile devices embedded motion sensors can be used for these types of studies and the most commonly used sensors are the magnetometer, accelerometer, and gyroscope available in off-the-shelf smartphones. The features analyzed in this paper are categorized as quantitative, quantitative + statistic, dynamic balance, gait properties, state transitions, and raw statistics. These features utilize the accelerometer and gyroscope sensors and facilitate recognition of daily activities, accidents such as falling, some diseases, as well as the measurement of the subject's performance during the test execution.

Keywords: older adults; inertial sensors; physical exercises; physiotherapy; systematic review; timed-up and go test measurement

1. Introduction

People with disabilities or older adults are two essential groups that can benefit from technology advancements. Currently, around 9% of the world's population is aged 65 and above, and approximately 10% of the world's population lives with a disability [1,2]. Consequently, in countries with life expectancy over 70 years old, people spend on average about eight years, or 11.5 per cent of their life span, living with disabilities [1]. The increasing number of older adults is another cause for the growing number of people with impairments [1].

The number of older adults is increasing worldwide, and it is expected that by 2050, two billion individuals will be older than 60 years [3,4]. In parallel, the proliferation of information and communications technology brings numerous applications to the development and implementation of numerous methods for enhanced personalized healthcare systems [5,6]. Furthermore, the research interest in mobile computing technologies that focus on novel healthcare applications to promote public health and well-being is also increasing [7–9].

The use of mobile devices by older people was evaluated with the use of questionnaires and interviews [10]. In general, most older people only uses mobile phones for emergency situations, i.e., voice calls, and only a few of them use these devices for SMS and video calls [11,12]. Furthermore, mobile devices incorporate high processing power, numerous sensors, and connectivity methods for short-range and long-range communications [13]. Mobile devices are used in the implementation of numerous methods for clinical evaluation and personalized healthcare [14–17]. Several mobile sensors such as accelerometers, magnetometers, and gyroscopes that are incorporated in the majority of today's smartphones can be used to support numerous clinical evaluation procedures such as activity recognition and fall detection [18–22]. The continuous technological enhancements on mobile sensing promote novel applications for enhanced living environments and well-being; however, the collaboration between information and communications technology and medical researchers is mandatory for the efficient applicability of these methods [23].

The development of these solutions is related to the progress of the Ambient Assisted Living (AAL) domain, fueled using different types of sensors, that should not be intrusive and at the same time correctly positioned to acquire reliable data [24]. There are plenty of studies that demonstrate the applicability of mobile device sensors for recognition of different physical and physiological parameters, including the recognition of Activities of Daily Living (ADL) [25,26], environments [27], or even for reduction of false alarms in intensive care units [28]. Likewise, mobile devices have been used for the measurement of the results of the Heel-Rise test [29], proving that the implementation of physiotherapy tests is feasible with the mobile device sensors.

The Timed-Up and Go (TUG) test is a quick and straightforward clinical method for assessment of lower extremity function, mobility, and fall risk [30]. During it, the person is performing the following actions: getting up from the chair, walking for 3 meters, turning around, walking another 3 meters in a reverse direction, and sitting down on the chair. The typical duration of this test is a maximum of 12 seconds.

This method has been used to evaluate numerous individuals with pathological problems such as Parkinson's disease, amyotrophic lateral sclerosis, post-stroke, and orthopedic disturbances [30,31]. Therefore, clinicians would benefit from the implementation of mobile sensors to support efficient and effective methods for pathological symptom evaluation to promote agile interventions for enhanced public health [32].

A specific example of how a sensor-enhanced version of the TUG test outperformed the stopwatch version at classifying fall risk is provided in [33], demonstrating that measuring accelerometry during the TUG test improved the classification of fallers to 87% (compared with 63% using duration alone). Other publications, such as [34], have reported considerably higher scores of the stopwatch TUG test. An additional justification for performing TUG tests on a smartphone instead of the simple smartwatch version is the automated data collection and measurement [35] that can facilitate additional long-term analysis that could discover trends in the results of a single patient. This could lead to early detection of health issues and concerns before they come to a serious level [36].

Nowadays, artificial intelligence is taking a major role in the medical field. Numerous emerging applications of artificial intelligence methods have been designed and developed for enhanced patient treatment [37]. The TUG test has also been used to measure the functional performance of patients during their recovery process using unsupervised machine learning methods by several studies [38–41]. The calculation of features can be integrated with the feature engineering and selection process in a systematic way for supervised learning problems, such as in [25,42].

The main contribution of this paper is synthesizing the existing body of knowledge and identifying common threads and gaps that would open new research directions about the application of TUG tests on mobile devices. Furthermore, this literature review provides a comparison between the duration of the TUG test and the features used.

This work presents a systematic review of studies published between 2010 and 2018, focused on the application of the available sensors in off-the-shelf mobile devices to AAL and physical therapy, and specifically for the automation of the measurements performed during the TUG test [43]. The Timed-Up and Go test is especially important for the treatment and diagnosis of Parkinson disease and fall risk prediction [44–46]. For this purpose, this test analyzes the movement and recognizes different patterns related to various diseases, facilitating identifying future risky situations. The Timed-Up and Go test is executed in five distinct phases: (1) the individual sits in a chair (see Figure 1a); (2) the individual walks 3 meters (see Figure 1b); (3) the individual reverses the gait (see Figure 1c); (4) the individual walks back (see Figure 1d); and, finally, (5) the individual sits back in the chair (see Figure 1e). Throughout this test, the movements and speed can be measured using the embedded inertial sensors in smartphones. As a result, it is possible to identify patterns that highlight issues related to falls of older adults. It is noteworthy that several results presented, in general, calculations of the individuals' angles of movements or the speed and acceleration throughout the test. Several statistical methods and people of different ages were used for differentiating and defining patterns, which allowed for validation of the studies [47–52].

