Wearable Body Sensors

Subjects: Physics, Applied

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The use of wearable body sensors for health monitoring is a quickly growing field with the potential of offering a reliable means for clinical and remote health management. This includes both real-time monitoring and health trend monitoring with the aim to detect/predict health deterioration and also to act as a prevention tool. The aim of this systematic review was to provide a qualitative synthesis of studies using wearable body sensors for health monitoring. The synthesis and analysis have pointed out a number of shortcomings in prior research. Major shortcomings are demonstrated by the majority of the studies adopting an observational research design, too small sample sizes, poorly presented, and/or non-representative participant demographics (i.e., age, gender, patient/healthy). These aspects need to be considered in future research work.

Keywords: health monitoring ; IoT ; physical activity monitoring ; qualitative synthesis ; remote health management ; research shortcomings ; sensor systems ; user demography ; wearable body sensors

1. Introduction

The use of wearable body sensors for health monitoring as a means for supporting clinical and remote health monitoring in real-time and to provide health trend monitoring with the aim to predict/prevent health deterioration has the potential to lower the burden on the healthcare system and thereby reduce healthcare costs. The number of available wearable and wireless body sensors and systems are rapidly growing. Simultaneously, research on more energy-efficient and more accessible/smaller sensors for acquiring data as well as research on automatic data analysis of the Big Data, which the sensor-based systems are expected to generate, is being conducted. This advanced data analysis has the potential of generating personalized diagnoses and providing recommendations on treatments at a personalized level. While a promising area, we argue that the data collected for generating advanced data analysis algorithms need to come from participants representing the expected users of these systems.

This systematic review provides a qualitative synthesis of the articles retrieved on using wearable body sensors for health monitoring. We analyze the articles from many perspectives including author affiliations in countries, publication years, context of use, sensor category, research methodology, sample sizes, and participant demographics (i.e., age, gender, patient/healthy). This analysis has identified a number of shortcomings in prior research with respect to both sample size, but also to participant demographics where the latter strongly affects the validity of the results. These shortcomings need to be considered in future research, not only for understanding the user experience, but also to ensure that the advanced data analysis algorithms can reason on data which are representative and valid for the expected users of the systems.

2. Qualitative Synthesis

Inspired by Kekade et al.'s review from 2018 [[1]], we conducted a qualitative synthesis of the 73 included research articles. They were published between 2010 and 2019, i.e., spanning approx. 9.5 years, among which one article was published in 2010, two in 2011, seven in 2012, two in 2013, seven in 2014, twelve in 2015, nine in 2016, fourteen in 2017, fourteen in 2018 and five before April 24th 2019, see Figure 1. In average, 7.6 articles were published per year during the period 2010–2018. The authors of the 73 research articles were affiliated in 32 countries representing six continents (Africa, Asia, Australia, Europe, North America and South America). See Figure 2 and Figure 3 for further information on which countries authors are affiliated in and the number of publications per country with affiliated authors. The articles were sorted into the following article categories: Asthma/COPD, Cardiovascular diseases, Diabetes and nutrition, Gait and fall, Neurological diseases, Physical activity recognition, Rehabilitation, and Stress and sleep. All articles not directly related to any of the aforementioned article categories were sorted into an article category named Additional. Figure 4 depicts the category-wise distribution of the selected articles. Studying the distribution of articles related to health and physical activity monitoring respectively, it can be seen that 47 % of the articles were related to health (Asthma/COPD, Cardiovascular diseases, Diabetes and Nutrition, Neurological diseases, and Stress and sleep). As much as 39 % of the articles were related to physical activity monitoring (Gait and fall, Physical activity recognition, and Rehabilitation). It is unclear why such a large portion of the articles were related to physical activity monitoring. Possible reasons include that it is easier to monitor physical activity using sensors whereas measures relating to health, e.g., vital signs, need to be provided in a more timely manner.

