Gait & Posture 63 (2018) 124–138

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Review

# The use of wearable devices for walking and running gait analysis outside of the lab: A systematic review

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ARTICLE INFO

*Keywords:*
Wearable devices
Gait
Walking
Running

ABSTRACT

*Background:* Quantitative gait analysis is essential for evaluating walking and running patterns for markers of pathology, injury, or other gait characteristics. It is expected that the portability, affordability, and applicability of wearable devices to many different populations will have contributed advancements in understanding the real-world gait patterns of walkers and runners. Therefore, the purpose of this systematic review was to identify how wearable devices are being used for gait analysis in out-of-lab settings.

*Methods:* A systematic search was conducted in the following scientific databases: PubMed, Medline, CINAHL, EMBASE, and SportDiscus. Each of the included articles was assessed using a custom quality assessment. Information was extracted from each included article regarding the participants, protocol, sensor(s), and analysis.

*Results:* A total of 61 articles were reviewed: 47 involved gait analysis during walking, 13 involved gait analysis during running, and one involved both walking and running. Most studies performed adequately on measures of reporting, and external and internal validity, but did not provide a sufficient description of power. Small, unobtrusive wearable devices have been used in retrospective studies, producing unique measures of gait quality. Walking, but not running, studies have begun to use wearable devices for gait analysis among large numbers of participants in their natural environment.

*Conclusions:* Despite the advantages provided by the portability and accessibility of wearable devices, more studies monitoring gait over long periods of time, among large numbers of participants, and in natural walking and running environments are needed to analyze real-world gait patterns, and would facilitate prospective, subject-specific, and subgroup investigations. The development of wearables-specific metrics for gait analysis provide insights regarding the quality of gait that cannot be determined using traditional components of in-lab gait analyses. However, guidelines for the usability of wearable devices and the validity of wearables-based measurements of gait quality need to be established.

## 1. Introduction

Quantitative gait analysis is an important clinical tool for both walking and running, and is commonly used to assist diagnosis and treatment of gait abnormalities, inform surgical procedures, and evaluate treatment effects [1–4]. Basic spatiotemporal gait parameters (e.g. step and stride length, step and stride time, cadence, speed) can be computed with minimal equipment, while more advanced measurement techniques can be used to determine kinematic (e.g. joint angles, angular velocity) and kinetic (e.g. ground reaction force, joint moments, joint power) variables [2]. However, the gold standard for these advanced techniques requires expensive 3D motion capture and force plate equipment, and trained personnel are needed to collect and analyze the data in what is typically a time-consuming process [3]. This not only limits the accessibility to these advanced gait analysis systems to select clinical and research facilities, but gait analyses conducted in this manner do not necessarily capture how an individual walks or runs in a real-world setting [5].

Wearable devices, on the other hand, are portable and affordable [6]. As a top worldwide fitness trend to improve health [7], wearable devices have become integrated into the daily lives of consumers [8], including healthy individuals [9], older adults [10], and those with chronic illnesses [11]. Evidently, wearable devices represent an opportunity to quantify the movement patterns of all types of individuals

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https://doi.org/10.1016/j.gaitpost.2018.04.047
Received 13 October 2017; Received in revised form 20 March 2018; Accepted 28 April 2018

in real-world settings. Sensors such as accelerometers, gyroscopes, and magnetometers [12], applied individually or in combination as an inertial measurement unit [13], have become a common alternative to the expensive and strictly lab-based methods of quantifying gait patterns, and recent systematic reviews have been published describing this trend [12,13]. Yet, these reviews often focus on a particular population (e.g. older adults [14], Parkinson's disease [15,16]), or walking [17] or running [18] exclusively. Since gait analysis methods are not exclusive to one population or type of gait, the use of wearable devices in one situation may be applicable in others. Therefore, a review that encompasses both walking and running as well as studies of multiple populations can provide a comprehensive summary of the state of wearables-based gait analysis. Additionally, even though wearable devices are well-suited for gait analyses in real-world settings, previously published studies often used wearable devices in gait labs or during contrived experiments. These analyses may not represent typical walking or running conditions since previous research using wearable devices for gait analysis have shown differences in walking [19] and running [20] patterns between treadmill and overground surfaces, as well as between clinical and daily-life overground walking conditions [21].

In recent years, studies have explored the use of wearable technology to analyze out-of-lab walking and running gait patterns. It is expected that the portability, affordability, and applicability of wearable devices to many different populations will have contributed advancements in understanding the real-world gait patterns of walkers and runners. However, considering the many different protocols, devices, and environments featured in these investigations, it is important to summarize the existing literature and assess the quality of this body of work. Therefore, the purpose of this article was to provide a systematic review of studies that have utilized wearable devices for gait analysis in out-of-lab settings. Specifically, the review's aims were to identify the goals and outcomes of the studies, participants, gait analysis environment, wearable device characteristics, and the features extracted from the wearable device signals. Considering the differences between the capabilities of wearable devices and traditional gait analysis systems, the following findings were anticipated: (i) gait analyses would be performed during long walking and running bouts within a single session (e.g. all waking hours or a complete training run) and/or during the course of many sessions (e.g. a full week or an entire training program), which would facilitate prospective studies and the development of subject-specific models of gait patterns; (ii) studies would include large numbers of participants, which would facilitate the identification of subgroups of walking and running patterns; (iii) gait analyses would be performed in the participants' actual walking or running environment, and not just a controlled out-of-lab setting; (iv) wearable devices would be small, easy to use and unobtrusive, while containing the necessary hardware components for the desired gait analysis; (v) the features extracted from the wearable device signals would provide information regarding the quality – not just quantity – of gait, using variables unique to the wearable device gait analysis process.

## 2. Methods

### *2.1. Eligibility criteria*

The focus of this review was on journal articles or conference proceedings published in English since the year 2001 that described the use of wearable devices to assess gait quality during walking or running outside of a laboratory setting. Book chapters and review papers were excluded. Studies were excluded if their sole purpose was the determination of step counts or level of physical activity, classification or recognition of types of physical activity, biometric identification, quantification of pedestrian navigation, the testing of new techniques or systems related to wearable devices, or the use of wearables for any purpose other than gait analysis. Additionally, if the study protocol involved the use of robotic orthoses, exoskeletons, virtual reality environments, gait analysis during a clinical test (e.g. Timed Up and Go) or other prescribed mental or motor task (e.g. dual task or scripted task that mimics daily life), or gait analysis while walking or running on a treadmill or constrained (less than 200 m) walkway, then that portion of the study was not considered for this review.

### *2.2. Search strategy and study selection*

The review process was completed in four steps. First, potentially relevant records were identified through a systematic search for published papers in the following scientific databases: PubMed, Medline, CINAHL, EMBASE, and SportDiscus. The search terms used were *(wearable* OR inertial sensor* OR inertial measurement unit* OR gyroscope* OR magnetometer* OR acceleromet* OR cell phone OR smart phone*) AND (gait OR run* OR walk* OR jog* OR kinematic* OR biomechanic* OR acceleration* OR center of mass OR centre of mass OR center of gravity OR centre of gravity OR cadence OR step length OR step width OR step time OR stride length OR stride time OR stance phase OR swing phase OR stance time OR swing time OR single support OR double support OR ground contact OR gait speed OR walking speed OR running speed OR heel strike OR heel-strike OR toe off OR joint adj4 angle OR hip adj4 angle OR knee adj4 angle OR ankle adj4 angle)*, where '*' indicates that the search term can have any ending, and 'adj4' searches for both terms within four words of each other. The search of the databases was completed on May 24, 2017. In the second phase, the title and abstract of all records identified through database searching were screened for relevance. If the record appeared relevant or if relevance was not immediately clear, the full text of the article was retrieved. All records deemed irrelevant based on title and abstract screening were excluded. Third, the full text records were read, and eligibility was determined using the eligibility criteria defined above. In the fourth stage, relevant information was extracted from the records that were included, and the quality of each record was assessed. Additionally, the references of all included studies were checked for additional publications that could be included in this review. At all stages of the study selection process, decisions regarding inclusion or exclusion were made by two authors (LB and EB), with a third author (CC) serving as the tie-breaker.

### *2.3. Data extraction*

Information was extracted from each included article regarding the participants, protocol, sensor(s), and analysis. Participant information included number and type of participants, age, and sex. Information about the type, brand/model, size, weight, sampling frequency, range, and location on the body of each wearable sensor was also recorded. The study protocol included information about the environment (i.e. indoor or outdoor, type of surface, or location), as well as the speed and distance or time the gait analysis was conducted. If participants ambulated at a comfortable speed but were required to maintain that speed, the speed was labeled "self-selected." If participants were able to walk at their own pace without restriction, the speed was labeled "not controlled." Analysis information included a record of all variables computed from each wearable sensor signal.