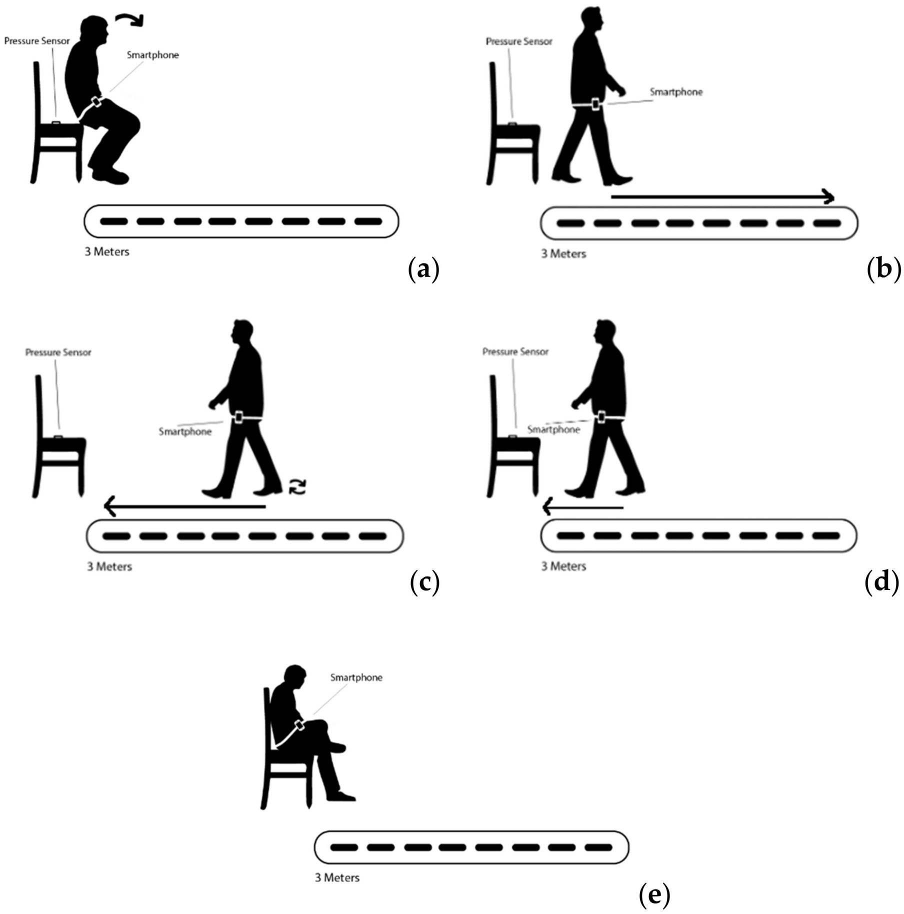

Figure 1. Timed-Up and Go test execution phases. (**a**) the individual sits in a chair; (**b**) the individual walks 3 meters; (**c**) the individual reverses the gait; (**d**) the individual walks back; (**e**) the individual sits back in the chair.

There are different types of TUG tests, including the standard TUG test, the Extended TUG test, the Smart Insole TUG test, and the Instrumented TUG test. The TUG test consists of a set of five phases, as represented in Figure 1 [43]. The Extended TUG test also includes a set of five stages [53], including standing up from a chair, walking for a ten meters distance, turning around, walking back to the chair and sitting down. The Smart Insole TUG (SITUG) test implements the TUG test with a Smart Insole device to provide real-time and fine-grained results in a more multifaceted analysis for the fall risk evaluation [54]. The Instrumented TUG (ITUG) test uses sensors to perform quantitative data extraction during the TUG test [55].

This remainder of the paper is organized as follows. Section 2 defines the applied methodology, explaining the research questions, the inclusion criteria, and the search strategy. Section 3 presents the results of this systematic review, which are subsequently discussed in Section 4. Finally, Section 5 concludes the paper.

2. Materials and Methods

2.1. Research Questions

The primary research questions of this review were as follows: (RQ1) In what ways are low-cost inertial measurement unit (IMU) sensors used to enhance TUG? (RQ2) Which methods for analysis of the TUG test results can be implemented on mobile devices? (RQ3) In what ways can IMU sensors improve the automation of TUG for assessing fall risk?

2.2. Inclusion Criteria

The inclusion criteria of studies and assessing methods for measurement of the results of the TUG test were: (1) Studies that measure the parameters of the TUG test using sensors; (2) Studies that present different approaches relative to the TUG test; (3) Studies that utilize at least motion or magnetic sensors; (4) Studies that focus on the use of sensors embedded in mobile devices; (5) Studies that were published between 2010 and 2018; (6) Studies which correctly define the participants population; (7) Studies written in English.

2.3. Search Strategy

The team searched for studies meeting the inclusion criteria in the following electronic databases: IEEE Xplore, ACM Digital Library, BMC, and PubMed. The research terms used to write this systematic review were: "Time-Up and Go test", "sensors", and "mobile devices". Every study was independently evaluated by eight reviewers, and its suitability was determined with the agreement of all parties. The studies were examined to identify the different approaches relative to the measurement of the results of TUG test, using the onboard sensors available in an off-the-shelf mobile device.

2.4. Extraction of Study Characteristics

The following data were extracted from the studies and presented in Table 1: year of publication, population, purpose, devices used, sensors available, raw data available, source code available, implementation, and studied diseases. We contacted the corresponding author of each study by email and asked for the source code and raw data. The implementation column groups the articles in two categories: "Calculation of the features" and "Implementation of machine learning methods". The "Calculation of the features" includes analytical features, such as angular velocity, which is not directly measured by the sensors, but rather derived from the original sensory measurements while considering the time factor. In general, the applicable statistical metrics on such sensors for this domain as well as their mathematical definition are provided in [42]. The second group of articles goes beyond and utilizes such features as inputs to machine learning models which are automatically trained and tuned.

