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A review of frailty analysis in older adults: from clinical tools towards fully automated preventive systems^{*}

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ABSTRACT

Objectives: Frailty is a geriatric syndrome characterized by sarcopenia and physiological impairment. Although the majority of older adults wish to age at home, being frail threatens this choice since it increases the risk of falls and loss of functional independence. Hence, frailty screening and early detection are needed to stop or at least slow down the physical weakening process. In this paper, we present a review in which we discuss the proposed methods from the literature that targets frailty detection and analysis, starting from traditional clinical tools then introducing data-driven studies before highlighting the importance of fully automated systems.

Material and methods: We conducted a review study by searching several databases such as Google Scholar, IEEE Xplore, MDPI, and ScienceDirect to name a few. This work presents clinical tools and classical performance tests to assess the health status and the physical function, as well as statistical and observational studies to analyze the frailty syndrome. Moreover, we discuss briefly the work of our research team in this context, represented by the development of a telemonitoring system which aims at the transition from a curative to a preventive model.

Results: Firstly, this review points out the absence of a gold standard to detect frailty in older individuals. Secondly, it discusses the limitations of self-reported measures/questionnaires and other traditional performance tests which are based on subjective data and done under supervised conditions. Thirdly, our study emphasizes the lack of robust approaches that target the early detection of frailty and the prediction of a future risk of physical worsening. We propose new research directions based, on the one hand, on automatic activity identification and tracking and, on the other hand, on the analysis of spontaneous speech of elderly.

Conclusion: This paper describes research findings and highlights the existing gaps in the context of frailty, and serves as a state of the art for researchers. Additionally, this work suggests future research directions regarding the early detection and prevention of frailty.

1. Introduction

With the increase in life expectancy, the world is currently facing the phenomenon of an aging population, and the number of older adults may soon exceed the number of younger people for the first time in history [81]. Hence, one of the main stakes in the early future of our society facing this demographic shift is the promotion of healthy aging and continuous tracking of physical activity during daily routine. Firstly, old people who are physically active have in general better biomarker profiles to prevent certain diseases like cardiovascular disease and type 2 diabetes, and to enhance the bone health [82]. Secondly, exhibiting higher levels of physical activities helps to lower the risk of falling and keep the elderly independent, reverse some effects of chronic diseases, and preserve the cognitive function [41]. Thirdly, the number of steps per day is associated with the risk of mortality in an inversely proportional relationship [49], and seems more important than the step intensity [50, 65]. These elements justify why researchers are conducting studies in

the elderly care field and are targeting telemonitoring solutions to identify certain diseases and/or syndromes.

Frailty in elderly people is one of the major public health problems. It is a geriatric syndrome characterized by physiological weakening that can lead to a lack of autonomy, hospitalization and even death [62, 72]. Globally, 13.6% of non-frail older individuals become frail (a median follow-up of three years), with an incidence rate of 43.4 cases per 1000 person-years [51]. In a country like France, 4 out of 5 people over 85 years old are frail [67], meaning that hundreds of thousands of older individuals need medical assistance. It is worth mentioning that medical consumption of frail seniors constitutes the biggest part of healthcare costs in industrialized countries [17]. Therefore, frailty has become an increasingly important clinical and public health issue in recent decades [22, 15, 45, 76].

In this paper, we present a review of frailty in older adults. Explicitly, we describe conducted studies and methods which aim at frailty screening and analysis. This review includes clinical tools and performance tests, as well as observational studies and sensors-based techniques. Furthermore, we discuss the drawbacks and the limitations of the literature, in order to introduce future research directions which might provide a complement to the past and current studies, and ensure the transition from curative to preventive monitoring systems.

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The paper is organized as follows. Section 2 defines frailty and introduces the medical context. Section 3 presents on the one hand, the widely-used clinical tools and performance tests for frailty screening and mobility assessment, and on the other hand, data-driven and observational studies which analyse the frailty syndrome and its consequences on the physical function. Section 4 discusses the current challenges and the limitations of the literature, by highlighting the importance of automated systems in frailty early detection and prevention. This section introduces the developments in the context of activity recognition and monitoring including the works of our research team, before proposing new perspectives and axes to be followed in future research studies in section 5. Finally, section 6 concludes the paper.