### *2.4. Quality assessment*

The quality of each of the included articles was assessed using a custom quality assessment worksheet (Table 1). This worksheet was adapted from the methods of quality assessment outlined by Campos et al. [22] and Downs and Black [23]. Each article was evaluated by two authors (LB and CC) on 13 questions that considered the reporting, external validity, internal validity and power of the study. Each question had three possible answers: "Yes", "No", or "Unable to determine." Any discrepancies in scoring between authors were discussed until an agreement was reached. As this review represents a qualitative

**Table 1**
Quality assessment questions.

| Number | Question |
|---|---|
| Q1 | Is the hypothesis/aim/objective of the study clearly described? |
| Q2 | Are the main outcomes clearly described in the Introduction or Methods? |
| Q3 | Are the characteristics of the participants clearly described (including age, sex, and status as healthy/injured/pathological)? |
| Q4 | Are the inclusion/exclusion criteria described and appropriate? |
| Q5 | Are the main findings of the study clearly described? |
| Q6 | Are estimates of the random variability in the data for the main outcomes provided? |
| Q7 | Have actual probability values been reported for the main outcomes? |
| Q8 | Are the participants representative of the entire population from which they were recruited? |
| Q9 | Are the setting and conditions typical for the population represented by the participants? |
| Q10 | Are retrospective unplanned analyses avoided? |
| Q11 | Are the statistical tests used to assess the main outcomes appropriate? |
| Q12 | Are the main outcome measures used accurate (valid and reliable)? |
| Q13 | Is a sample size justification, power description, or variance and effect estimates provided? |

summary of wearables-based gait analysis outside of the lab, no total score was computed for the quality assessment, nor was the quality assessment used as an exclusion criterion.

## 3. Results

### 3.1. Search results

A total of 7448 articles were identified through the database search, and 36 additional articles were identified through a hand search of reference lists. Following the removal of duplicates, 3163 articles remained. Screening of the titles and abstracts led to the removal of 2902 articles, leaving 261 for full-text analysis (Fig. 1). A total of 61 articles met the inclusion criteria, of which 47 involved gait analysis during walking (Tables 2 and 4), 13 involved gait analysis during running (Tables 3 and 5), and one study examined both walking and running and is therefore included in Tables 2–5 [24].

### 3.2. Quality assessment

The results of the quality assessment are outlined in Tables 2 and 3 for the walking and running studies, respectively. All studies clearly described the aim, main outcomes and main findings. Nearly all studies also clearly described the participants and inclusion/exclusion criteria.

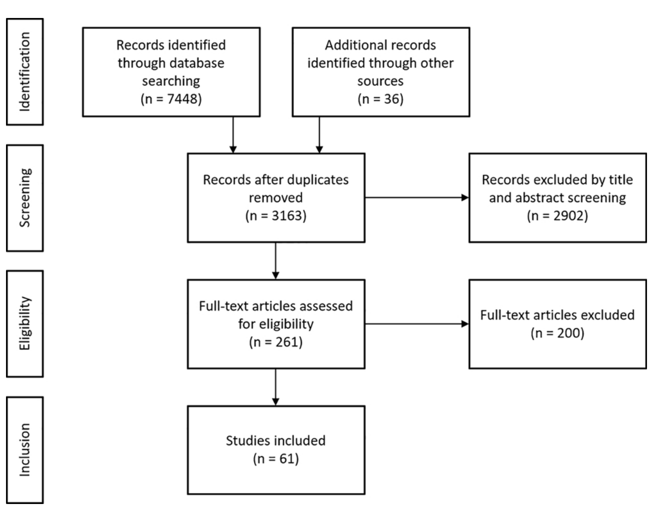


**Fig. 1.** Flow diagram for the search strategy.

Studies by Hogarth et al. [25] and Zhao et al. [26] did not meet these standards, but were published as abstracts. While the inclusion/exclusion criteria were not explicitly stated by Brodie et al. [27], the authors provided references to access this information. For the remaining questions related to the reporting of information, eight walking studies [24,28–34] and two running studies [24,35] did not provide estimates of the random variability in the data for the main outcomes, while 12 walking studies [24,26,32,36–44] and seven running studies [20,24,35,45–48] did not report actual probability values for the main outcomes. For an additional three walking studies [28,29,34], the reporting of probability values was marked "unable to determine" as reporting probability values was inappropriate for the analysis used in those studies.

The eighth and ninth questions in the quality assessment evaluate the external validity of the study. As indicated above, the abstracts by Hogarth et al. [25] and Zhao et al. [26] did not adequately describe the participants or inclusion/exclusion criteria, therefore, it could not be determined if the participants were representative of the population from which they were recruited. Among the running studies, the participants tended to be representative of the populations being studied. Nevertheless, a case study by Giandolini et al. [49] involved the world-leading trail runner, suggesting that he is only representative of extremely elite runners. For the external validity of the experiment procedure, it was expected that all studies included in this review would have settings and conditions that are typical for the population represented by the participants, considering that the purpose of this review was to examine how wearable devices are used for gait analysis outside of the lab. However, four studies involved knee osteoarthritis patients [50,51] and older adults [52,53] walking on an indoor track, a somewhat unlikely real-world setting for these specific populations. Also, the exact location of the gait analysis and the use of poles while walking for Parkinson's disease patients make it difficult to determine if the setting was appropriate for the population studied by Warlop et al. [33]. On the other hand, the tracks, paths, and trails in the running studies are common settings for runners.

Internal validity was evaluated based on retrospective unplanned analyses, appropriate statistical tests, and valid and reliable main outcome measures. It was not possible to determine the reliability or validity of the main outcome measures of principal component scores for the study by Rahimi et al. [29]. The appropriateness of the statistical test was unable to be determined for two studies that performed a qualitative analysis [28,34], two studies that did not clearly define which statistical tests were being performed [32,54], and one study that did not describe any statistical analyses [26]. Most studies did not provide sample size justification, power description, or variance and effect estimates. Only six walking studies [36,50–52,55,56] and three running studies [45,57,58] provided estimates of effect size for main outcomes.

### 3.3. Application of wearables in gait analysis

The purpose of the walking studies was to quantify walking patterns among a specified group and/or to compare the walking patterns of that group to a set of control participants. The primary groups of interest in the walking studies were healthy young adults [24,40,43,54,56,59–63], older adults [19,26,42,52,53,64,65], fallers [21,27,30,31,37,66–69], and individuals with various pathologies [25,28,29,32–34,36,38,39,41,44,50,51,55,70–77]. Studies examining the walking patterns of older adults revealed differences in variability, regularity, and symmetry between young and older adults [52,64]. Additionally, walking characteristics of older adults in their daily lives were compared to clinical measures, such as lower extremity strength and power, and treadmill-based gait analysis [19,65]. There were some conflicting results regarding differences in walking patterns between fallers and non-fallers. For example, Ihlen et al. [37] reported greater irregularity and complexity in trunk acceleration and velocity for fallers, and Rispens et al. [30] also

**Table 2**
Quality assessment of walking studies organized by primary type of participants.

| | Author [Ref.] | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | Q11 | Q12 | Q13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Healthy Young Adults | Fasel et al. [43] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Khandelwal et al. [24][a] | Y | Y | N | Y | Y | N | N | Y | Y | Y | Y | Y | N |
| | Schimpl et al. [59] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Schutz et al. [60] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Storm et al. [40] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Terrier et al. [56] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| | Tudor-Locke et al. [54] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | U | Y | N |
| | Tudor-Locke et al. [61] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | van Schooten et al. [62] | Y | Y | N | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | van Schooten et al. [63] | Y | Y | N | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| Older Adults | Kang et al. [64] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Kobsar et al. [52] | Y | Y | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y |
| | Kobsar et al. [53] | Y | Y | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | N |
| | Puthoff et al. [65] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Rispens et al. [19] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Tudor-Locke et al. [42] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Zhao et al. [26] | Y | Y | N | N | Y | Y | N | U | Y | Y | U | Y | N |
| Fallers | Brodie et al. [21] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Brodie et al. [27] | Y | Y | Y | N | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Brodie et al. [66] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Ihlen et al. [67] | Y | Y | N | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Ihlen et al. [37] | Y | Y | N | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Pozaic et al. [68] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Rispens et al. [30] | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | Y | N |
| | Rispens et al. [31] | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | Y | N |
| | Weiss et al. [69] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| Injured/Pathological | Barden et al. [50] | Y | Y | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y |
| | Clermont et al. [51] | Y | Y | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y |
| | Kanade et al. [38] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Lamoth et al. [55] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| | Prajapati et al. [72] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Punt et al. [76] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Sanchez et al. [73] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Sosnoff et al. [39] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Andrzejewski et al. [36] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | Y |
| | Hogarth et al. [25] | Y | Y | N | N | Y | Y | Y | N | Y | Y | Y | Y | N |
| | Del Din et al. [70] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Moore et al. [28] | Y | Y | Y | Y | Y | N | U | Y | Y | Y | U | Y | N |
| | Rahimi et al. [29] | Y | Y | Y | Y | Y | N | U | Y | Y | Y | Y | U | N |
| | Terashi et al. [41] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Terashi et al. [44] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Terashi et al. [74] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Utsumi et al. [32] | Y | Y | Y | Y | Y | N | N | Y | Y | Y | U | Y | N |
| | Warlop et al. [33] | Y | Y | N | Y | Y | N | Y | Y | U | Y | Y | Y | N |
| | Weiss et al. [71] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Weiss et al. [77] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Weiss et al. [34] | Y | Y | Y | Y | Y | N | U | Y | Y | Y | U | Y | N |
| | Yoneyama et al. [75] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |

*Note*: Y = Yes, N = No, U = Unable to determine.
[a] Study involved both walking and running and is included in both Tables 2 and 3.