Table 1. Study analysis.

Paper	Year of Publication	Population	Purpose of the Study	Devices	Sensors	Raw Data Available	Source Code Available	Implementation	Studied Diseases
Yang et al. [56]	2018	10 patients aged between 19 and 44 years old	Prevention of fall risks in the elderly subjects with the TUG test	Smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Healthy people
Bao et al. [57]	2018	12 subjects aged between 65 and 85 years old	Shows the efficacy of the balance training to help the elderly, using the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Healthy people
Yang et al. [54]	2018	6 subjects with unknown age	Appreciate the feasibility of the TUG test and using a complex system	Smartphone	Accelerometer Gyroscope	yes	yes	Implementation of machine learning methods	Healthy people
Silva et al. [58]	2018	18 older adults aged between 68 and 78 years old	Methodology to prevent and identify fall risks, using sensors and based on the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Rheumatic diseases; chronic pain; hypertension; dizziness; polypharmacy
Hellmers et al. [59]	2018	157 subjects aged between 70 and 85 years old	Automated analyses using inertial measurement units and the TUG test	Smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Parkinson disease
Chigateri et al. [60]	2018	23 older adults aged 75 years old or over	Measure the fall risk using sensors and the TUG test	Mobiles devices	Accelerometer	no	no	Calculation of the features	Healthy people
Mellone et al. [61]	2018	49 subjects aged between 43 and 75 years old	Validate a method for measuring the TUG test	Smartphone	Accelerometer	no	no	Calculation of the features	Parkinson disease
Madhushri et al. [62]	2017	10 geriatric patients aged between 78 and 86 years old	Mobility assessment with the TUG test	Smartphone	Gyroscope Accelerometer	no	no	Calculation of the features	Mobility problems
Beyea et al. [63]	2017	12 individuals aged between 21 and 64 years old	A mobile device using sensors and the TUG test separated in the different phases of the test	Mobiles devices	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Healthy people
Coni et al. [64]	2017	239 subjects aged between 65 and 93 years old	Study the decline associated with the evolution of age using the TUG test and sensors	Smartphone	Accelerometer Gyroscope	no	no	Implementation of machine learning methods	Healthy people
Salarian et al. [65]	2017	28 subjects aged between 52 and 68 years old	Instrumented the TUG test using sensors in people with Parkinson's disease	Mobiles devices	Accelerometer	no	no	Calculation of the features	Parkinson disease

Table 1. *Cont.*

Paper	Year of Publication	Population	Purpose of the Study	Devices	Sensors	Raw Data Available	Source Code Available	Implementation	Studied Diseases
Suppa et al. [66]	2017	28 patients aged between 63 and 77 years old	Inspect and associate the gait in people with Parkinson's disease using the TUG test and the sensors	Mobiles devices	Microsoft Kinect Accelerometer Gyroscope	no	no	Implementation of machine learning methods	Parkinson disease
Madhushri et al. [67]	2016	2 patients with unknown age	Application for mobility assessment helping the elderly to use the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Mobility problems
Cippitelli et al. [68]	2016	20 subjects aged between 22 and 39 years old	Quantify the possibility of the falls using data captured with sensors and tested with TUG test	Computer mobile devices	Microsoft Kinect Accelerometer	yes	no	Implementation of machine learning methods	Healthy people
Williams et al. [69]	2015	5 subjects aged between 21 and 36 years old	The system that helps the subjects in stroke rehabilitation using the TUG test	Smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Healthy people
Cuesta-Vargas et al. [70]	2015	30 subjects over 65 years old	Evaluation of the people and their mobility difficulty using sensors embedded in the smartphone and using the TUG test.	Smartphone	Accelerometer	no	no	Calculation of the features	Frailty syndrome
Milosevic et al. [71]	2015	7 subjects with unknown age	Application to automate instrumented the TUG test using sensors	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Parkinson disease
Dzhagaryan et al. [72]	2015	4 subjects with unknown age	Wearable system for older adults using the TUG test	Small wearable computing; smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Healthy people
Greene et al. [73]	2014	124 older adults aged between 69 and 83 years old	The mobile platform using inertial and pressure sensors to check the mobility of older adults, using the TUG test	Mobiles devices	Accelerometer Gyroscope	no	no	Implementation of machine learning methods	Frailty syndrome
Galán-Mercant et al. [74]	2014	30 subjects aged over 65 years old	Quantify and describe the acceleration, angular velocity and the motions of the body using a smartphone and the TUG test	Smartphone	Accelerometer	no	no	Implementation of machine learning methods	Frailty syndrome
Galán-Mercant et al. [75]	2014	18 subjects aged over 70 years old	Quantify and define the magnitude of inertial sensors using a smartphone test assessment, based on the TUG test	Smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Frailty syndrome