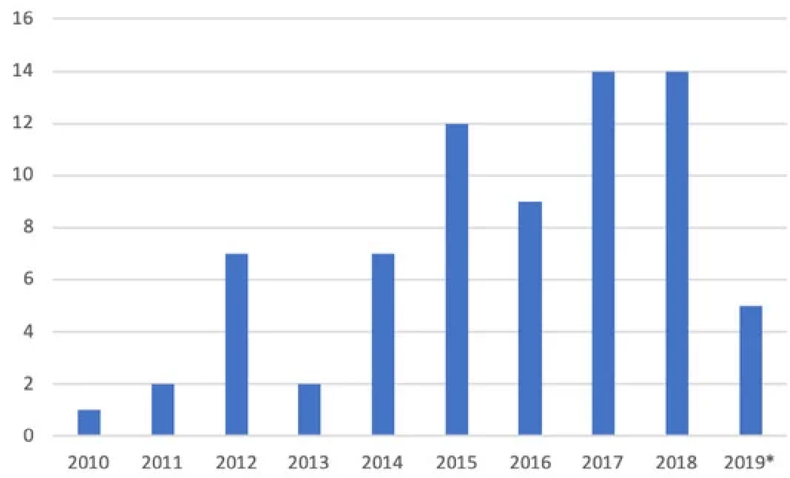

Figure 1. Number of articles per year. * only the articles published prior to 24 April 2019 are counted.

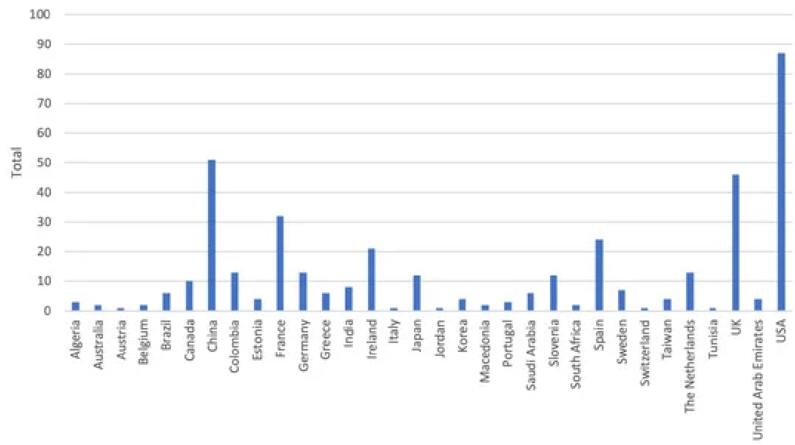

Figure 2. Number of authors affiliated in each country. Authors are calculated for each article, i.e., an author may be calculated more than once and in more than one country.

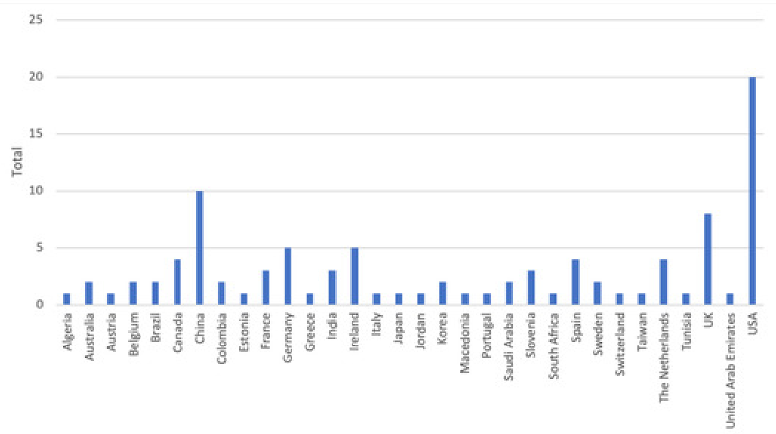

Figure 3. Number of articles per country. Papers with several authors may be counted for several countries.