2. Medical context: what is frailty?

The definition of frailty is controversial [19]. Nonetheless, this clinical syndrome is characterized by reduced resistance to stressors caused by age-related declines in physiological function across various organ systems [37, 23, 30]. It is identified by functional weakening and sarcopenia, *i.e.* loss of muscle tissue, and causes adverse health outcomes. Frailty has been historically given a wide range of meanings [21]. It is worth mentioning that frailty is not synonymous with either comorbidity or disability. Comorbidity is an etiologic risk factor for frailty, while disability is one of its outcomes. This syndrome is divided into three stages, namely (1) non-frailty or robustness, (2) pre-frailty, (3) frailty, and followed by disability or loss of autonomy. This transition from one level to another occurs during the frailty time-window period. In theory, both pre-frail and frail statuses might be attenuated or reversible by medical interventions, *i.e.* the older person could regain her physical capacity, while the transition towards disability is hardly reversible. This potential reversibility is one of the major points justifying the interest in the frailty syndrome, if detected and treated early enough [33, 39, 78]. It has been demonstrated that frailty increases the risk of falls, lack of autonomy, and hospitalization [62, 72]. Moreover, it is a strong predictor of 1-year and 5-year mortality [47], while being independently associated with increased ICU (Intensive Care Unit) and 6-month mortality [36].

Frailty is being quantified using different approaches. On the one hand, the frailty index (FI), proposed by Rockwood *et al.*, is based on a comprehensive geriatric evaluation by counting the accumulated deficits, including cognitive and functional impairments, diseases, and psycho-social risk factors [43, 63]. On the other hand, Fried *et al.* defined frailty based on a specific phenotype [24]. Figure 1.a illustrates the cycle of frailty. The blue terms constitute its simplified version. In brief, the sarcopenia (1), which is caused by chronic undernutrition (8), changes in the musculoskeletal system (9), and/or various diseases (10), reduces the resting metabolic rate (2), the strength and the power of the patient (3) as well as the maximum volume of oxygen

consumption (4). The two latter (*i.e.* (3) and (4)) reduce the walking speed (5) thus the person's activity (6). The resting metabolic rate (2) and the activity (6) lead to a decrease in the total energy expenditure (7), which could cause chronic undernutrition (8), thus closing the cycle. Hence, the frailty phenotype (FP) characterizes frailty as a clinical syndrome meeting at least three out of five criteria (highlighted in Figure 1.b): (i) unintentional weight loss (10 lbs in past year), (ii) self-reported exhaustion (power), (iii) weakness (grip strength), (iv) slow walking speed and (v) low physical activity (through a questionnaire). Older adults with none of these five criteria are classified as non-frail, whereas elderly with one or two criteria are considered as pre-frail. FP was tested in the Cardiovascular Health Study [24]. It was observed that frailty increases with age and is greater in women than in men. Besides, intermediate frailty stage (1 or 2 criteria) increased the risk of becoming frail over the next 3-4 years.

3. Frailty screening and physical assessment

Researches and studies have been multiplied to find approaches and models with a view to frailty detection, analysis, and risk assessment, as well as physical function examination. In this section, we first discuss clinical diagnosis and performance tests before introducing and discussing sensors-based techniques and data-driven studies.