**Table 3**
Quality assessment of running studies organized by primary type of participants.

| | Author [Ref.] | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | Q11 | Q12 | Q13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Injured | Gilgen-Amman et al. [57] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| | Luedke et al. [58] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| | Meardon et al. [78] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| Recreational athlete | Bigelow et al. [79] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Friesenbichler et al. [46] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Khandelwal et al. [24][a] | Y | Y | Y | Y | Y | N | N | Y | Y | Y | Y | Y | N |
| | Norris et al. [81] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| All | de Ruiter et al. [45] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | Y |
| | Strohrmann et al. [35] | Y | Y | Y | Y | Y | N | N | Y | Y | Y | Y | Y | N |
| Experienced runner | Garcia-Perez et al. [20] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Giandolini et al. [80] | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | N |
| | Giandolini et al. [49] | Y | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | N |
| | Le Bris et al. [47] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |
| | Reenalda et al. [48] | Y | Y | Y | Y | Y | Y | N | Y | Y | Y | Y | Y | N |

*Note*: Y = Yes, N = No.
[a] Study involved both walking and running and is included in both Tables 2 and 3.

**Table 4**
List of the walking studies and the data extracted from each article. Values are in the format mean (SD) unless otherwise noted.

| Ref. | Participants | | | Protocol | | |
|---|---|---|---|---|---|---|
| | Number and Type | Age [years] | Sex | Environment | Speed | Distance/Time (analyzed) |
| [43] | Healthy: 29 | 39.1 (10.8) | 7F, 22M | Outdoor | Not controlled | 4.7 km |
| [24][a] | Healthy: 9[b] | ND | ND | Outdoor, Street | Self-selected | 3 min |
| [59] | Adults: 303 | 49.9 (17.0) | 205F, 98M | Indoor/Outdoor, Home/ Community | Not controlled | ≥6 h/day (7 days) |
| [60] | Adults: 6 | 25.8 (1.7) | 0F, 6M | Outdoor, Course (720 m) | Various, Self-selected | 720 m |
| [40] | Healthy: 10 | 28 (3) | 3F, 7M | Outdoor, Footpath | Not controlled | 15 min |
| [56] | Healthy: 20 | 35 (7) | 0F, 20M | Indoor, Course (800 m) | Self-selected | 10 min |
| [54] | Adults: 3522 | ≥20 | 1742F, 1780M | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [61] | Adults: 3744 | ≥20 | 1963F, 1781M | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [62] | Young adults: 20 | 28.5 (3.3) | ND | Outdoor, Footpath | Self-selected | 2 bouts of 500 m (mid 200 strides), 2 separate days |
| [63] | Young adults: 20 | 28.5 (3.3) | ND | Outdoor, Footpath | Self-selected | 2 bouts of 500 m (mid 200 strides) |
| [64] | < 60: 749; ≥60: 533 | > 17 | < 60: 374F, 375M; ≥60: 262F, 271M | Indoor/Outdoor, Home/ Community | Not controlled | ≥10 h/day (7 days) |
| [52] | Older adults: 41; Young adults: 41 | Older adults: 76 (5); Young adults: 24 (3) | Older adults: 25F, 16M; Young adults: 22F, 19M | Indoor, Track (200m) | Self-selected | 10 min (mid 9 min) |
| [53] | Older adults: 41 | 75.68 (5.39) | 25F, 16M | Indoor, Track (200m) | Self-selected | 10 min (mid 9 min) |
| [65] | Older adults: 30 | 77.3 (7.0) | 25F, 5M | Indoor/Outdoor, Home/ Community | Not controlled | ≥8 h/day (6 days) |
| [19] | Older adults: 18 | 72.3 (4.5) | 7F, 11M | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [42] | Older adults: 15 | Range: 61–81 | 8F, 7M | Indoor/Outdoor, Home/ Community | Not controlled | 24 h/day (7 days) |
| [26] | Adults: 10 | Range: 55–80 | ND | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [21] | Fallers: 33; Non-fallers: 63 | Fallers: 74.9 (8.5); Non-fallers: 75.8 (7.3) | Fallers: 27F, 6M; Non-fallers: 30F, 33M | Indoor/Outdoor, Home/ Community | Not controlled | ≥6 h/day (7 days) |
| [27] | Impaired: 14; Restrained: 25; Active: 34; Athletic: 23 | Impaired: 79.5 (9.2); Restrained: 80.2 (7.0); Active: 72.1 (5.8); Athletic: 73.0 (6.8) | Impaired: 13F, 1M; Restrained: 13F, 12M; Active: 23F, 11M; Athletic: 8F, 15M | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [66] | Fallers: 7; Non-fallers: 11 | Fallers: 82.2 (5.9); Non-fallers: 84.0 (7.9) | Fallers: 7F, 0M; Non-fallers: 7F, 4M | Indoor/Outdoor, Home/ Community | Not controlled | 14 weeks |
| [67] | Fallers: 32; Non-fallers: 39 | 78.36 (4.71) | ND | Indoor/Outdoor, Home/ Community | Not controlled | 3 days |
| [37] | Fallers: 32; Non-fallers: 39 | 78.36 (4.71) | ND | Indoor/Outdoor, Home/ Community | Not controlled | 3 days |
| [68] | Adults: 239 | Range: 50–85 | 126F, 113M | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [30] | Fallers: 70; Non-fallers: 132 | Fallers: 75.6 (6.1); Non-fallers: 75.1 (6.6) | Fallers: 37F, 33M; Non-fallers: 66F, 66M | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [31] | Older adults: 110 | 78.4 (7.8) | 77F, 33M | Indoor/Outdoor, Home/ Community | Not controlled | 14 days (two separate weeks) |
| [69] | Fallers: 32; Non-fallers: 39 | Fallers: 77.86 (5.09); Non-fallers: 78.77 (4.39) | Fallers: 21F, 11M; Non-fallers: 25F, 14M | Indoor/Outdoor, Home/ Community | Not controlled | 3 days |
| [50] | KOA: 15; Cont: 15 | KOA: 64.7 (6.7); Cont: 66.1 (10.0) | KOA: 8F, 7M; Cont: 8F, 7M | Indoor, Track (200 m) | Self-selected | 9 min (mid 6 min) |
| [51] | KOA: 15; Cont: 15 | KOA: 64.57 (6.75); Cont: 66.07 (10.04) | KOA: 8F, 7M; Cont: 8F, 7M | Indoor, Track (200 m) | Self-selected | 9 min (mid 6 min) |
| [38] | TTA: 21; Cont: 21 | TTA: 62.90 (6.23); Cont: 63.81 (5.71) | TTA: 2F, 19M; Cont: 3F, 18M | Indoor/Outdoor, Home/ Community | Not controlled | 8 days (7 days) |

(*continued on next page*)

**Table 4** (*continued*)

| Ref. | Participants | | | Protocol | | |
|---|---|---|---|---|---|---|
| | Number and Type | Age [years] | Sex | Environment | Speed | Distance/Time (analyzed) |
| [55] | TFA: 8; Cont: 8 | TFA: 43.8 (14.8); Cont: 45.0 (13.4) | TFA: 3F, 5M; Cont: 3F, 5M | Outdoor, Even (260 m), Rough (250 m) Circuits | Self-selected | 6 min |
| [72] | Stroke: 16 | 59.7 (15.3) | 4F, 12M | Indoor, Inpatient hospital | Not controlled | 8 h |
| [76] | Stroke-Fallers: 25, Non-fallers: 31; Cont-Fallers: 20, Non-fallers: 30 | Stroke-Fallers: 69.0 (9.2), Non-fallers: 64.1 (11.6); Cont-Fallers: 74.9 (8.0), Non-fallers: 71.9 (4.1) | Stroke-Fallers: 15F, 10M, Non-fallers: 15F, 16M; Cont-Fallers: 14F, 6M, Non-fallers: 13F, 17M | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [73] | Stroke-Mild: 12, Severe: 11; Healthy: 20 | Stroke-Mild: 64.33 (10.10), Severe: 51.36 (11.82); Healthy: 55.35 (12.70) | Stroke-Mild: 3F, 9M, Severe: 1F, 10M; Healthy: 9F, 11M | Indoor/Outdoor, Home/ Community | Not controlled | 7 h/weekday (weeks 1, 12 and 48 after stroke) |
| [39] | MS: 22 | 46.9 (11.7) | 17F, 5M | Indoor/Outdoor, Home/ Community | Not controlled | 1 day |
| [36] | HD: 15; Cont: 5 | HD: 56.8 (6.6); Cont: 53.4 (20.4) | HD: 6F, 9M; Cont: 3F, 2M | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [25] | HD: 5; Cont: 5 | ND | ND | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [70] | PD: 47; Cont: 50 | PD: 69.1 (8.3); Cont: 69.8 (7.2) | PD: 13F, 34M; Cont: 23F, 27M | Indoor/Outdoor, Home/ Community | Not controlled | 7 days |
| [28] | PD: 2; Cont: 1[b] | PD: 82.0 (4.2); Cont: 37 | PD: 2F, 0M; Cont: 0F, 1M | Indoor/Outdoor, Home/ Community | Not controlled | 6 h |
| [29] | PD: 11 | Range: 56–78 | 3F, 8M | Indoor, Home | Not controlled | 1 h |
| [41] | PD: 39; VP: 9; Cont: 15 | PD: 70.8 (5.8); VP: 72.6 (5.0); Cont: 67.9 (4.7) | PD: 18F, 21M; VP: 2F, 7M; Cont: 6F, 9M | Indoor/Outdoor, Home/ Community | Not controlled | 1 day |
| [44] | PD-Mild: 13, Moderate: 25, Severe: 6; Cont: 17 | PD: 67.5 (5.7); Cont: 64.6 (4.4) | PD: 29F, 35M; Cont: 9F, 8M | Indoor/Outdoor, Home/ Community | Not controlled | 24 h |
| [74] | PD: 40; Cont: 17 | PD: 66.2 (5.7); Cont: 64.7 (4.5) | PD: 14F, 26M; Cont: 9F, 8M | Indoor/Outdoor, Home/ Community | Not controlled | 1 day |
| [32] | PD: 54; Cont: 17 | PD: 71.4 (7.0); Cont: 64.7 (4.5) | PD: 24F, 30M; Cont: 9F, 8M | Indoor/Outdoor, Home/ Community | Not controlled | 24 h |
| [33] | PD: 14 | ND | ND | ND | Self-selected | 2 (with and without poles) × 12 min (512 strides each) |
| [71] | PD-Freezer: 28, Non-freezer: 44 | PD-Freezer: 64.35 (8.70); Non-freezer: 66.51 (8.78) | PD-Freezer: 24F, 4M, Non-freezer: 32F, 12M | Indoor/Outdoor, Home/ Community | Not controlled | 3 days |
| [77] | PD-Fallers: 40, Non-fallers: 67 | PD-Fallers: 66.50 (8.21), Non-fallers: 64.00 (9.76) | PD-Fallers: 14F, 26M, Non-fallers: 13F, 54M | Indoor/Outdoor, Home/ Community | Not controlled | 3 days |
| [34] | PD: 1; Cont: 1[b] | PD: 64; Cont: 77 | PD: 0F, 1M; Cont: 0F, 1M | Indoor/Outdoor, Home/ Community | Not controlled | 3 days |
| [75] | PD-Moderate: 13, Severe: 13; Dementia-Moderate: 13, Severe: 13; Cont: 13 | PD-Moderate: 68.6 (8.1), Severe: 69.6 (8.1); Dementia-Moderate: 75.5 (8.0), Severe: 72.8 (3.5); Cont: 69.6 (7.6) | PD-Moderate: 2F, 11M, Severe: 4F, 9M; Dementia-Moderate: 6F, 7M, Severe: 8F, 5M; Cont: 8F, 5M | Indoor/Outdoor, Home/ Community | Not controlled | 1 day |