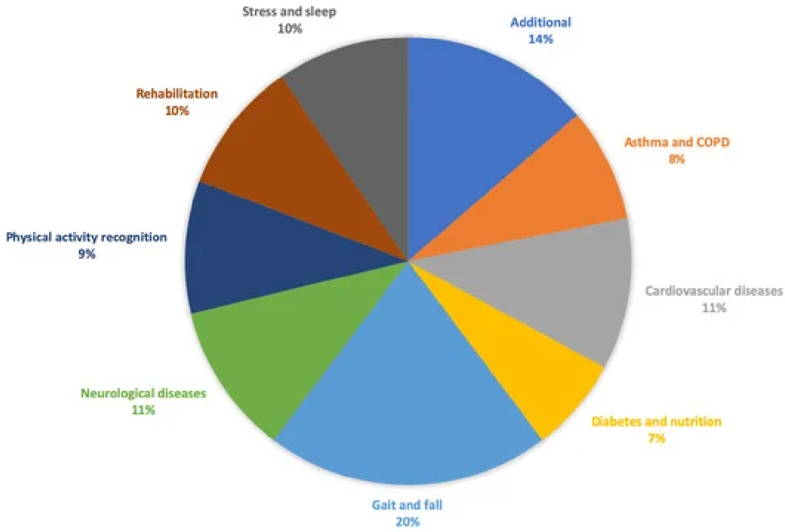

Figure 4. Category-wise distribution of the selected articles. Number of articles for Additional = 10, Asthma/COPD = 6, Cardiovascular diseases = 8, Diabetes and nutrition = 5, Gait and fall = 15, Neurological diseases = 8, Physical activity recognition = 7, Rehabilitation = 7, Stress and sleep = 7.

Sixty research articles reported on studies conducted with people at some level, these are reported in Table 1. We categorized the sensors according to the sensor categories used in [1], namely, physical activity, vital signs, electrocardiography (ECG) and other. Studies reporting on devices measuring movement or activity were classified under the sensor category physical activity. Vital signs include the parameters: blood pressure (BP), body temperature (BT), respiratory rate (RR), heart rate (HR)/pulse, and peripheral oxygen saturation (SpO_2). Studies measuring ECG were classified under ECG. Finally, studies using sensors for diabetes, swallowing, etc., or a combination of sensors from several sensor categories were classified under the sensor category other. The sensor categories physical activity and other include 23 studies each, vital signs includes three studies, and ECG includes ten studies reported upon in seven research articles.

Table 1. List of articles reporting on conducted studies. —indicates that information is missing.

Author, Year	Ref.	Article Category	Research Design	No. of Participants	Sensor Category
Bonnevie et al. 2019	[[2]]	Asthma/COPD	Observational	104 5	Vital signs
Caulfield et al. 2014	[[3]]	Asthma/COPD	Observational	10	Physical activity
Estrada et al. 2016	[[4]]	Asthma/COPD	Observational	1	Other
Katsaras et al. 2011	[[5]]	Asthma/COPD	Randomized control	48	Other
Naranjo-Hernández et al. 2018	[6]	Asthma/COPD	Observational	2 9	Vital signs
Huang et al. 2014a	[7]	Cardiovascular diseases	-	225	ECG

Author, Year	Ref.	Article Category	Research Design	No. of Participants	Sensor Category
Huang et al. 2014b	[[8]]	Cardiovascular diseases	Case-control	84	ECG
Javaid et al. 2018	[9]	Cardiovascular diseases	Observational	60	Other
Li et al. 2019	[[10]]	Cardiovascular diseases	Observational	16	Other
Raad et al. 2015	[11]	Cardiovascular diseases	-	30	ECG
			-	2	
Simjanoska et al. 2018	[[12]]	Cardiovascular diseases	Observational	16	ECG
				3	
				25	
				7	Dataset ECG
Susič and Stanič 2016	[13]	Cardiovascular diseases	-	13	ECG
Al-Taee et al. 2015	[[14]]	Diabetes and nutrition	-	22	Other
Alshurafa et al. 2014 and Alshurafa et al. 2015	[[15] [16]]	Diabetes and nutrition	Observational	10	Other
				20	
Dong and Biswas 2017	[17]	Diabetes and nutrition	Observational	14	Other
Onoue et al. 2017	[18]	Diabetes and nutrition	Randomized control	101	Physical activity
Atallah 2012	[19]	Gait and fall	Observational	34	Physical activity
Godfrey et al. 2014	[20]	Gait and fall	Observational	24	Physical activity