3.1. Clinical tools and performance tests

Table 1 gives a summary on approaches done in clinical settings to analyze the frailty syndrome and assess the physical capacities. Self-reported measures and some other evaluation questionnaires have been proposed to evaluate the frailty status of older individuals, and they constitute the first category. We start by the widely used approach, which is Fried's FP [24] previously discussed. The test begins by denoting the possible existence of unintentional weight loss (not due to exercise or dieting) of at least 5% of previous year weight and the self-reported exhaustion by asking two multiple choices questions. Next, the number of calories per week is calculated. It is stratified by gender and compared to a threshold, based on the short version of the Minnesota Leisure Time Activity questionnaire. Finally, the 15 feet walk time, which is stratified by gender and height, and the grip strength, which is stratified by gender and body mass index, are evaluated and compared to a threshold. Moreover, in the literature, FI is one of the commonly used ways to assess frailty as mentioned previously. It is used as a proxy measure of aging and vulnerability leading to poor outcomes. The index is calculated using health deficits collected during medical assessments [55], such as cognitive impairments, diseases, and physical disabilities to name a few. Likewise, Clinical Frailty Scale (CFS) [62, 42] was also developed to stratify elderly (aged ≥ 65) into 9 different classes, from very fit to terminally ill.

The relationship between biomarkers and frailty has been also tackled in the literature [6]. It is worth mentioning that inflammatory markers, like C-Reactive Protein and