Table 1. *Cont.*

Paper	Year of Publication	Population	Purpose of the Study	Devices	Sensors	Raw Data Available	Source Code Available	Implementation	Studied Diseases
Greene et al. [76]	2014	21 patients aged between 18 and 60 years old	Examine the consistency of the quantifiable measures derivate of sensors and utilizing the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Multiple sclerosis
Galán-Mercant et al. [53]	2014	5 subjects aged over 65 years old	Analyze and quantify the reliability criterion-related with the utilization of sensors and using the extended TUG test	Smartphone	Accelerometer	yes	no	Implementation of machine learning methods	Healthy people
Tacconi et al. [77]	2014	3 subjects with unknown age	System to analyze the human falls using the TUG test	Smartphone	Accelerometer	no	no	Calculation of the features	Healthy people
Mellone et al. [22]	2014	200 subjects aged over 65 years old	Smartphone solutions to prevent and detect the human falls using the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Implementation of machine learning methods	Healthy people
Bernhard et al. [78]	2012	384 subjects aged between 40 and 89 years old	Analyses the effectiveness of mobile devices using sensors and the TUG test	Smartwatch	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Parkinson's disease; stroke; epilepsy; pain syndromes; multiple sclerosis; tumors; polyneuropathy; vertigo; dementia; meningitis; encephalitis
Palmerini et al. [79]	2011	49 subjects aged between 28 and 87 years old	Motion analysis systems incorporated in a smartphone, to study the possibility of falls for people with Parkinson's disease using the TUG test and inertial sensors	Smartphone	Accelerometer	no	no	Calculation of the features	Healthy people
King et al. [80]	2010	28 subjects with unknown age	Predict the risks of falls, using a BSN attached with inertial sensors using the TUG test	Mobiles devices	Accelerometer Gyroscope	no	no	Calculation of the features	Healthy people

3. Results

As illustrated in Figure 2, our review identified 265 papers that included twenty-four duplicates, which were removed. The remaining 241 works were evaluated in terms of title, abstract, and keywords, resulting in the exclusion of 95 citations. The main criterion for the exclusion of papers was because 95 articles were not related to the applicability of mobile sensors available in an off-the-shelf mobile device. We performed the full-text evaluation of the remaining 146 papers, excluding 118 articles that did not match the defined inclusion criteria. The remaining 28 papers were included in the qualitative synthesis and quantitative synthesis. In summary, our review examined 28 documents.

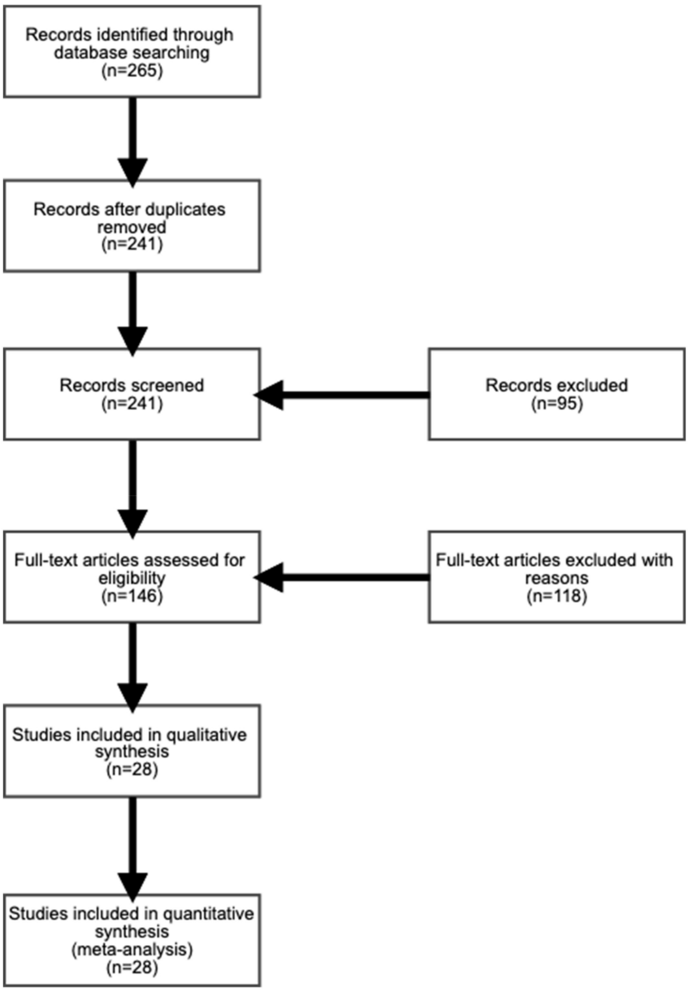

Figure 2. Flow diagram of identification and inclusion of papers.

We refer the interested readers to the original cited works to find relevant information about the details of the TUG test measurements analyzed in this review. As shown in Table 1, all studies were performed with mobile devices. The studies analyzed were published between 2010 and 2018 with one study in 2010 (4%), one study in 2011 (4%), one study in 2012 (4%), seven studies in 2014 (25%), four studies in 2015 (14%), two studies in 2016 (7%), six studies in 2017 (21%), and seven studies in 2018 (25%). The analyzed studies indicate that 20 studies used smartphones (71%) and eight used other types of mobile devices (29%). Therefore, related to the sensors used in the analyzed studies, the studies indicate the sensors used were the accelerometer in 27 studies (97%), the gyroscope in 19 studies (68%), and the magnetometer in seven studies (25%). Moreover, only eight studies (29%) present the accuracy of the results obtained with the different experiments related to the TUG test. Finally, the analysis of the diseases by the different studies was researched, where 14 studies (50%)

performed the TUG test with healthy people, 5 studies (18%) analyzed people with Parkinson's disease, four studies (14%) analyzed people with frailty syndrome, and, the remaining 5 studies (18%) analyzed people with other diseases.

The following sections present the results categorized by the different diseases listed in Table 1.

3.1. Healthy People

The authors of [56] implemented a method to assess the subject's balance, proposing four environment adapters designed to evaluate the ability to adapt to walking in complex environments associated to a compatible system that provides, in real-time, characteristics spatially related to walking. Thus, the authors proposed a four environment-adapting TUG test to asses one's aptitude to adjust gait in multifaceted environments and a compatible system called Smart Insole TUG (SITUG) [56]. These report an average precision of 92% and 23% in the segmentation of the 5 phases of the TUG test [56]. The features used in the study are the duration, the threshold of the forefoot, the limit of the rearfoot, the full contact time, the foot-ground contact time, the non-foot-ground contact time, the initial contact time, the gait cycle time, the gait cycle count, the gait cycle pace, the stride length and the sole average pressures [56]. The results show that SITUG reports an accuracy of over 92% in the recognition of the different phases of the test [56].