Author, Year	Ref.	Article Category	Research Design	No. of Participants	Sensor Category
Lee et al. 2015	[[21]]	Gait and fall	Observational	11	Physical activity
Liang et al. 2012	[22]	Gait and fall	Observational	8	Physical activity
Liang et al. 2018	[23]	Gait and fall	Observational	18	Physical activity
Paiman et al. 2016	[[24]]	Gait and fall	Observational	2	Other
Tino et al. 2011	[[25]]	Gait and fall	Observational	3	Other
Williams et al. 2015	[26]	Gait and fall	Observational	5–6	Physical activity
Wu et al. 2013	[27]	Gait and fall	Observational	7	Physical activity
Wu et al. 2019	[[28]]	Gait and fall	Observational	15	Physical activity
Zhao et al. 2012	[29]	Gait and fall	Observational	8	Physical activity
Zhong et al. 2019	[30]	Gait and fall	Observational	56	Physical activity
Giuberti et al. 2015	[31]	Neurological diseases	Observational	24	Physical activity
Gong et al. 2015, Gong et al. 2016	[[32] [33]]	Neurological diseases	Case-control	41	Physical activity
Kuusik et al. 2018	[34]	Neurological diseases	Observational	51	Physical activity
Sok et al. 2018	[[35]]	Neurological diseases	Observational	13	Physical activity
Stamate et al. 2017 and Stamate et al. 2018	[[36] [37]]	Neurological diseases	Observational	12	Other
Castro et al. 2017 and Rodriguez et al. 2017	[[38] [39]]	Physical activity recognition	Observational	3	Other

Author, Year	Ref.	Article Category	Research Design	No. of Participants	Sensor Category
Doron et al. 2013	[40]	Physical activity recognition	Observational	65	Other
				20	
Rednic et al. 2012	[41]	Physical activity recognition	Observational	17	Physical activity
Xu et al. 2014	[42]	Physical activity recognition	Observational	14	Other
Xu et al. 2016	[43]	Physical activity recognition	Observational	4	Other
				3	Physical activity
				5	
				6	
Argent et al. 2019	[[44]]	Rehabilitation	Observational	15	Physical activity
Banos et al. 2015	[[45]]	Rehabilitation	Observational	10	Other
Lee et al. 2018	[46]	Rehabilitation	Case-control	30	Physical activity
Timmermans et al. 2010	[47]	Rehabilitation	Observational	9	Physical activity
Whelan et al. 2017	[48]	Rehabilitation	Observational	55	Physical activity
Xu et al. 2017	[[49]]	Rehabilitation	Observational	6	Other
Lin et al. 2012	[[50]]	Stress and sleep	Case-control	18 (6/12)	Physical activity
Nakamura et al. 2017	[[51]]	Stress and sleep	Observational	4	Other
Parnandi and Gutierrez-Osuna 2017	[52]	Stress and sleep	Randomized control	25	Other
Uday et al. 2018	[53]	Stress and sleep	Observational	10	Other

Author, Year	Ref.	Article Category	Research Design	No. of Participants	Sensor Category
Umemura et al. 2017	[[54]]	Stress and sleep	Case-control	54	Other
Velicu et al. 2016	[55]	Stress and sleep	Observational	-	-
Ayzenberg and Picard 2014	[56]	Additional	Crossover	10	Other
Pagán et al. 2016	[[57]]	Additional	Observational	2	Other
Rawasdeh et al. 2017	[58]	Additional	Observational	55	ECG
Seeger et al. 2012	[59]	Additional	-	-	Other
Wannenburg and Malekian 2015	[60]	Additional	Observational	4–8	Vital signs
Wu et al. 2018	[61]	Additional	Observational	20	ECG

Similarly to Kekade et al. 2018 [1], we also assessed the studies' reporting of research design (Table 1), and the reported participant demography, i.e., number of participants, age, gender and the distribution of healthy participants and patients (Table 2). Many studies presented the participant demographics poorly, or not at all [10][27][38][39][40][42][43][55][59][60]. Rather than excluding these from the tables, we indicate missing information with a "-". However, we question the fact that all these studies were accepted for publication without providing any information on the participants.

Table 2. Demographic information on conducted studies. - indicates that information is missing.