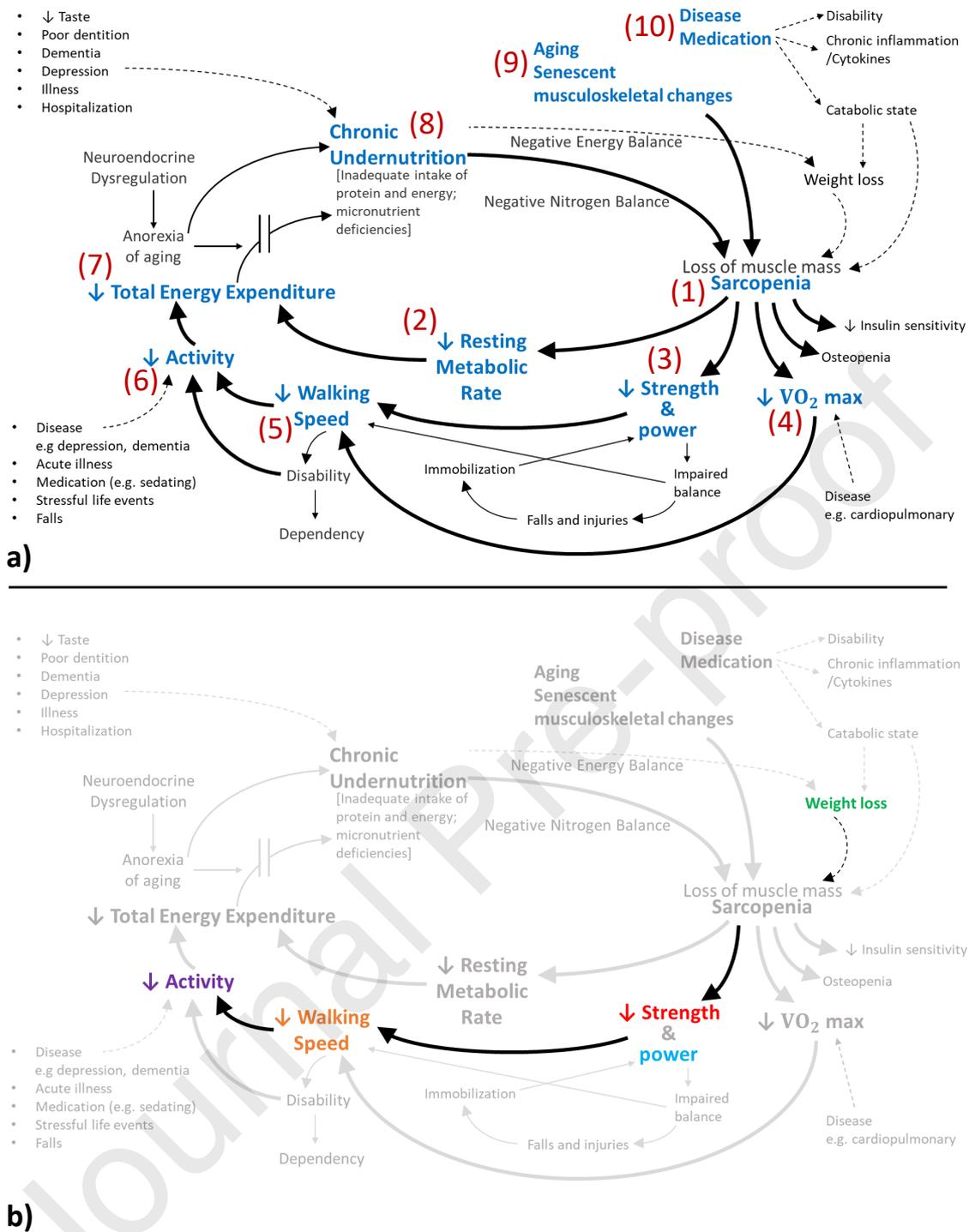


Figure 1: Frailty cycle ([24, 21]): (a) its simplified version in blue and (b) the frailty phenotype criteria.

Interleukin-6, which increase with age [18], have not been shown to be reliable predictors of transitions from robust to pre-frail then frail [58, 61]. Metabolic markers, particularly Glycated hemoglobin HbA_{1C} (a simple laboratory test), have been also subject to several studies. Very low HbA_{1C} levels have been linked to increased falls and mortality risk in frail individuals [5, 48]. Nevertheless, its capacity to detect the transition between the three frailty classes is yet to be

proven. Meanwhile, hormonal changes, such as Vitamin D and testosterone, occur as the human body ages, leading to physiological impairment. Although Vitamin D deficiency has been associated with increased rates of frailty [29, 7], its quantification into a specific diagnostic metric is challenging and complicated due to its highly variable normal range among seasons, racial groups, and geographical regions. Moreover, there are some doubts on testosterone being used

Table 1

Summary of clinical tools and tests in the context of frailty and well-being assessment

Category	Name	Authors and Reference	Year
Frailty status	Frailty Phenotype (FP)	Fried <i>et al.</i> [24]	2001
	Frailty Index (FI)	Rockwood <i>et al.</i> [63]	2005
	Clinical Frailty Scale (CFS)	Rockwood <i>et al.</i> [62]	2007
Biomarkers	Inflammatory markers	Puts <i>et al.</i> [58]	2005
		Reiner <i>et al.</i> [61]	2009
	Metabolic markers	Abdelhafiz <i>et al.</i> [5]	2015
		Nelson <i>et al.</i> [48]	2007
	Hormonal changes	Hirani <i>et al.</i> [29]	2013
Carcaillon <i>et al.</i> [11]	2012		
Performance tests	Short Physical Performance Battery (SPPB)	Guralnik <i>et al.</i> [25]	1994
	Timed Up and Go (TUG)	Podsiadlo <i>et al.</i> [57]	1991
	Dynamic Gait Index (DGI)	Shumway-Cook <i>et al.</i> [70]	1995

as a screening tool for frailty, seeing that a small amount of evidence exists to suggest a correlation between this hormonal change and the frailty trajectory [32, 11]. These diagnostic tools are not directly connected with biological changes of frailty, and thus might not be able to predict the frailty status [6].

Furthermore, some performance tests were proposed to evaluate the health conditions and mobility of elderly. The Short Physical Performance Battery (SPPB) [25], which is a mixture of three tests, was proposed to evaluate the muscle strength, balance, and mobility. We start by a balance test, where the older adult must be able to stand unassisted, without the use of a cane or walker, following three positions, namely side-by-side, semi-tandem, and tandem [25]. Next, a gait speed test is done, where the participant has to perform a 4-meter walk with his usual pace (two attempts are possible). Finally, a chair stand test is done where the senior has to stand up then sit down for five times as quickly as he can, while keeping his arms folded across the chest. The subject gets a score for each test depending on his performances and the final score is the sum of these three scores. The higher the final score, the healthier the subject is. The Timed Up and Go (TUG) is another screening tool used to test the mobility abilities of frail elderly patients over 60 years old [57]. The TUG is a physical performance test assessing the ability to perform sequential motor tasks related to walking and turning abilities [46]. Hence, it evaluates mobility, balance, and locomotive performance in older adults. Additionally, the Dynamic Gait Index (DGI) was also proposed as a test for pre-frail and frail people who are at risk of falling [70]. It evaluates the ability to maintain balance during walking periods while responding to external task demands (under a variety of dynamic conditions), including eight items such as changing speeds, stepping over and around obstacles, and stair ascent and descent. It is worth mentioning that a 4-item DGI was also proposed as a short form of a clinical measurement [38].