| Ref. | Sensor | | Analysis |
|---|---|---|---|
| | Type | Location | Quality of Gait Assessed by Wearable Device |
| [43] | 3D accelerometer, 3D gyroscope | Wrist, Foot (bilateral), Head | Cadence (steps/min), Speed (m/s) |
| | Barometer | | Change in height (m) |
| | GPS | Head | Speed (m/s) |
| [24][a] | 3D accelerometer | Waist, Wrist (bilateral), Ankle (bilateral) | Heel-strike, Toe-off, Stride time (s) |
| [59] | 3D accelerometer | Waist | Time spent in active and exercise mode (min), Coherence length (s), Number of walking steps, Number of running steps, Step frequency, Speed, Distance (m), Longest non-stop distance (m), Step length (m) |
| [60] | 1D accelerometer | Waist | Acceleration RMS (AP; $m/s^2$) |
| | Datalogger | Waist | NA |

(*continued on next page*)

Table 4 (*continued*)

| Ref. | Sensor | | Analysis |
|---|---|---|---|
| | Type | Location | Quality of Gait Assessed by Wearable Device |
| [40] | 3D accelerometer, 3D gyroscope, 3D magnetometer | Lower back, Ankle (bilateral) | Stride time (s), Stride time CV (%), Step time (s), Step time CV (%), Stance time (s), Stance time CV (%) |
| | Pressure sensor | Insole | Heel-strike, Toe-off |
| [56] | 3D accelerometer | Lower back (L4-L5) | Acceleration SD (V, ML, AP; $m/s^2$), Stride time (s), Stride time CV (%), Scaling exponent, Short term stability (V, ML, AP), Long term stability (V, ML, AP) |
| | Datalogger | Waist | NA |
| [54] | Accelerometer | ND | Peak 1-min cadence (steps/min), Peak 30-min cadence (steps/min) |
| [61] | Accelerometer | Waist | For each cadence group (0, 1–19, 20–39, 40–59, 60–79, 80–99, 100–119, and ≥120 steps/min): Time (%) and Steps (%); Prevalence of accumulating ≥30 min/day at ≥100 steps/min |
| [62] | 3D accelerometer | Lower back (L5) | Local dynamic stability |
| [63] | 3D accelerometer | Lower back (L5) | Stride time (s), Stride time SD (s), Acceleration SD (ML; $m/s^2$), Local dynamic stability |
| [64] | 3D accelerometer | Waist | Peak 1-min cadence (steps/min), Peak 30-min cadence (steps/min), Number of steps |
| [52] | 3D accelerometer | Lower back (L3) | Step time (s), Stride time (s), Step time CV (%), Stride time CV (%), Stride time fractal scaling index, Step regularity (V, ML, AP), Stride regularity (V, ML, AP), Symmetry (V, ML, AP) |
| [53] | 3D accelerometer | Lower back (L3) | Step time (ms), Stride time (ms), Step time SD (ms), Stride time SD (ms), Step time fractal scaling index, Stride time fractal scaling index |
| | Footswitch | Insole (bilateral) | Step time (ms) |
| | Datalogger | Waist | NA |
| [65] | 3D accelerometer | Ankle | Number of steps, Walking distance (m), Speed (m/s) |
| [19] | 3D accelerometer | Waist | Stride time (s), Stride time variability (s), Stride regularity (V, ML, AP), Acceleration RMS (V, ML, AP; $m/s^2$), Symmetry (V, ML, AP), Local divergence exponent (V, ML, AP; $s^{-1}$), Low frequency percentage (V, ML, AP; %), Index of harmonicity (V, ML, AP), Amplitude of dominant frequency (V, ML, AP) |
| [42] | 3D accelerometer | Waist | Number of steps, Peak 1-min cadence (steps/min), Peak 30-min cadence (steps/min) |
| | Pedometer | Waist | Number of steps |
| [26] | 3D accelerometer, 3D gyroscope | Chest | Energy of combined accelerometer and gyroscope, Acceleration SD (V, ML, AP; $m/s^2$), Angular velocity SD (V, ML, AP), Step frequency (Hz), Peak power at step frequency |
| [21] | 3D accelerometer | Pendant worn at sternum | Number of steps, Cadence (steps/min), Vigor (V; cm/s), Short walk exposure (% walks < 8 s), Vigor IQR (V; cm/s), Bimodal cadence (Ashman's D), Step time variability (ms) |
| | Barometer | | Change in height (m) |
| [27] | 3D accelerometer | Pendant worn at sternum | Number of steps, Short walk exposure (% walks < 8 s), Cadence (steps/min), Vigor (V; cm/s), Bimodal cadence (Ashman's D), Vigor IQR (cm/s), Step time variability (ms) |
| | Barometer | | Change in height (m) |
| [66] | 3D accelerometer | Pendant worn at sternum | Number of steps, Number of walks, Steps per walk, Longest walk (s), Short walk exposure (%), Walk time at 50% exposure (s), Moderate walk exposure (%), Cadence (steps/min), Bimodal cadence (Ashman's D), Vigor (V; cm/s), Step time variability (s) |
| | Barometer | | Change in height (m) |
| [67] | 3D accelerometer | Lower back | Local dynamic stability |
| [37] | 3D accelerometer | Lower back | Refined composite multiscale entropy (V, ML, AP; Acceleration, Velocity), Refined multiscale permutation entropy (V, ML, AP; Acceleration, Velocity) |
| [68] | 3D accelerometer, 3D gyroscope, 3D magnetometer | Wrist | Local dynamic stability, Multi scale sample entropy, Harmonic ratio |
| [30] | 3D accelerometer | Waist | Speed (m/s), Speed variability (m/s), Stride frequency, Frequency variability (V, ML, AP), Stride regularity (V, ML, AP), Acceleration RMS (V, ML, AP; $m/s^2$), Low frequency percentage (V, ML, AP; %), Index of harmonicity (V, ML, AP), Harmonic ratio (V, ML, AP), Local dynamic stability (V, ML, AP), Entropy (V, ML, AP), Amplitude of dominant frequency (V, ML, AP) |
| [31] | 3D accelerometer | Waist | Speed (m/s), Speed SD (m/s), Stride time (s), Stride regularity, Stride time SD (s), Stride frequency, Movement intensity (V, ML, AP; $m/s^2$), Frequency variability (V, ML, AP), Harmonic ratio (V, ML, AP), Index of harmonicity (V, ML, AP), Low frequency percentage (V, ML, AP; %), Local dynamic stability (V, ML, AP), Local dynamic stability per stride (V, ML, AP), Amplitude of dominant frequency (V, ML, AP), Width of dominant frequency (V, ML, AP), Slope of dominant frequency (V, ML, AP), Acceleration range (V, ML, AP; $m/s^2$) |

(*continued on next page*)