Ref.	Article Category	No. of Participants	Age Group	Age Statistics	Male	Female	Patient	Healthy
[2]	Asthma/COPD	104	57–70	64	67 (64%)	37 (36%)	104	
		5	50–66	62	-	-	5	
[62]	Asthma/COPD	10		61.5 ± 5.7	5	5	10	
[[4]]	Asthma/COPD	1	-	-	1			1
[5]	Asthma/COPD	48	-	-	48		48	
[[6]]	Asthma/COPD	2	36 and 42		2			2
		9	55–76	64±6.6	6	3	9	2
[[7]]	Cardiovascular diseases	225	-	-	-	-	225	-

Ref.	Article Category	No. of Participants	Age Group	Age Statistics	Male	Female	Patient	Healthy
[[8]]	Cardiovascular diseases	84	-	-	-	-	1 group	1 group
[[9]]	Cardiovascular diseases	60	-	26.9±6.1	28	32	-	60
[[10]]	Cardiovascular diseases	16	-	-	-	-	-	-
[[11]]	Cardiovascular diseases	30	20–23	-	-	-	-	-
		2	-	-	-	-	2	-
[[12]]	Cardiovascular diseases	16	16–72	-	-	-	-	-
		3	25–27	-	-	-	-	-
		25	20–73	-	-	-	14	11
		7	20–74	-	-	-	-	7
[[13]]	Cardiovascular diseases	13	-	50.6±9	8	5	-	13
[[14]]	Diabetes and nutrition	22	-	-	-	-	22	-
[[15], [16]]	Diabetes and nutrition	10	20–40	-	8	2	-	-
		20	20–40	-	12	8	-	-
[[17]]	Diabetes and nutrition	14	-		9	5	-	14
[[18]]	Diabetes and nutrition	101		57.1±12.5	56	45	101	-
[[19]]	Gait and fall	34	-	28.22±12.77	21	13	-	34
[[20]]	Gait and fall	24 (12/12)	20–40	32.5±4.8	7	5	-	12
	Gait and fall	-	-	65.0±8.8	5	7	-	12
[[21]]	Gait and fall	11	-	27.6±4.3	11	-	-	11
[[22]]	Gait and fall	8	-	23±3.45	8	-	-	8

Ref.	Article Category	No. of Participants	Age Group	Age Statistics	Male	Female	Patient	Healthy
[[23]]	Gait and fall	18	-	25±3.24	12	6	-	18
[[24]]	Gait and fall	2	28 and 24	-	1	1	-	2
[[25]]	Gait and fall	3	40–70	-	-	-	-	-
[[26]]	Gait and fall	5–6 (1/5)	27	-	1	-	-	-
		-	21–36	27	4	1	-	-
[[27]]	Gait and fall	7	-	-	-	-	-	-
[[28]]	Gait and fall	15	20–27	-	-	-	-	15
[[29]]	Gait and fall	8	-	28.5±4.3	-	-	-	8
[[30]]	Gait and fall	56 (28/28)	-	24.6±2.7	14	14	-	28
		-	>55	66.1±5.0	18	10	-	28
[[31]]	Neurological diseases	24	31–79	65.9±12.3	17	7	24	-
[[32], [33]]	Neurological diseases	41 (28/13)	-	40.5±9.4	25%	25%	28	13
		-	-	39.3±10.3	47%	53%	-	-
[[34]]	Neurological diseases	51	-	-	-	-	51	-
[[35]]	Neurological diseases	13	22–50	-	9	4	13	-
[[36], [37]]	Neurological diseases	12	-	-	-	-	12	-
[[38], [39]]	Physical activity recognition	3	-	-	-	-	-	-
[[40]]	Physical activity recognition	65	-	-	-	-	-	-
		20	-	-	-	-	-	-
[[41]]	Physical activity recognition	17	-	-	10	7	-	-