3.2. Data-driven and observational studies

In this sub-section, we focus on a second way to investigate frailty. Expressly, we discuss studies based on the interpretation of some databases, as well as wearable sensors and other technologies. Table 2 summarizes the main recent analyses, with the corresponding authors, references, and the publication year.

Firstly, statistical studies and data science were considered to extract knowledge and insights from collected data in order to examine the correlation/relationship between physical weakness and well-being/frailty status. The sedentary behavior and physical activity level, which were assessed using the International Physical Activity Questionnaire (IPAQ), have been linked to frailty in elderly, using chi-square and Poisson regression tests with a statistical significance of 5% [71]. By the same token, hourly activity data from wrist accelerometry measurement were analyzed to determine the relation between frailty and activity among older adults, using mixed-effects linear regression, to model the logarithm of hourly counts per minute [31]. Moreover, two predictive models were proposed, namely frailty risk model and worsening risk model, by exploiting socioclinical databases [10]. The former stratifies subjects older than 65 years old into five classes (non-frail, pre-frail 1, pre-frail 2, pre-frail 3, frail), *i.e.* divides the pre-frail level into three sub-levels, using personal, health, and social data as inputs for logistic regression. The latter further classifies each subject, identified as non-frail by the first model, into two classes according to risk of becoming frail within the year (“not-at-risk” and “at-risk”). A classification tree was also designed to assist inexperienced raters in decision-making and routine scoring of the CFS [75]. It has been shown that the CFS classification tree achieved an intraclass correlation coefficient (ICC) of 0.833 when compared with the geriatricians’ CFS scoring, and 0.805 when compared with the clerk/resident scores. Meanwhile, another study suggested that daily patterns of accelerometer activity were good indicators to predict changes in sleep, cognition, and mortality of older men, particularly worsening of sleep,

Table 2

Summary of data-driven and observational studies in the context of frailty analysis

Authors and Reference	Year	Source of data	Findings
da Silva <i>et al.</i> [71]	2019	IPAQ	Activity < 150 min/wk & Sedentarity \geq 540 min/day: cut-off values for frailty screening
Bertini <i>et al.</i> [10]	2018	Socioclinical databases	Frailty risk model* & Worsening risk model [†] : prediction of frailty level and risk of becoming frail respectively
Theou <i>et al.</i> [75]	2021	CFS	Proposal of a classification tree for CFS routine scoring
Razjouyan <i>et al.</i> [59]	2018	Pendant sensor	Body posture, activity behavior, steps: three parameters statistically correlated with pre-frailty
Razjouyan <i>et al.</i> [60]	2020	Chest-worn sensor	Sleep, activity, percentage of walk, steps: correlated with physical worsening and cognitive impairment
Apega <i>et al.</i> [9]	2020	Inertial sensors	Stride, stance, cadence: most sensitive to distinguish robust subjects from others [‡]

* Output: five frailty levels

[†] Output: two classes ("not-at-risk" vs "at-risk")[‡] Outputs: pre-frail vs robust – frail vs robust

changes in cognition, and shorter survival [83]. Functional principal component analysis was used to inspect the aforementioned patterns over the course of 4–7 days. Likewise, frailty and time-varying comorbidities were revealed as important parameters for clinical decision making, by using temporal features and non-temporal data which feed a Deep Neural Network (DNN) to predict death within one year [69]. More importantly, the gait speed has been a trending topic in the past two decades. It was described as one of the strongest predictors of incident disability [54], as well as health-related outcomes of well-being [13]. This variable was also linked to survival in older adults [73]. Some other gait parameters were also discussed in the literature. Kressig *et al.* proposed a set of temporal and spatial features like cadence, stride length, stance, etc. to better understand the effect of frailty on the movements [35]. The gait variability, measured using computerized walkways, wireless sensors and reflective markers was also targeted, and it was associated with frailty in elderly [44, 27]. Additional variables like displacement and smoothness of the center of pressure trace were inspected [26].