**Table 4** (*continued*)

| Ref. | Sensor | | Analysis |
|---|---|---|---|
| | Type | Location | Quality of Gait Assessed by Wearable Device |
| [69] | 3D accelerometer | Lower back | Number of walking bouts, Walking time (%), Number of steps, Walking bout duration (s), Number of steps per bout, Amplitude of dominant frequency (V, ML, AP; psd), Width of dominant frequency (V, ML, AP; Hz), Slope of dominant frequency (V, ML, AP; psd/Hz), Step time (s), Stride time (s), Step regularity (V, ML, AP), Stride regularity (V, ML, AP), Step symmetry (V, ML, AP), Harmonic ratio (V, ML, AP), Acceleration range (V, ML, AP; $m/s^2$) |
| [50] | 3D accelerometer | Lower back (L3) | Step time (ms), Stride time (ms), Stride regularity (V, ML, AP), Step regularity (V, ML, AP), Symmetry (V, ML, AP) |
| [51] | 3D accelerometer | Lower back (L3) | Number of steps, Stride time (ms), Stride time SD (ms), Stride time fractal scaling index, Step time (ms), Step time SD (ms) |
| [38] | 3D accelerometer | Ankle | Number of strides |
| [55] | 3D accelerometer | Lower back (L3) | Stride time (s), Stride time CV (%), Acceleration RMS (ML, AP; $m/s^2$), Stride time long-range correlations, Local stability exponents, Sample entropy |
| [72] | 3D accelerometer | Ankle (bilateral) | Walking time (%), Number of walking bouts, Number of steps, Walking bout duration (s), Swing symmetry, Cadence (steps/min) |
| | Portable computer | Waist | NA |
| [76] | 3D accelerometer | Lower back | Walk time (min), Number of walking bouts, Short walking bouts (%), Short walking bout epochs (%), Speed (m/s), Stride time (s), Harmonic ratio (V, ML, AP), Stride frequency variability (V, ML, AP), Index of harmonicity (V, ML, AP), Amplitude and Width of dominant frequency (V, ML, AP), Local divergence exponent (V, ML, AP) |
| [73] | 3D accelerometer | Sternum, Thigh (bilateral) | Walk time (%), Walking bout duration (s), Number of walking bouts, Walking CV, Sedentary exponent, Step regularity (V, AP), Stride regularity (V, AP), Symmetry (V, AP), Step time ratio |
| [39] | 3D accelerometer | Waist | Activity counts per hour (V, ML, AP) |
| | 1D accelerometer | Sternum, Thigh (bilateral), Foot (bilateral) | Time walking (%), Speed (m/min) |
| [36] | 3D accelerometer | Chest | Step time SD (s), Cadence (steps/min), Step peak acceleration ($m/s^2$), Speed (ML; m/s), Displacement (ML; m) |
| [25] | Inertial sensors | Foot (bilateral) | Stride length (% height), Stride velocity (% height/s), Step time (s), Double support time (% stride), Pitch at toe off (deg), Pitch at heel strike (deg), Cadence (steps/min); Variability in all measures |
| [70] | 3D accelerometer | Lower back (L5) | Step velocity (m/s), Step length (m), Swing time SD (s), Step velocity SD (m/s), Step length SD (m), Step time SD (s), Stance time SD (s), Step time (s), Swing time (s), Stance time (s), Step time asymmetry (s), Swing time asymmetry (s), Stance time asymmetry (s), Step length asymmetry (m) |
| [28] | 3D accelerometer, 3D gyroscope | Shank | Stride length (m), Stride length variability (m) |
| | Portable computer | Waist | NA |
| [29] | 3D accelerometer, 3D gyroscope | Head, Trunk, Pelvis, Upper arm (bilateral), Wrist (bilateral), Thigh (bilateral), Shank (bilateral) | 10 joint angular velocities (deg/s), 48 joint angles (deg) |
| [41] | 3D accelerometer | Waist | Amount of overall movements ($m/s^2$), Stride time, Acceleration amplitude ($m/s^2$) |
| [44] | 3D accelerometer | Waist | Cadence (strides/s), Mean of gait acceleration ($m/s^2$) |
| [74] | 3D accelerometer | Waist | Cadence (strides/s), Mean of gait acceleration ($m/s^2$) |
| [32] | 3D accelerometer | Waist | Cadence (steps/min), Mean of gait acceleration ($m/s^2$) |
| [33] | 1D accelerometer | Ankle | Cadence (steps/min), Speed (m/s), Stride length (m), Long-range autocorrelations |
| [71] | 3D accelerometer | Lower back | Number of walking bouts, Walking time (%), Number of steps, Walking bout duration (s), Number of steps per bout, Cadence (steps/min), Width of dominant frequency (V, ML, AP; Hz), Stride regularity (V, ML, AP), Harmonic ratio (V, ML, AP) |
| [77] | 3D accelerometer | Lower back | Number of walking bouts, Walking time (%), Number of steps, Median walking bout duration (s), Median number of steps per bout, Cadence (steps/min), Amplitude of dominant frequency (V, ML, AP; psd), Width of dominant frequency (V, ML, AP; Hz), Stride regularity (V, ML, AP), Harmonic ratio (V, ML, AP) |
| [34] | 3D accelerometer | Lower back | Dominant frequency (Hz), Amplitude of dominant frequency (psd), Width of dominant frequency (Hz), Slope of dominant frequency (psd/Hz) |
| [75] | 3D accelerometer | Waist | Stride time (s), Acceleration (V; $m/s^2$) |

Abbreviations: ND = not described; NA = not applicable; Cont = control; HD = Huntington's disease; KOA = knee osteoarthritis; PD = Parkinson's disease; TTA = transtibial amputee; TFA = transfemoral amputee; MS = multiple sclerosis; VP = vascular parkinsonism; V = vertical axis; ML = medial-lateral axis; AP = anterior-posterior axis; SD = standard deviation; CV = coefficient of variation; RMS = root mean squared.

[a] Study involved both walking and running and is included in both Tables 4 and 5.

[b] Only participants performing tasks that meet the inclusion/exclusion criteria of this review are included.

**Table 5**
List of the running studies and the data extracted from each article. Values are in the format mean (SD) unless otherwise noted.

| Ref. | Participants | | | Protocol | | |
|---|---|---|---|---|---|---|
| | Number and Type | Age [years] | Sex | Environment | Speed | Distance/Time (analyzed) |
| [57] | Exp (410 (205) min/week)-Prev. injured: 6, Not prev. injured: 6 | 35.7 (10.1) | Previously injured: 2F, 4M; Not previously injured: 3F, 3M | Outdoor, Track | Subjective intensities of 80% to 100% | 10 × 400 m, 8 × 600 m, 7 × 800 m, 6 × 1000 m; 2/week × 4 weeks |
| [58] | High school cross country-Pros. shin injury: 11, Pros. knee injury: 3, H: 54 | 16.2 (1.3) | Pros. shin injury: 3F, 8M; Pros. knee injury: 2F, 1M; H: 42F, 12M | Outdoor, Track (400 m) | 80% of 5-km race pace, 3.3 m/s | 400 m each speed |
| [78] | Rec-Prev. injured (30.3 (9.7) km/week): 9, Not prev. injured (33.3 (12.3) km/week): 9 | Prev. injured: 29.3 (10.3), Not prev. injured: 25.9 (8.5) | ND | Indoor, Track (300 m) | Self-reported 5 km pace | Max laps (3 sections) |
| [79] | H, Rec: 12 | 32.8 (9.8) | ND | Indoor, Track (200 m) | Not controlled | 4 miles (each 0.25 mile) |
| [46] | H, Rec: 10 | F: 31.7 (7.3), M: 26.7 (2.3) | 7F, 3M | Outdoor, Course (230 m) | Best 10 km pace | Max laps (50 steps first, last 5 laps) |
| [24][a] | H: 9[b] | ND | ND | Outdoor, Course (450 m) | Self-selected | 3 min |
| [81] | Rec novice half-marathon runners: 6 | 33.5 (5.8) | 5F, 1M | Not controlled | Not controlled | 340 km: 48 runs, 1 half marathon race over 12 weeks (5 strides 1 run) |
| [45] | H-No running: 2, Some running: 10, Exp (50 km/wk): 2 | H-No running: 23.0 (0.0), Some running: 25.8 (9.2), Exp: 27.0 (1.4) | H-No running: 1F, 1M, Some running: 5F, 5M, Exp: 0F, 2M | Outdoor, Course (2 km) | 20–80% max, Not controlled | 1.5 km, 4 km; repeated 2 days (each 125 m) |
| [35] | Beginner (0–5 km/week): 6; Intermed (5–25 km/week): 6; Adv (25–45 km/week): 6; Expert (> 45 km/week): 3 | ND | ND | Outdoor, Track (400 m) | 85% of maximum speed | 45 min (first, mid and last 5 min) |
| [20] | H, Exp (49.8 (17.8) km/week): 20 | 34 (8) | 9F, 11M | Outdoor, Track (400 m) | 4 m/s | 400 m (10 s) |
| [80] | H, Exp trail (4.8 (2.4) hr/week): 23 | 39 (11) | 0F, 23M | Outdoor, Trail | Not controlled | 8.5 km (6 sections 559 (352) m, −16.8 (5.6) % grd) |
| [49] | World leader in trail running: 1 | 26 | 0F, 1M | Outdoor, Trail | Not controlled | 45 km (11 sections 1.35 (0.85) km, 7.11 (6.61) % grd over first 20 km) |
| [47] | H, Sub-elite: 6 | 21.6 (4.0) | 0F, 6M | Outdoor, Track (400 m) | Maximal aerobic speed | Max laps (3 sections 32.2 (1.4) steps) |
| [48] | H, Exp with marathon finish time ∼3 h: 3 | 38.7 (8.2) | 0F, 3M | Outdoor, Marathon course | Not controlled | 42.2 km (stages at 8, 18, 27 and 36 km) |