Ref.	Article Category	No. of Participants	Age Group	Age Statistics	Male	Female	Patient	Healthy
[[42]]	Physical activity recognition	14	-	-	-	-	-	-
[[43]]	Physical activity recognition	4	-	-	-	-	-	-
		3	-	-	-	-	-	3
		5	-	-	-	-	5	-
		6	-	-	3	3	-	-
[[44]]	Rehabilitation	15	-	63±8.32	6	9	15	-
[[45]]	Rehabilitation	10	21–37	-	8	2	-	-
[[46]]	Rehabilitation	20	-	54.4±10.1	-	-	20	-
		10	-	53.8±11.4	-	-	-	10
[[47]]	Rehabilitation	9	-	60.7	5	4	9	-
[[48]]	Rehabilitation	55	-	24.21±5.25	37	18	-	55
[[49]]	Rehabilitation	6	-	72.5±6.0	3	3	-	-
[[50]]	Stress and sleep	18 (6/12)	19–22 overall	-	5	1	-	-
		-	-	-	11	1	-	-
[[51]]	Stress and sleep	4	25–36	-	4	-	-	4
[[52]]	Stress and sleep	25	19–33	-	15	10	-	-
[[53]]	Stress and sleep	10	-	-	-	-	-	10
[[54]]	Stress and sleep	54 (26/28)	-	22	-	-	-	54
		-	-	21	-	-	-	-
[[55]]	Stress and sleep	-	-	-	-	-	-	-
[[56]]	Additional	10	25–35	30.8±4.2	9	1	-	10

Ref.	Article Category	No. of Participants	Age Group	Age Statistics	Male	Female	Patient	Healthy
[[57]]	Additional	2	-	-	-	2	2	-
[[58]]	Additional	55	18–22	-	50%	50%	-	-
[[59]]	Additional	-	-	-	-	-	-	-
[[60]]	Additional	4–8 (4/4)	-	-	-	-	-	-
		-	-	-	-	-	-	-
[[61]]	Additional	20	-	-	-	-	-	-

For completeness, the remaining 13 articles not listed in Table 1 and Table 2 were distributed over eight article categories: Asthma/COPD [[63]], Cardiovascular diseases [64], Gait and fall [[65][66][67]], Neurological diseases [[68]], Physical activity recognition [[69]], Rehabilitation [[70]], Stress and sleep [[71]], and Additional [[72][73][74][75]]. Six articles report on systems where studies are upcoming [63][64][72][73][74][75]]. One of them [64] is a continuation of the study reported in [[13]]. Three articles report on studies using datasets [[66][67][69]. Two articles report on qualitative studies of observational and/or interview nature [68][70]. The continuation of the qualitative study [[70]] is reported upon in [[44]]. The evaluation in [65] is not clearly presented and the system developed in [71] uses wearable body sensors only to collect ground truth data for a contactless sleep monitoring system. Therefore, [71] was excluded from further qualitative analysis.

3. Discussion and Conclusions

In this systematic review, we provide a qualitative synthesis on retrieved articles on using wearable body sensors for health monitoring. The articles found were categorized as relating to: Asthma/COPD, Cardiovascular diseases, Diabetes and Nutrition, Gait and fall, Neurological diseases, Physical activity recognition, Rehabilitation, Stress and sleep, and Additional. Section 3 provided a qualitative synthesis of the studies with respect to research methodology and participant demography, i.e., number of participants, age, gender and the distribution of healthy participants and patients. Using this information, we have identified a number of shortcomings. Below follows a discussion on these shortcomings in relation to prior research.

There are many age-related health issues such as changing biological factors, the onset of illnesses which are often chronic and the decline of cognitive abilities. For example, "fall prediction is a challenging problem due to the combination of intrinsic and extrinsic fall risk factors that contribute to a fall. Intrinsic factors include age, fall history, mobility impairments, sleep disturbances, and neurological disorders", pp. 1 [76]. It is reported in [77] that 35% of non-institutionalized adults had abnormal gait and that sleep disturbances are very common among older people. Further, chronic conditions affect physical activity levels, and activities such as rising from a chair is demanding for older people [77]. It is clear that the whole motion pattern changes with age and the onset of illnesses related to the human locomotor system. Yet, the majority of the studies focusing on gait and fall in this review were simulations that include none or few old participants. This shortcoming is also discussed in [76], "It is evident that existing systems have mainly been tested in laboratory environments with controlled conditions and do not include frequent fallers and aging adults as test subjects.[.] future work should focus on longitudinal studies of fall detection and prediction systems in real-life conditions on a diverse group that includes frequent fallers, aging adults, and persons with neurological disorders." p.8 [76]. Not studying the sensor systems in real-life conditions affect the validity of the results since the performance is not studied in realistic conditions. The low number of studies with older people is also a shortcoming since age-related issues are not taken into consideration to a sufficient degree.