More recently, wearable sensors were used to conduct observational studies, by tracking some activity-related parameters and investigating their relationship with frailty level. In [59], a necklace device was used to characterize the physical activity of older adults (\geq 60 years old) over 48 hours. Three parameters were statistically correlated with the frailty status, namely (i) the body posture (walking, sitting, standing), (ii) the activity behavior (sedentary, light, moderate-to-vigorous), and (iii) the steps, and their mixture achieved an Area Under Curve (AUC) of 0.88 for identifying pre-frail elderly. However, sleep parameters were not able to classify older adults into three frailty levels. This study was expanded to detect both physical worsening determined by FP and cognitive impairment determined by Mini-Mental State Examination with a sensor fixed on the chest [60].

The considered features, namely sleep parameters, physical activity behavior, percentage of walk, and step counts, were shown to be statistically significant for this application ($p < 0.05$). A decision tree classifier reached an AUC of 0.75. Gait parameters have been also considered when it comes to the identification of frailty levels [9]. Participants were recruited and instructed to walk a distance of 4 m at the self-selected usual pace, and variables like stride time, swing/stance phase, gait velocity, cadence (steps per minute), the score of DGI, TUG test (in s), and the double support time (in ms) were calculated using wireless sensors placed on the lower limb segments. Stride time, stance phase, and cadence were shown to be the most sensitive parameters to discriminate populations in pairs, *i.e.* separate frail or pre-frail individuals from robust, using multinomial logistic regression models and statistical significance (p values). Additionally, an evaluation of the reliability of wearable devices for assessing frailty in older home care clients has also been conducted [34]. Over a period of 9.43 (\pm 1.99) days, several variables including daily step count, sleep quality and quantity, and heart rate were estimated using data of participants over 55 years old. It was demonstrated that frail seniors walked less and slept longer. A logistic regression model fitted with number of steps, age, education level, and deep sleep time was able to distinguish frail people from non-frail with an AUC of 0.9.

4. Transition towards preventive systems

4.1. Current challenges and limitations

Despite the aforementioned efforts and approaches to detect and analyze the frailty syndrome in older adults, there are still a number of limitations and drawbacks that should be mentioned. On the one hand, FP criteria determine the pre-frailty and frailty states in clinical settings at a particular moment. Nevertheless, their effectiveness is limited when it comes to the prediction and identification of the progression from robust/pre-frail to frail. Moreover, and despite its

clinical usefulness in risk assessment, FI presents a major drawback. Instead of discerning between frailty and disability/comorbidity, it includes their associated deficits, making it hard to inspect the underlying factor of this syndrome. Both FP and FI are also sensitive to the conditions (like the emotional state of the subject for instance) under which they were done. Furthermore, the capability of questionnaires and performance tests (like IPAQ and SPPB) to monitor and recognize the frailty trajectory is questionable. These approaches are (i) based on some subjective and auto-declared measurements, thus might affect the analysis, and (ii) the measures are done in supervised conditions, *i.e.* the subject has to complete these questionnaires/tests with the assistance of a practitioner, which is in contradiction with the notion of prevention. These tests also provide short-term estimation of physical capacities at a single point in time. On the other hand, it was seen that there is a lack of robust biomarkers for frailty detection and worsening risk prediction. Despite being clinically plausible diagnostic tools, these markers and hormonal changes might fail to stratify elderly into different frailty states, *i.e.* discriminate frail/pre-frail from robust elderly people. Therefore, their relationships to the syndrome are not clear.