In [57], the authors evaluated the efficacy of long-term balance training with and without inertial sensors. Participants attended the sessions at home with one 45-minute session per week, using smartphone balance trainers that provided written, graphic, and video guidance, and monitored trunk sway [57]. The sensors, including gyroscopes and accelerometers, were used to measure angular changes [57]. They also estimated the duration of the TUG test as well as the gait speed, fast gait speed, sit-to-stand duration, and others [57].

The authors of [54] proposed a SITUG test to obtain the motor performance information in complex environments, to identify the probability of falls. The authors calculated the time variance, reporting an average accuracy of 94.1% in the extraction of subcomponents within a stride, and 93.13% in deriving the stride length based on the distance travelled [54]. Thus, the five phases of the test were recognized with an accuracy of around 90%, using pressure features, spatial features, temporal features, and spatial-temporal features [54].

In [60], the authors proposed the assessment of automatic real-time feedback provided by a shoe-mounted inertial-sensor-based gait therapy system is feasible in individuals with gait impairments after incomplete spinal cord injury. A way to identify parameters associated with gait was proposed, implementing several tests, including the TUG test with an accelerometer sensor [60]. The median overall agreement between the processed accelerometer data and the annotated video was an approximate match of 92.8% and 95.1% for walking episodes in scripted and unscripted activities, respectively [60]. In addition, based on the duration of each activity, the results reported an accuracy of 92.2% for recognition of the non-walking event and 88.7% for the recognition of walking activity

Beyea et al. [63] developed a protocol to acquire the Inertial Measurement Unit (IMU) data and measure the results of two versions of the TUG test, such as a test with 3 meters walking and another with 5 meters walking to compare the performance based on the different durations. The authors recognized the different phases of the test and calculate the average of the acceleration and the time of the TUG test [63]. Finally, the authors calculated the total time of the test and walking times, reporting an accuracy of 87% in the recognition of the different phases of the test [63].

In [64], the authors proposed research on the functional decline associated with ageing and its differences through a set of sensor-based measures by using the Instrumented TUG test, recognizing the different activities. The authors also examined the decline related to age-related and gender-related variances through a set of sensor-based measures [64].

Based on the TUG test, Cippitelli et al. proposed fall detection algorithms using the Inertial Measurement Units (IMUs) and an RGB depth sensor (Microsoft Kinect) [68]. The authors identified the sit-to-stand, walk, turn, walk, and turn-to-sit phases [68]. The authors also evaluated the maximum inclination of the torso angle and the time required to perform the movement [68]. They implemented three algorithms, where the first algorithm reports an accuracy of 79%, the second one presents an accuracy of 90%, and the latest algorithm shows an accuracy of 99% [68]. The orientation angle must be around 90° during a not very extensive period to check the fall [68].

In [69], a system to rehabilitate patients who have suffered a stroke was proposed, implementing the Smart Insole TUG test at the individuals' own homes. They measured the angles, stride length, total distance traveled, average velocity, and execution time of the TUG test, and identified the sitting and standing activities [69]. This system, featuring a simple configuration and a relatively low cost, provides feedback to the user, showing that it is possibly even better than current physiotherapy methods [69]. The system also checks the health status of knees [69]. The results show that the difference between the app's timer and the mobile devices represents a difference a Root Mean Square Error (RMSE) of 0.907 [69].

In [72], the authors introduced a wearable system titled Smart Button designed to assist the mobility of older adults and assess people with Parkinson's and the elderly with regards to the movement, balance, strength limits, and risks of falling, while calculating the highest and lowest accelerations as well as the angular velocity. The parameters extracted from the TUG test are total duration of the TUG test, active TUG test, and lift-up phase of the sit-to-stand transition, the length of the lean forward period, and the duration of the lift-up phase of the sit-to-stand, maximum change, and maximum angular velocity during the trunk angle in the lean-forward, maximum angular velocity during the lift-up, duration of the stand-to-sit transition, duration of the prepare-to-sit in the stand-to-sit, duration of the sit-down phase in the stand-to-sit, and number of steps during the walking phase [72].

The authors of [53] proposed the evaluation of the reliability and concurrent criterion validity of the acceleration using a smartphone application, inertial sensors, and the Extended TUG test. They implemented the Bland–Altman method with the data acquired from the accelerometer available in the mobile devices to obtain the different results [53]. Thus, they identified the sit-to-stand, gait-go, turn, gait-come, and stand-to-sit activities with the features available in a previous study protocol and the angles of the movement [53].

Based on a mobile platform, the authors of [77] presented a system for the study of falls and mobility, using the data captured by an inertial sensor and the Extended TUG test for validation. They calculated several features, including total, gait, sit-to-stand, and stand-to-sit durations, Root Mean Square (RMS) of sit-to-stand and stand-to-sit, maximum acceleration, mean cadence, cadence standard deviation, and cadence coefficient of variation [77]. The algorithm chosen was the single-threshold algorithm, and several simulations were made for the detection of falls, including forward fall, lateral fall, backward fall, fall sliding against a wall final position vertical, fall slipping against a wall, and falling out the bed actions [77].

A study presented by [22] is based on the techniques for the implementation of FARSEEING using smartphones to detect falls and prevent falls. The inertial sensors are used in the smartphone to calculate the probabilities of fall. For this application, they created a mobile application to perform the tests and use the TUG test as a study centre [22]. Based on the orientation of the device, the authors proposed a wearable system to identify the reasons for the falls using inertial sensors and the TUG test [22]. The results show the total duration and the maximum acceleration during the trial [22].