| Ref. | Sensor | | Analysis |
|---|---|---|---|
| | Type | Location | Quality of Gait Assessed by Wearable Device |
| [57] | 3D accelerometer | Foot (bilateral) | Ground contact time (L, R; ms), Gait asymmetry (%) |
| [58] | Footswitch | Top of foot | Cadence (steps/min) |
| [78] | 1D accelerometer | Tibia | Stride time (s), Stride time SD (s), Stride time CV (%), Stride time long-range correlations |
| | Datalogger | Waist | NA |
| [79] | 3D accelerometer | Lower back (L5) | Peak acceleration (V, AP; $m/s^2$), Peak acceleration SD (V, AP; $m/s^2$) |
| [46] | 1D accelerometer | Heel | Heel strike |
| | 3D accelerometer | Triceps surae | Vibration intensity (V, ML, AP; $m^2/s^4$), Vibration frequency (V, ML, AP; Hz), Timing of max vibration intensity (V, ML, AP; ms) |
| [24][a] | 3D accelerometer | Waist, Wrist (bilateral), Ankle (bilateral) | Heel-strike, Toe-off |
| [81] | 3D accelerometer | Tibia (bilateral) | Stride time (s), Stride time SD (s) |
| [45] | 3D accelerometer, 3D gyroscope | Instep of foot | Ground contact time (ms) |
| | GPS | Wrist | Speed (m/s) |
| [35] | 3D accelerometer, 3D gyroscope, 3D magnetometer | Upper back, Lower back, Wrist, Thigh, Shank, Foot | Cadence (steps/min), Normalized foot contact (%), Vertical oscillation (m), Arm movement ($m/s^2$), Upper body impact acceleration ($m/s^2$), Forward trunk lean (deg), Heel lift (deg), Shoulder rotation (deg), Maximum knee rotation velocity (deg/s), Foot strike pattern |
| [20] | 1D accelerometer | Tibia, Forehead | Peak impact acceleration (Tibia and Forehead; g), Impact rate (Tibia and Forehead; g/s), Shock attenuation (%) |
| [80] | 3D accelerometer | Heel, Top of foot, Tibia, Sacrum | Peak acceleration (AP, V, resultant; $m/s^2$), Median frequency (AP, V, resultant; Hz), Shock attenuation (dB), Time between heel and metatarsal peak accelerations (ms), Foot strike pattern (Rearfoot, Midfoot, Forefoot; %) |
| | Barometer | | Altitude |

(*continued on next page*)

**Table 5** (*continued*)

| Ref. | Sensor | | Analysis |
|---|---|---|---|
| | Type | Location | Quality of Gait Assessed by Wearable Device |
| [49] | 3D accelerometer | Heel, Top of foot, Tibia | Peak acceleration (V, ML, AP; m/$s^2$), Median frequency (V, ML, AP; Hz), Step frequency (Hz), Time between heel and metatarsal peak accelerations (ms), Foot strike pattern (Rearfoot, Midfoot, Forefoot; %) |
| | GPS | | Speed (km/h), Slope (%) |
| [47] | 3D accelerometer | Lower back | Stride frequency (V), Stride symmetry (V), Stride regularity (V), Signal energy (V, ML, AP; $G^2$.s), Impulse (V, ML, AP; %BW.s) |
| | Datalogger | Waist | NA |
| | Heart rate monitor | Chest | Heart rate (bpm) |
| [48] | 3D accelerometer, 3D gyroscope, 3D magnetometer | Sternum, Pelvis, Thigh (bilateral), Shank (bilateral), Foot (bilateral) | Stride length (m), Cadence (steps/min), Max hip angle (deg), Peak knee flexion midstance (deg), Peak knee flexion midswing (deg), Ankle angle initial contact (deg), COM displacement (V; m), COM acceleration (m/$s^2$) |
| | GPS | Wrist | Speed (km/h) |

Abbreviations;: H = healthy; Rec = recreational athlete; Exp = experienced runner; Intermed = intermediate runner; Adv = advanced runner; Pros. = prospective; Prev. = previously; ND = not described; NA = not applicable; grd = grade; ML = medial-lateral axis; AP = anterior-posterior axis; SD = standard deviation; CV = coefficient of variation; RMS = root mean squared.

[a] Study involved both walking and running and is included in both Tables 4 and 5.

[b] Only participants performing tasks that meet the inclusion/exclusion criteria of this review are included.

found differences between fallers and non-fallers in regularity, symmetry, and stability. However, Pozaic et al. [68] observed differences in just stability, not complexity or symmetry, between fallers and non-fallers. The incongruence between studies may be due to differences in sensor placement location (i.e. waist/lower back [30,37] vs. wrist [68]), and highlights the importance of determining the best practice for performing gait analyses using wearable devices.

Several studies used measures of variability, regularity, stability, and adaptability from wearable devices to identify differences between control participants and participants with Huntington's disease [25,36], knee osteoarthritis [50,51], Parkinson's disease [34,41,44,70,74,75,77], trans-tibial [38] and trans-femoral [55] amputations, and a history of stroke [72]. Additionally, these analyses were used to distinguish between individuals with distinct gait patterns [29] or stages of disease [28,32,44,71], and measure improvements in gait quality due to treatment [33] or recovery time [73]. Investigations of typical adults analyzed the feasibility of detecting gait events in non-lab settings [24,40,43], and established relationships between speed and age [59], accelerations and speed [60], walking patterns and physical performance [26], and differences in cadence across sex, age, body mass index and physical activity level [54].

The running studies either determined injury status [57,58,78], examined runners of different experience levels [35,45], captured the effect of fatigue [20,35,46–48,57,78–80], or detected run characteristics such as heel-strike and toe-off events [24], stride time [81], or foot strike pattern [49,80]. Injury-related results indicated that runners who were previously injured had greater asymmetry [57] and lower long-range correlations of stride time [78] than runners who were not previously injured. Additionally, prospective shin injuries among high school cross-country runners were associated with lower step rate [58]. Results of studies that investigated experience level, fatigue, or runner characteristics suggested that running patterns were likely individual- and task-specific. For example, across runners of multiple experience levels, the relationships between speed and foot contact time were strong for each individual [45]. Likewise, fatigue-induced changes in running gait were dependent on experience level [35], individual participants [35,48], and had different effects depending on the task (e.g. marathon race [48] vs. interval training [57] vs. running until exhaustion [47]), or level of experience within the same task (e.g. sub-elite [47] vs. recreational runners [78] running until exhaustion). Running gait patterns also appeared to be different depending on the length of the run [57,79], while the ability to detect gait events differed with varying speed and surface inclinations [24], and an individual's foot strike pattern affected shock intensity and shock attenuation [80].

### 3.4. Participant characteristics

The walking studies had between two [34] and 3744 [61] participants, with nearly half of the studies having at least 50 participants, and three studies had over 1000 participants [54,61,64]. The mean age of participants for 28 of the walking studies was greater than 60, with an additional five walking studies performing a comparison of gait patterns across age groups that included older adults. Three walking studies [34,56,60] had male participants only, while the rest had both male and female participants, of which five [21,42,50,54,61] investigated differences between males and females. One study utilized wearables-based gait analysis to identify subgroups within a sample of older adults, allowing for more individualized profiling of falls risk [27].

Just one running study had more than 50 participants [58], and the rest had under 30 participants, with ten out of the 14 running studies having less than 20 participants. The mean age for the participants in all running studies was less than 40. Four running studies [47–49,80] had only male participants, and of the remaining ten running studies, only one [58] conducted separate analyses for males and females.

### 3.5. Gait analysis environment

The environment for the walking studies was one of two settings: a predefined course or track, or each participant's residence or community setting. For the studies that involved a course or track with a known location, five were completed indoors [50–53,56] and seven were completed outdoors [24,40,43,55,60,62,63]. Additionally, the majority of these studies involved walking at a consistent self-selected pace between three [24] and 15 [40] minutes or between 500 m [62,63] and 4.7 km [43]. In contrast, the remaining 36 studies involved gait analysis in the participant's own home or community setting, and in one case, an inpatient hospital setting [72]. The length of time of the home/community-based gait analysis was between one hour and 14 weeks, with the majority of studies recording gait patterns between one and seven days. Three studies lasted less than one day [28,29,72], and three studies collected data over multiple weeks [31,66,73]. In all of the home/community-based studies, speed was not controlled, and participants could be either indoors or outdoors in their community setting except for in the study by Rahimi et al. [29], where the participants stayed within their home for one hour.

The running studies took place either on a track or on an outdoor path or trail. The duration and/or distance of the running protocol varied by study. Three studies analyzed running gait over short distances, namely 400 m [20], 2 × 400 m [58], or 3 min [24]. Three other studies examined gait patterns over longer distances that were more representative of a typical run. de Ruiter et al. [45] and Bigelow et al. [50] analyzed runs of 4 km and 4 miles, respectively, while Norris et al. [81] recorded information about running patterns during 48 training runs and a half marathon race over 12 weeks, but only analyzed five strides from one of the runs. The remaining studies examined running gait in fatiguing situations, including running until exhaustion [46,47,78], fatigue-inducing workouts [40,57,80], or long distance races [48,49]. A study by Garcia-Perez et al. [20] examined gait before and after, but not during, an exhaustive run. The speed for the running studies was either not controlled (e.g. during races and typical runs) [45,48,49,79–81], controlled at a self-selected pace [24,45], controlled at a speed based on individual performance (e.g. 85% of maximum speed) [35,46,47,57,58,78], or controlled at a set pace (e.g. 4 m/s) [20,58].