There are many differences between the two genders. As a first example, we want to mention the American Heart Association's (AHA) scientific statement from 2016 [[78]] on acute myocardial infarction (AMI) in women. "Sex differences occur in the pathophysiology and clinical presentation of MI and affect treatment delays.", p. 932 [78]. Further, AHA reports that the same perfusion therapies are recommended despite the fact that the risk of bleeding or other complications is higher among women. Further, women are being under-treated with guideline recommendations. This results in increased readmission, re-infarction, and death rates during the first year after a myocardial infarction. Cardiac rehabilitation is also underused and under-prescribed among women [78]. On the same lines, the results of a cohort study [[79]] with almost 5000 patients $\mu_{age} > 65$ who were admitted to 366 US hospitals in the period 2003–2009, has found that women are less likely to receive optimal care at discharge. Yet, only two of the studies retrieved within the category Cardiovascular diseases provide information on the participants' gender. This is not the only shortcoming for studies on Cardiovascular diseases however. Several studies, or sub-studies, were conducted with very large age spans without the provision of a mean age. Others were conducted with young people or lacks information on age. Further, several works report on studies with healthy participants.

Hence, studies taking both genders into consideration, but also the age factor, are highly desired in the category Cardiovascular diseases. Not including information on gender and/or not considering gender/sex during data collection is a shortcoming regardless of the category to which a study belongs. It is argued in [[80]] that there are areas were specific data on women is lacking while specific data on men is missing in other areas.

Regitz-Zagrosek [[80]] outlines a number of differences between men and women. These include: women more frequently having anemia, women suffering from coronary artery disease in average ten years later than men, a higher frequency of boys having asthma in young ages while the frequency changes to young adulthood, diabetes increasing the risk for coronary heart disease more among women, and osteoporosis being more frequent in women but under-diagnosed in men. Osteoporosis disease is characterized by a decreased bone mass density and a disrupted normal trabecular architecture reducing bone strength [81]. Therefore, Osteoporosis increases the risk of fractures after a fall but no symptoms of the disease are shown until a fracture occurs [[80]]. According to [81], there are several factors relating to Osteoporosis which increases the risk of falling. These include the fear of falling, which increases the risk of falling [[82][83]]. In addition, [[81]] reports on studies discussing women with osteoporosis or low bone mass where fear of falling is associated with more falls [84], and the confidence in balance is related to balance and mobility [85]. Further, [[84]] reports that an increased thoracic kyphosis is associated with recent falls among women with Osteopororosis. I.e., women with thoracic kyphosis were more likely to have had a recent fall. Thoracic kyphosis is an abnormal convex curvature of the spine at chest height which is much more common among older women than men due to estrogen losses [[86]]. All these works [[81][82][83][84][85]] date from 2004-2011, hence it is astonishing that some articles retrieved within the article category Gait and fall have not reported information on gender and that some other articles were conducted solely with men. Hence, we argue that future studies in the categories discussed in this article must take gender into consideration. This shortcoming was also highlighted in [1].

Undoubtedly, healthy participants and patients differ in many aspects. Yet, only 65% of the studies overall reported this information. A positive example here is the fact that the studies reported upon in the category Asthma/COPD were conducted almost entirely with patients. This indicates that the results in this area are reliable. On the contrary, none of the studies within Gait and fall, or Stress and sleep have reported that the studies were conducted with patients. Also [76][77]] have previously discussed the shortcoming of not conducting studies with patients in the category Gait and fall. Considering the research question for this review article, we question the fact that 35% of the retrieved articles lack information on whether the participants were healthy or patients. We argue that the use of healthy participants, or not providing this information, affect the validity of the study results. Future studies need to consider the inclusion of patients to a further extent.

Studying the sample size in the reported studies, 56% of the articles report on studies conducted with up to 20 participants, and only 20% of the articles report on studies conducted with 51 or more participants. The distribution of numbers vary between categories. The majority of the studies reported in the categories Asthma/COPD, Gait and fall, Physical activity recognition, Rehabilitation, and Stress and sleep were conducted with up to 20 participants. We find the overall low number of participants a shortcoming and recommend that future studies are conducted with larger study samples. However, taking demographic factors, i.e., age, gender and healthy/patient into consideration is highly needed prior to increasing the sample sizes in studies on health monitoring using wearable body sensors.

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