The authors proposed a method that uses accelerometer available in the smartphone as a measurement system for people with Parkinson's disease using the TUG test [79]. They extracted different features, including the duration, RMS, preparatory RMS and jerk of the sit-to-stand transition, the mean and standard deviation of step duration, phase coordination index, mean phase of gait phase, and maximum value of acceleration during the stand-to-sit period, recognizing the different stages [79].

The authors of [80] used a body sensor network (BSN) to detect the equilibrium to forecast falling. They extracted the mean, variance, number of peaks, and time as features to quantify 3100 amplitudes related to left–right movements, 2600 magnitudes related to up–down movements, and

2450 amplitudes related to forward–back actions [80]. For this purpose, they calculated the Tinetti score and the maximum and minimum amplitudes with the TUG test [80].

3.2. Parkinson Disease

The authors of [59] authors proposed the use of wearables for the assessment of gait and balance features in a clinical setting with an inertial measurement unit to use in people with Parkinson's disease for the evaluation of the possibility of falls using the TUG test. They extracted the auto-correlation, mean, pitch, standard deviation, RMS, energy, signal magnitude area (SMA), signal vector magnitude (SVM), spectral entropy, and correlation as features for the recognition of the different activities during the TUG test [59]. They reported that the use of self-learning methods presents a maximum acceleration of 12 m/s^2 and an angular velocity of 3 m/s [59].

The study presented in [61] evaluated the efficiency of the smartphone and its inertial embedded sensors in the implementation of the TUG test, and validation of the measurement of activity in frail elder people using inertial sensors. They extracted the total duration, jerk and range of sit-to-stand transition of the trial, the mean, and standard deviation of the step time, among others [61]. The reported results showed a balance when the smartphone was used and the McRoberts Hybrid device, which demonstrates that embedded sensors and smartphones are a viable alternative to more expensive equipment [61].

The study in [65] proposed the use of the instrumented TUG test with inertial sensors to improve the TUG test evaluation in several situations, employing automatic detection and separation of subcomponents, detailing the analysis of each of them and achieving a higher sensitivity than the TUG test. The Instrumented TUG test was different concerning the angular velocity duration of the turn, and the turning duration, and the time to perform turn-to-sit [65].

Suppa et al. [66] used the TUG test to examine and compare the gait in patients with Parkinson's disease for the recognition of freezing of gait based on the duration of the TUG test, and implemented treatment for the disease, reporting accuracy of 98% in recognition of the different phases of the test.

In [71], the authors presented a mobile application named sTUG that completely automated the ITUG test, measuring the total duration of the TUG test, sit-to-stand transition, and lean forward and lift phases in the sit-to-stand. Also, other features were measured, including the maximum change of the trunk angle, and maximum angular velocity during the lean forward and lift-up phases, the duration of the stand-to-sit transition, and the prepare-to-sit and sit-down periods in the stand-to-sit transition [71].

3.3. Frailty Syndrome

The authors of [70] implemented a method for the measurement of the Extended TUG test with a smartphone, identifying kinematic variables obtained with the inertial sensors, measuring the averages of time and the acceleration during the TUG test. The highest accuracy in discrimination between frail and non-frail elderly was reported as a value around 72.8% in recognition of the different phases of the test [70].

Based on the use of inertial sensors available on a mobile platform and other pressure sensors, the authors of [73] discussed the falls of older adults and the causes of serious injuries using the TUG test. The authors recognized different activities with 52 features quantifying the temporal, spatial, turning, and rotational characteristics [73]. The reported precision of the TUG test was a minimum accuracy of 78.11% in recognition of the different activities, and a minimum accuracy of 72.31% in recognition of the different phases of the test [73].

Galán-Mercant et al. [74] developed a method to measure and describe the angular velocity and acceleration variations and the trunk deviation with the Extended TUG test, to analyze the changes between healthy and frail individuals, and to identify the different activities. The significant difference between the groups in the sub-phases of sit-to-stand and stand-to-sit was in the vertical axis and vector, where the minimum acceleration in the stand-to-sit phase was –2.69 m/s^2 in the frail elderly and –5.93 m/s^2 in the non-frail elderly [74].

The authors of [75] used the smartphone application using inertial sensors as a measurement device to measure. They described the magnitude of acceleration values with frail and non-frail individuals. The features extracted are the maximum and minimum values of the acceleration of each axis [75]. Finally, they reported that the most significant differences were verified in the use of the accelerometer with eyes closed and the feet parallel with a maximum acceleration on the lateral axis of ($p < 0.01$), minimum acceleration peak on the lateral axis ($p < 0.01$), and peak acceleration of the resulting vector ($p < 0.01$) [75].

3.4. Other Diseases

The authors of [58] extracted several features for the recognition of the different phases of the Instrumented TUG test, including RMS, standard deviation, median deviation, interquartile range (IQR), skewness, kurtosis, number of times the magnitude signal crosses the mean value, maximum and second maximum frequencies of the fast Fourier transform (FFT), maximum and second maximum amplitudes of the FFT, minimum, maximum, average of the peak height, energy, and entropy.

The authors of [62] developed a customized three-segment form to quantify body forces and evaluate the optimization of each sit-to-stand transition. The evaluation of the model was performed by testing the action and optimal transition time for 10 older adults, comparing their best performance with the best performance of the model to use the results to evaluate possible improvements in the mobility of individuals [62]. They calculated the real angles and the averages of the sit-to-stand transition time and the actions of 10 geriatric patients 80 years old [62]. Using mobile phone inertial sensors and a smartphone mounted on the chest, the total power and action of each stand up during the test verified the force action derives between 170 joules at 0.2 seconds and 250 joules at 2 seconds [62].