Diversely, some attempts were made to analyze this syndrome via data-driven researches and observational studies, by associating collected data and estimated parameters with frailty status and studying their correlations. Even though the importance of remote monitoring was demonstrated by these works, wider sets of variables are required, and researchers still need to consider which outcomes are mostly useful to quantify physical activity of elderly [40]. Additionally, frailty is a complicated syndrome which should be symbolized by an ensemble of heterogeneous parameters, thus the discrimination power of systems involving a combination of features should be evaluated instead of inspecting the correlation between the frailty status and one single metric. In the current state of knowledge, the main discriminatory features are not yet identified. Apart from that, most study cohorts include relatively young volunteers who are less than 65 years old [34, 59] and are based on clinical trials with a predefined protocol [12, 9]. Even in free-living conditions, a short-term evaluation (such as 24-48 h or some few days) is usually considered [64, 59, 60, 34]. The short-term monitoring and/or clinical trials may be insufficient to represent the overall activities of elderly in natural conditions, leading to biased results.

Furthermore, the human gait is a complex activity of daily routine and cannot be only restricted to the gait velocity under supervised conditions, despite its great importance. Although features like the stance and swing phases, the stride time, and the cadence may be good indicators to physical worsening, their association with categorical frailty classes is still unclear [68]. Further analysis is needed to define a robust module which is able to predict the transition between frailty classes using a set of descriptive gait indicators [52], without being limited to the statistical significance of these basic and redundant parameters. There is a lack of

predictive systems being able to extract features from acquired signals in unsupervised conditions, in order to assess the frailty trajectory of older adults and target preventive interventions.

Considering all the aforementioned points and remarks, frailty clearly remains an open research challenge and an active area to date. Some aspects still need clarification prior to proposing innovative preventive solutions, although frailty has been a hot topic in recent years. Fully automated telemonitoring systems are required for frailty early detection and prevention to avoid adverse outcomes and make people age healthily at home.

4.2. Fully automated monitoring systems

Several studies and works targeted sensors-based tracking systems that monitor the subject's movements and detect abnormal incidents automatically. As seen previously, frailty is considered as one of the main risk factors for falling in elderly [15, 62, 30, 24]. As a result, fall detection has been heavily targeted over the past decades [77, 74, 14] and is still an active research area [66, 84, 80]. Fall detectors are divided into ambient/external sensors (like cameras) and wearable sensors. The goal is to automatically detect the fall in order to inform authorized teams and/or family members, or provide immediate help/medical intervention. Note that, in addition to the emergency alerts, the geographical position of the elderly must be sent. Nonetheless, fall detection does not solve the problem of frailty since the older person may suffer serious injuries as hip or pelvic fractures, even after receiving medical assistance, resulting in loss of independence or disability. Moreover, falling frequently means that the subject is already vulnerable/frail. Hence, the goal should be a transition from curative systems to preventive systems, *i.e.* researchers should target fall prevention instead of fall detection, in order to avoid dramatic consequences and interrupt the progression towards frailty then disability later.

Activity tracking has also been a talking point in the past decade. Dubois *et al.* used depth cameras to analyze the displacement of elderly in real-time [16], by providing daily information on the senior's activity and his habits. Tsipouras *et al.* tested several machine learning classifiers to predict the frailty level of elderly using a set of Bluetooth beacons [79]. The daily in-house activities and room-to-room transitions and movements were analyzed by extracting a set of features including variables like the number of room transitions and slow/fast room transitions. Additionally, human activity recognition (HAR) has been targeted to identify the daily movements and body postures of older adults [53, 56, 3, 28]. The senior's motion and activities of daily living might reveal a certain routine in case of physical worsening. If most of published HAR studies are limited to the recognition of the performed activity over a sliding window, without going further in monitoring the evolution of the activity, we believe that activity tracking through fully automated systems is the solution to detect early signs of physical damage and thus to prevent frailty and its consequences. This justifies why our research team has been working on