### 3.6. Wearable device characteristics

All walking studies used some type of accelerometer. 1D accelerometers were used exclusively in two studies [33,60], three studies featured accelerometers of unknown dimensions [25,54,61], one study used both 1D and 3D accelerometers [39], and all other studies utilized 3D accelerometers only. The range of the accelerometer in the walking studies was between ± 3 g [52,53] and ± 8 g [21,24,43,66,70], and the sampling frequency was between 50 Hz [21,27,36,66,72] and 1000 Hz [52,53], with 22 studies utilizing a sampling frequency of 100 Hz [19,26,28–32,37,41,44,50,51,55,59,62,63,67,69,70,74,76,77]. The accelerometers used in the walking studies had a large range of sizes and weights, from as small as 15 × 15 × 10 mm [73] to 80 × 60 × 20 mm [32,41,44,74], and from 9 g [70] to 120 g [75].

Accelerometers were used in all running studies, except for the study by Luedke et al. [58], which only used a footswitch. Two running studies used a 1D accelerometer only [20,78], one study used both 1D and 3D accelerometers [78], and the remaining running studies used 3D accelerometers exclusively. The lowest sampling frequency for the running studies was 100 Hz, present in just three studies [20,35,47]. The highest sampling frequency was 2400 Hz [46], and the accelerometer range was between ± 6 g [35,47,81] and ± 160 g [48]. The range of sizes and weights of accelerometers used in the running studies was 38 × 37 × 8 mm and 13 g [70] to 64 × 42 × 24 mm and 53 g [20].

The accelerometers used in both walking and running studies were attached to upper body segments (head, chest/trunk, upper arm, and wrist/forearm) and lower body segments (waist/lower back/pelvis, thigh, shank/ankle, and foot). Among the 48 walking studies, the most common accelerometer placement was near the center of mass, with 31 studies placing an accelerometer at the waist/lower back/pelvis [19,24,26,29–32,34,39–42,44,50-53,55,56,59–64,69–71,74,76,77], and in all but four cases that was the only accelerometer used. The next most common placement of a single accelerometer was at the shank/ankle [28,33,38,65,72], followed by the chest/trunk [21,26,27,36,66], then the foot [25] and wrist/forearm [68]. Six walking studies utilized accelerometers on multiple body segments [24,29,39,40,43,73], and five of those studies accounted for nine of the 15 upper body accelerometer placements within the walking studies, suggesting that the upper body accelerations were typically only considered in conjunction with a lower body analysis.

Only four running studies placed accelerometers on the upper body [20,24,35,48], and these were always in combination with a lower body accelerometer placement. The most common accelerometer locations for the running studies were almost evenly distributed among the shank/ankle [20,24,35,46,48,49,78,80,81], foot [35,45,46,48,49,57,80], and the waist/lower back/pelvis [24,35,47,48,79,80]. Each of these locations served as the sole accelerometer placement for two studies, accounting for six of the 13 running studies that included accelerometers. An additional three studies placed multiple accelerometers on lower body segments only [46,49,80].

In addition to accelerometers, other sensors were included in some of the studies. When present, 3D gyroscopes, 3D magnetometers and barometers were part of the same device that included the accelerometer. Pedometers, GPS systems, footswitches, pressure sensing insoles, and heart rate monitors, if included, were stand-alone devices. A datalogger or personal computer, a device that does not produce its own signal but records signals from other devices, was also worn at the waist by the participants in some studies. Seven [25,26,28,29,40,43,68] and three [25,40,68] walking studies included 3D gyroscopes and 3D magnetometers, respectively. Walking studies also utilized step counters such as a pedometer [42], footswitch [53], and pressure sensing insoles [40], and one study had participants wear a GPS system [43]. In six walking studies [28,52,53,56,60,72], a datalogger ranging in size from 11 × 8 x 1.5 cm [52] to 13.0 × 6.8 × 3.0 cm [56], and weighing between 146 g [28] and 286 g [56] was worn. Two running studies included both a 3D gyroscope and a 3D magnetometer [35,48], while one study had a 3D gyroscope only [45]. Additional wearable devices used in running studies included GPS systems [45,48,49], a heart rate monitor [47], and a footswitch [58]. A datalogger was present in two running studies, weighing between 82 g [78] and 140 g [47].

### 3.7. Extracted features

The information extracted from an accelerometer signal was processed into variables that describe the quantity of movement, individual gait characteristics, spatiotemporal gait parameters, actual acceleration values, variability, or advanced metrics that provide information about the symmetry and quality of the gait signal. The quantity of movement was established for walking studies and included measures of the number of steps or walking bouts [21,27,38,39,42,51,59,61,64–66,69,71–73,76,77], distance walked [59,65,66], and time walking [39,59,61,66,69,71–73,76,77]. Gait events were reported as main outcome measures in two studies [24,40].

Measures of distance, such as step length and stride length, were reported for five walking studies [25,28,33,59,70]. Many walking studies investigated a time component of gait, including step time [25,40,50–53,69,70], stride time [19,24,40,41,50–53,55,56,63,69,75,76], or time for a particular phase of the gait cycle [25,40,70]. Cadence was determined in 16 studies [21,25–27,32,33,36,43,44,59,61,66,71,72,74,77], with several studies reporting additional variables related to step rate, including peak 1- and 30-min cadence [42,54,64], and the presence of bimodal cadence [21,27,66].

Additionally, accelerometer-based measures of speed were reported in 13 walking studies [21,25,30,31,33,36,39,43,59,65,66,70,72]. As for accelerations, walking studies tended to report the mean [26,32,41,44,74] or root mean squared [19,30,55,60] of the accelerometer signal. Traditional measures of variability were computed as the standard deviation or coefficient of variation of spatiotemporal gait parameters and acceleration variables. The most common measures of variability among the walking studies were step time variability [21,25,27,36,40,51–53,66,70] and stride time variability [19,31,40,51–53,55,56,63], followed by acceleration variability [26,31,56,63]. Other measures of distance variability [25,28,70], time variability [25,40,70], cadence variability [25], and speed variability [21,25,30,31,70] were also reported.

Beyond the basic variables described above, other metrics provided information about the accelerometer signal. Symmetry or the harmonic ratio was a common variable reported in the walking studies [19,30,31,50,52,68,69,71,73,76,77], and is closely related to stride regularity [19,30,31,50,52,69,71,73,77] and step regularity [50,52,69,73]. Other asymmetry indices were also utilized in walking studies [70,72,73]. Another technique for processing the accelerometer signal was to do a frequency analysis, which led to quantification of the frequency content [30,31,34], power [19,26,30,31], and variability or consistency of the signal [19,30,31,34,69,76,77]. Dynamic stability was quantified using non-linear measures of variability, including Detrended Fluctuation Analysis, Fractal Scaling Index, and maximal Lyapunov exponent [19,30,31,51–53,55,56,62,63,67,68,76], while entropy was used to describe the complexity of the accelerometer signal [30,37,55,68], and the index of harmonicity described the smoothness of the signal [19,30,31,76] among walking studies.

Among the running studies, features extracted from the accelerometer signal included gait events [24,46], and foot strike patterns [35,49,80]. Measures of distance included stride length [48] and center of mass displacement [35,48], while stride time [78,81], ground contact time [35,45,57] and time between heel and metatarsal peak accelerations [49,80] were temporal variables used in running analyses. Cadence was reported in three running studies [35,48,49]. Measures of acceleration included the peak acceleration [20,49,79,80] or acceleration of a particular body segment [35,48]. Additionally, the energy and impulse [47], impact rate [20] and shock attenuation [20,80] were variables of interest. Stride time variability [78,81] and acceleration variability [79] were the only traditional measures of variability reported in running studies. Advanced metrics used in running studies included stride regularity and symmetry [47], frequency content [46,47,49,80], and stability [78].

Outcome measures were also reported based on signals from devices other than accelerometers. In walking studies, a gyroscope and/or magnetometer was used to determine joint and segment angles and angular velocities [25,26,29], a barometer identified a change in height [21,43,66], GPS recorded speed [43], and a pedometer [42], pressure sensing insoles [40] and a footswitch [53] produced step counts. Among the running studies, similar variables were reported from a gyroscope [35,48], barometer [80], GPS [45,48,49], and footswitch [58], with a heart rate monitor also recording heart rate [47]. However, in several cases in both walking and running studies, a gyroscope [28,40,43,45,68] or magnetometer [40,68] was reported as part of the wearable devices included in the study, but none of the outcome measures were based on a gyroscope or magnetometer signal.

## 4. Discussion

Recent improvements in wearable technology have allowed gait analysis to move out of the lab and into real-world environments. Nevertheless, all of the expected findings regarding the use of wearable devices for gait analysis in out-of-lab settings were not observed, thus opportunities for future wearables-based gait analyses to improve the understanding of real-world walking and running patterns are identified.