Madhushri et al. proposed a smartphone application for assessing flexibility in the aged population using inertial sensors [67]. They also presented a set of applications to evaluate the implementation of the Smart Insole TUG test with older adults, extracting several parameters from the inertial sensors [67]. The parameters extracted include the duration of the TUG test, the sit-to-stand transition, the lean forward phase, the stand-to-sit shift, the prepare-to-sit period, the sit-down phase, and the lift up phase, the total time of walk, the maximum change of trunk angle during the lean forward phase, the maximum angular velocity during the lean forward and the lift up phases, the total number of steps during walking, and before turn [67]. The average error for the implementation of the Smart Insole TUG test is around 2% [67].

The authors of [76] implemented the TUG test with inertial sensors for the assessment of the disability status in people with sclerosis disease, measuring the time of the different phases, the angular velocity peaks as well as other spatiotemporal and statistic features. Moreover, this study also examines the reliability of the TUG test [76]. The authors tried to verify the existence of some diseases like Parkinson's and its evaluation [76].

The authors of [78] explored options using wearables, which can provide more objective information for the evaluation of hospitalized neurological patients, with an assessment procedure that gets acceptance in the communities. Based on the TUG test, the authors validated the use of inertial sensors embedded in a smartphone, extracting the angles of the movement [78].

4. Discussion

As it emerges from this systematic review, we can verify the importance that mobile devices have for studies related to the health of elderly subjects. Among the most evaluated variables or features, it has been identified that the studies in this area go a long way towards temporal measures, such as duration, and for angular measures, such as the angular velocity. Finally, it should be noticed that the sensors embedded in mobile devices are an inexpensive way to carry out studies of this importance, i.e., the accelerometer, gyroscope, and magnetometer. Also, they reported a high level of efficiency and they are used in numerous research studies. However, several artificial intelligence methods such as machine learning can be used for enhanced TUG test data analysis.

The TUG test consists of the execution of different activities. After the analysis, it was verified that the most used sensor in the literature is the accelerometer. Also, the most used features in the research are the duration of the test, the average of the angles obtained with the raw data, the edges of the movement, the number of steps, the maximum change of the trunk angle, the threshold, and the full contact time. In the normal TUG test, the most widely used features for the measurement of the different parameters of the test are the duration, the mean and standard deviation, and the RMS of the raw data extracted from the embedded sensors the mobile device (Table 2). Secondly, in the Extended TUG test, the most used features for the measurement of the different parameters of the test are the duration, the acceleration, and the number of steps extracted from the data acquired by the sensors available in the mobile devices (Table 2). Finally, in the Smart Insole TUG test, the most used features for the measurement of the different parameters of the test are the duration and the stride length extracted from the data acquired by the sensors available in the mobile devices (Table 2). The most used features are highlighted in Table 2.

Table 2. Features relative to the different types of Timed-Up and Go tests.

Features	Interpretation	Number of Studies		
		TUG	Extended TUG	Smart Insole TUG
Duration		6	3	6
Number of steps			2	1
Stride length				2
Step time		1		
Orientation		1		
Position		1		
Step length		1		
Cadence	Quantitative	1		
Turning duration		1		
Time to perform turn-to-sit		1		
Reaction time			1	
Contact times (i.e., initial, forefoot, rearfoot, full, foot-ground, and non-foot-ground)				1
Distance				1
Threshold				1
Standard deviation of the step time		1		
Cadence standard deviation			1	
Cadence coefficient of variation			1	
Mean cadence			1	
Averages of time	Quantitative + Statistic		1	
Mean stride length			1	
Medio-lateral and medio-lateral interstride autocorrelations		1		
Maximum change of the trunk angle		1		
Acceleration			2	
Maximum angular velocity		2	1	1
Average speed			1	
Averages of the sit-to-stand transition		1		
Real velocity	Dynamic balance	1		
Average velocity				1
Angular velocity of arm-swing		1		
Gait speed		2		
Gait duration			1	
Gait cycle time	Gait properties			1
Gait cycle count				1
Gait cycle pace				1

Table 2. *Cont.*

Features	Interpretation	Number of Studies		
		TUG	Extended TUG	Smart Insole TUG
Real angles of the sit-to-stand transition	State transitions	2		
Range of sit-to-stand transition		1		
Jerk		1		
Mean of raw data	Raw statistic	3		
Standard deviation		3		
Root mean square (RMS)		3	1	
Signal energy		2		
Signal magnitude area (SMA)		2		
Signal vector magnitude (SVM)		2		
Spectral entropy		2		
Variance		1		
Number of peaks		1		
Median deviation		1		
Interquartile range (IQR)		1		
Skewness		1		
Kurtosis		1		
Number of times the magnitude signal crosses the mean value		1		
Maximum frequency of the FFT		1		
Maximum amplitude of the FFT		1		
Minimum average		1		
Maximum average		1		
Average of the peak height		1		
Energy		1		
Entropy		1		
Angles				1
Maximum change of trunk angle				1

The Interpretation column in Table 2 shows the category of the feature: quantitative, which explains some aspects of the TUG test or another physical characteristic; quantitative + statistic, which denotes a derived quantitative feature with some statistical operation; dynamic balance, which mainly describes the dynamic balance of the person; gait properties, which can help in describing the gait specifics and can help in identifying some gait abnormalities; state transitions, which contribute to better discerning different states and transitions from between them; and raw statistic, which denotes features calculated with a statistical function directly on the raw sensory data.

The main strengths of the methods rely in the capability to demonstrate that it is possible to establish that people with different diseases can perform this test, obtaining different results. The data acquired from the sensors allows accurate calculation of different results of this test, where the use of low-cost sensors may help in the obtention of results by the healthcare professionals belonging to the physiotherapy domain.