this issue in the context of the ANR ACCORDS project [8] for a few years. A telemonitoring system based on wearable sensors is currently being developed, and is divided into two modules. The first one is dedicated to activity identification in real-time. This module makes a prediction every second by analyzing acquired signals over sliding windows with overlapping. Two techniques have been proposed, either (i) a complex architecture based on feature fusion, where the input consists of three sensors, namely an accelerometer, a gyroscope and a magnetometer [4], or (ii) a multinomial decomposition algorithm [1] which is a low complexity method that exploits local temporal characteristics, and is based solely on acceleration. Once identified and located, the activities, represented by acquired signals, are analyzed by the second module to assess the physical condition of the elderly subject. The human gait can be characterized by extracting features during walking periods [2]. Other parameters like inactivity periods, the number of steps, and the intensity of movements can also be calculated thanks to the list of predictions provided by the first module of human activity recognition. Such system accompanies the older individual during his daily routine. Hence, it appears as a relevant and robust tool to detect the transition from one frailty state to another, where a medical intervention can be needed to prevent adverse outcomes. A longitudinal study is currently being conducted under unsupervised conditions during the daily life of elderly people in order to validate the effectiveness of this solution.

5. Discussion

Based on the literature and the different elements of this paper, we propose some future research directions and suggestions to further understand the physical weakening phase and detect its early signs, in order to prevent frailty or at least slow down its process. Firstly, a long follow-up of elderly people in their daily routine and a longitudinal study give us the opportunity to assess frailty trajectories of the participants and see how activity metrics change over time. For instance, we have seen that the cadence of the person's gait decreases when the subject becomes frail. Nonetheless, we still do not know whether this feature decreases linearly, exponentially or in another way, during the transition towards frailty. This finding might increase the ability to predict future physical worsening over different time scales (unlike the current trend where the goal is to detect the current frailty status), consisting in a second research direction. In other words, predicting future physical worsening based on (i) the current physical state or (ii) the difference between the current and past states should be the next goal of research studies. Moreover, it is worth noting that some researches have considered text analysis in frailty detection [20]. The older adults' typed texts have been investigated, starting by an automatic extraction of 160 distinct features from texts, followed by a feature selection process where the initial features have been ranked using Pearson's correlation coefficient technique. The participants were then classified into three frailty levels with an average accuracy

of 64%. This axis should be further investigated using robust techniques since the psycho-cognitive health might have an important weight in the evaluation of frailty conditions. In other words, a Natural Language Processing (NLP) module can be developed to analyze the speech of elderly and their responses to certain questions. The frailty cycle (Figure 1) includes cognitive impairment, depression and dementia. It is worth mentioning that cognitive, behavioral, social and psychological states can be very useful in extracting indicators of frailty. All these aforementioned factors are acquired by asking questions and collecting answers as texts. In this context, the role of NLP is huge: it is essential to analyze these texts and to extract some patterns and useful indicators of frailty. As a matter of fact, the exhaustion for example, which is one of FP criteria, cannot be estimated by an accelerometer. A transformer-based machine learning technique like BERT (developed by Google) could be used in this context by applying some fine-tuning techniques. In other words, a pre-trained BERT model (on another large dataset) could be used to further train it on a relatively smaller dataset consisting of the speech of older adults. In this way, the weights of the initial layers of the model are kept frozen while only the upper layers are re-trained. Thus, the old subjects can be classified into several sub-populations based on their frailty status. Finally, a multimodal system, combining different types of data (physical activity measured by sensors, clinical data like weight and heart rate, elderly's speech represented by texts), should be targeted for an accurate early detection and efficient preventive system.

6. Conclusion

Frailty is a clinical syndrome leading to physiological degradation and adverse health consequences, such as increased falls, lack of independence, hospitalization and death. It might be reversible or attenuated by medical interventions, hence the need for preventive systems. This paper presented a review regarding the analysis of this geriatric syndrome. It first described this illness from a medical point of view, then discussed diagnostic tools and tests done in clinical settings, before presenting some data-driven and observational studies which tried to associate collected data with frailty status and physical capacities. Nevertheless, it is clear from the literature that there are a number of limitations. As a result, there is a recognized need to develop strategies to meet the challenge of detecting and preventing frailty, an actual world health organization priority. This proves the importance of fully automated monitoring systems which was highlighted in this work and justifying new investigations.

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Author responsibilities, integrity, ethics



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