### 4.1. Application of wearables in gait analysis

It was expected that gait analyses would be performed during long individual bouts and/or over the course of many sessions, facilitating prospective studies and the development of subject-specific models of gait patterns. For the most part, walking and running bouts were longer than can typically be achieved in a laboratory setting, and the majority of walking (but not running) studies included analyses of more than one day. However, most of the studies in the current review performed retrospective group-based analyses, identifying differences in walking and running mechanics between pathological or injured groups and controls. The finding in many of the running studies that running patterns may be specific to individuals suggests that subject-specific models should be used in running gait analyses. For example, de Ruiter et al. [45] took this approach by creating individual models to predict running speed from foot contact time, and this method could be expanded in future studies to examine other running characteristics and situations such as fatigue or injury status.

Notably, there were few prospective studies among the articles included in this review. Only one running study examined prospective injury risk, using only a footswitch to predict future injury based on step rate [58]. All other injury-based analyses involved previously injured runners that were healthy at the time of testing [57,78]. Therefore, it cannot be determined if the observed differences in gait between the injured and uninjured groups was a cause or effect of their previous injury. Likewise, several walking studies sought to retrospectively identify differences between fallers and non-fallers [21,37,66–69,76], when it is possible that a previous fall instilled a fear of falling that led to the noted gait abnormalities [82]. Only three studies looked at differences between prospective fallers and non-fallers [27,30,77]. Future investigations into the gait characteristics of injured runners or individuals at risk for falling might consider a prospective study design to determine the gait patterns that represent risky mechanics.

### 4.2. Participant characteristics

It was also expected that the reviewed studies would include large numbers of participants, which would facilitate the identification of subgroups of walking and running patterns. While large numbers of participants were included in some walking studies, this was not the case for running, and subgroups were rarely identified based on observed gait patterns. The contrast in the number of participants in walking studies versus running studies is glaring. The more than 1000 participants [54,61,64] in three walking studies provides convincing evidence that real-world gait analysis can be done on a large scale using wearable sensors. With the portability and ease of use of these devices, future studies should consider monitoring the gait patterns of larger samples of pathological groups. An advantage of including larger numbers of participants is the ability to identify subgroups within the population of interest. Functional subgroups can be determined based on the observed mechanics, not *a priori* designations with potentially arbitrary cut points. For example, Strohrmann et al. [35] stratified runners based on their weekly mileage, but did not find universal differences in mechanics across these groups. Similarly, Parkinson's disease patients at various pre-determined stages of disease displayed differences in some, but not all, walking parameters [44]. In contrast, the study by Brodie et al. used real-world gait patterns – not *a priori* designations – to distinguish between subgroups of older adults at risk for falling due to frailty or greater exposure [27]. In addition to identifying subgroups of runners or patients, wearables-based gait analysis can be used to determine sex differences. The lack of sex-based analyses in this review is particularly surprising for the running studies considering the established differences in running mechanics between males and females [83].

### 4.3. Gait analysis environment

Even though the studies in this review were included because gait analysis was performed in an out-of-lab setting, it was anticipated that this location would be the participants' actual walking or running environment. This expectation was met for most walking but not running studies. For many of the walking studies, the residential location or typical community setting was the exact natural environment for the participants. The walking studies that did not monitor participants in their daily activities seldom imposed restrictions on speed. In contrast, while tracks, footpaths, and trails are common running locations, the running tasks were created for an experiment, and were not necessarily the actual location of the participants' training runs. Several running studies required a specific speed that may not necessarily represent a pace the runners typically encounter [20,35,46,47,57,58,78]. In the cases where running patterns were recorded during race situations [48,49], the environment and pace were not prescribed. However, these studies only captured one aspect of running: racing. It is common for runners to train for months for just one race, during which time a runner may encounter different types of workouts, improvements in fitness, and a plethora of different running environments. Therefore, the training done in preparation for a race accounts for most of an individual's running, and can be vastly different from the race itself. For example, Norris et al. [81] showed that 12 weeks of training consisted of approximately 320 km over 48 training runs in preparation for a half marathon race. The data collected during all of these runs represents a true running environment for those participants, yet only five strides of one run were included in the actual analysis. Three additional studies [20,24,58] reported on gait patterns over just a small distance, meanwhile Bigelow et al. [79] showed that the gait pattern over distances less than a mile may not be indicative of gait patterns exhibited at longer distances. Therefore, collecting and using data from actual training runs, and over longer distances, may help to identify the typical gait patterns of runners.

### 4.4. Wearable device characteristics

As anticipated, the reported information regarding the size, placement, and hardware components of the wearable devices appears unobtrusive and appropriate. However, future studies should incorporate user feedback to explicitly address the issue of usability of wearable devices for gait analysis. The use of a single device that is small, lightweight, and does not require additional components such as a datalogger decreases the potential influence of the device on running or walking gait [84], and many (though not all) of the wearable devices in this review met these criteria. Placement of wearable devices on the lower extremity is common for both walking and running and an overwhelming number of studies placed an accelerometer near the center of mass during the daily life walking analyses, suggesting that this location is easy to use for long-term data collection. However, the wearable device's anatomical placement should be chosen appropriately based on the research question [84–87]. For example, placement on the foot is likely appropriate for investigations of foot strike pattern [49,80], whereas placement on the lower back can be used to describe whole-body running patterns in relation to stiffness, impact, and attenuation [88]. As suggested by Del Din et al. [16], the usability of common wearable devices for gait analysis appears reasonable, but accurate reporting of study dropout rates, missing data, and participant feedback is lacking. This information will be invaluable when determining the design recommendations for the development of wearable devices that can be easily used among various populations [10].

Many different types and brands of wearable devices were used in the included studies, but the accelerometer was the most popular device for walking and running gait analyses. Intuitively, a greater sampling frequency and range is required for running compared to walking analyses, as well as for devices placed on more distal lower body segments (i.e. shank and foot), and this trend was observed in the reviewed studies. Other sensors such as gyroscopes and magnetometers have been used more sparingly, but are relevant when analyzing specific joint or segment angles [25,26,29,35,48].

### 4.5. Extracted features

As anticipated, several features extracted from the wearable device signals were unique to the wearable device gait analysis process and represented measures of gait quality, however, future research should investigate the validity of these metrics. Spatiotemporal gait parameters are frequent components of in-lab gait analyses [2], and the studies in this review demonstrate the ability to calculate spatiotemporal gait parameters in non-lab settings with wearable devices. While these were among the most common features extracted from the accelerometer signals, several advanced features were also introduced, particularly for walking studies, that provide insight into the quality of gait in various situations that would not be detected with an in-lab gait analysis. The presence of biomodal cadence was an indication of different types of walks in different environments [21,27,66], while a loss of complexity (reduced entropy) suggested a reduced adaptability of daily life walking [37]. Dynamic stability was defined as the ability to maintain functional locomotion despite the presence of internal (i.e. noise in the neuromuscular system) or external (i.e. walking surface) disturbances, and is a feature of a healthy locomotor system [33,52,56]. Evidence to support the suggestion that the advanced metrics describe different locomotor characteristics includes the lack of association between stride-to-stride kinematic variability based on spatiotemporal gait parameters and non-linear measures of variability [56]. For example, van Schooten et al. [63] demonstrated that local dynamic stability is comparable between short and long bouts of walking, which is not the case for stride time variability or medial-lateral trunk variability. However, although short-term local dynamic stability exhibits good within-day reliability, it exhibits poor between-day reliability and can only be used to detect substantial changes on the individual level [62]. Therefore, important questions regarding the features extracted from wearable devices still need to be addressed, including the most important metrics for gait analysis of certain populations [21], the validity of wearables-based metrics [16], and the length of time needed for reliable observation of gait patterns using these metrics [65,69].

Only a handful of running studies considered features that defined gait variability using either linear [78,79,81] or non-linear [78] measures, which was a bit surprising considering the potential relationship between variability and injury status [89,90]. However, compared to walking studies, there was a greater focus among running studies on peak acceleration, energy, impulse, impact rate and shock attenuation. These variables may be relevant to running injuries [91] and should be considered in future investigations of running injury risk.

In both walking and running studies, it was rare for features extracted from gyroscope and magnetometer signals to be included in the gait analysis. In several cases, a gyroscope and/or magnetometer were present, but features from these sensors were not computed [28,40,43,45,68]. Considering the number of reported standalone accelerometer-based investigations, it is possible that other studies used inertial measurement units that produced accelerometer as well as gyroscope and magnetometer signals, but only reported on the accelerometer data. Future studies should elucidate the roles of traditional and more complex features of accelerometer signals, as well as variables extracted from other components of inertial measurement units, for gait analyses performed in out-of-lab settings.

## 5. Conclusion

While wearable devices offer freedom from the constraints of in-lab gait analysis systems, this advantage has not been adequately exploited to increase the understanding of real-world gait patterns of walkers and runners. Future work in this field should involve long-term data collection on large cohorts of runners and walkers in their natural environment, thus enabling prospective studies, the development of subject-specific models of gait, and the identification of subgroups based on gait patterns. Additionally, guidelines for the usability of wearable devices and the validity of wearables-based measurements of gait quality need to be established.

### Conflict of interest statement

The authors have no conflicts of interest to disclose.

### Acknowledgements

This work was supported by a University of Calgary Eyes High Postdoctoral Fellowship award and, in part, through an NSERC Idea-2-Innovation (I2I) grant (493875-16), a Strategic Operating grant from the University of Calgary Vice-President (Research) and a seed grant from the Faculty of Kinesiology at the University of Calgary. The sponsors had no role in the study design; in the collection, analysis and interpretation of data; in the writing of the manuscript; or in the decision to submit the manuscript for publication.

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