There is no information available regarding the confidentiality and protection of data acquired during the experiments. We performed a rigorous evaluation of each study to verify the existence of a validation of the study protocol by a human subject research ethics committee, but the information was not conclusive. Thus, we contacted the authors and research group to obtain more clarifications about the data protection of each study, but we have not yet received the responses.

The results of this review demonstrate that the data acquired from the sensors available in off-the-shelf mobile devices may be used to identify patterns in the acquired data depending on different diseases. Consequently, it is possible to reveal patterns of the diseases related to the test by grouping persons with different diseases. On the one hand, the results show that the data acquired from the sensors available in off-the-shelf mobile devices facilitate the detection of different diseases such as Parkinson's disease, amyotrophic lateral sclerosis, post-stroke, and orthopedic disturbances.

On the other hand, the TUG test can be performed reliably by the patients without having to visit physiotherapists. Likewise, physiotherapists can monitor the progress of a disease by having an integrated and reliable log of patient's TUG test results for an extended period of time.

However, there is no correlation between the most used features for each type of analysis and each study. Also, any research uses the most used features at the same time, and the studies have different purposes, including the measurement of various parameters and recognition of the different activities.

The measurement of the general TUG test has some limitations, as presented in [45]. By instrumenting the TUG test with sensors and by extracting multiple features in addition to the duration, we aim to overcome these issues:

- Falling risk in healthy older populations may not affect the measurement of the duration;
- The user may perform the different phases with other involuntary movements or trajectories;
- The effects of the medication therapy and movement deficiencies may not be detected;
- The high reliability and discrimination of the health may not be evaluated in only 3 meters;
- The measurement of the results of the test depends on the personal and environmental conditions;
- The conditions of the chair may also introduce the possibility of different results.

Generally, all studies use multiple features in a single recognition model. Despite the fact that some features are redundant to some extent, which could be intuitively understood solely by their mathematical definition, the recognition systems use them. The motivation is that while only a few of them are most important for recognition of a task, for an alternative task, some others would be useful. For example, for simply scoring the TUG test, the duration is usually enough. However, for fall detection, other features become important. Even more features are required for detection of more complex Activities of Daily Living.

Even though most studies do not provide specific ranges of the values of certain features to help in understanding the classifications, for any "black box" classification model, there are methods, such as local interpretable model-agnostic explanations (LIME) [81] or SHAP (shapley additive explanations) [82], which efficiently provide insights in the classification process.

Several studies have been performed, but a framework for the use of the TUG test for the recognition of different diseases and automation of the calculation of the various parameters of the test with low-cost sensors is still not available. Finally, the creation of a standard for the evaluations of the physical conditions with this type of test is essential.

As a result of the review of the related works, we believe that a standard for conducting the TUG test on mobile devices can be defined. Most importantly, multiple approaches show that simple statistical features based on the raw time-domain data is sufficiently accurate. Therefore, such computation is feasible on mobile devices with limited computing and battery capacity. For this test, more complex approaches, such as ones relying on deep learning models, are not recommended. Another recommendation is that mobile devices performing this test need to be integrated with the electronic health records of patients and to be available for their doctor, when required and after the approval of the patient. Of course, this raises many other technical challenges related to privacy and security. However, this can be proved instrumental in allowing the doctor to identify complex emerging patterns, such as progress of a disease, and to be able to act upon it proactively, instead of reactively.

5. Conclusions

This systematic review analyzes, verifies, and identifies the use of inertial sensors available in the mobile devices to detect movements and reactions during the TUG test. The use of sensors together with these tests allows drawing essential conclusions about how to prevent falls in the elderly or those with a disabling disease, and how measures can be created that can help avoid these events. In general, several approaches to the topic of typical use of technology (mobile devices and sensors) and health areas are reported in the literature. Motion sensors with more demanding architecture can capture more data more accurately and with greater efficiency. Thus, combined with a constant evolution of mobile technology and mobile devices, it is possible to achieve a continually growing number of events previously mentioned due to the increased life expectancy. Finally, the test that was the central target of this analysis is an adequate test, with excellent use for its ease of implementation and it does not require large equipment or technological devices to be carried out. Along with mobile devices using open source technologies, the TUG is very accessible to all.

Twenty-eight studies were examined, and the main findings are summarized as follows:

- (RQ1) Most of the low-cost IMU sensors used in the TUG tests are the gyroscope, magnetometer, and accelerometer. These sensors are widely used in the physiotherapy domain and can be used to detect all the five phases of the TUG test, which can be identified by sensors available onboard off-the-shelf mobile devices. Moreover, mobile sensors can be a low-cost approach for the TUG test and consecutively to clinical diagnostics of several diseases. The data collected by mobile sensors can be analyzed to create patterns for the evaluation of different diseases.
- (RQ2) The methods and features most used to measure the results are related to the time of the TUG test, the angular velocity and the angular analysis of the body movements, and the number of steps performed.
- (RQ3) One of the main purposes of the TUG test is to help in the recognition of the probability of the risk of falls, where eight studies present the relation between it and the TUG test in elderly people.

In conclusion, the literature review identified numerous studies reporting applicability of the TUG test for multiple evaluations in the medical domain, namely for detection of different diseases such as Parkinson's disease, amyotrophic lateral sclerosis, post-stroke, and orthopedic disturbances. The reviewed studies claim that the embedded sensors on mobile devices increase the reliability of the test. Therefore, the ubiquitous mobile devices present a low-cost, efficient, and reliable tool for performing the TUG test.

In the future, personal digital life coaches can be designed to evaluate different parameters of the subjects' physical conditions for medical and recreational use. Such systems, depending on the application scenario, would rely on multiple machine learning algorithms to cope with computational and battery limitations, while aiming to provide exceptional accuracy.

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