A systematic review of human activity recognition using

smartphones

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**Abstract** 

Smartphones have become a global communication tool and more recently a technology for studying human

behavior. Given their numerous built-in sensors, smartphones are able to capture detailed and continuous

observations on activities of daily living. However, translation of measurements from these consumer-grade

devices into research-grade physical activity patterns remains challenging. Over the years, researchers have

proposed various human activity recognition (HAR) systems which vary in algorithmic details and statistical

principles. In this paper, we summarize existing approaches to smartphone-based HAR. We systematically

screened the literature on Scopus, PubMed, and Web of Science in the areas of data acquisition, data

preprocessing, feature extraction, and activity classification. We ultimately identified 72 articles on

smartphone-based HAR. To provide an understanding of the literature, we discuss each of these areas

separately, identify the most common practices and their alternatives, and propose possible future research

directions for this interesting and important field.

Keywords

Wearable computing; accelerometer; gyroscope; data acquisition; data processing; feature extraction;

activity classification; digital phenotyping machine learning; pattern recognition.

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# **Highlights**

- Accelerometers and gyroscopes are frequently used in human activity recognition
- Most studies investigate human behavior in controlled environments
- Conscientious data processing and feature selection enhance classification accuracy
- Complex classification algorithms have been increasingly explored in recent years
- Variety of approaches and lack of standardization hinder comparison of studies

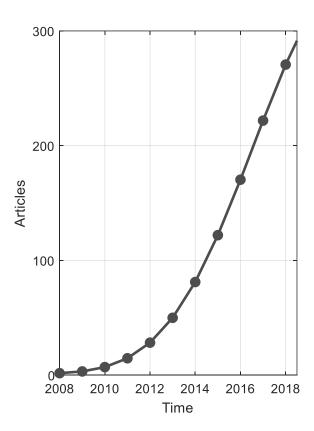
### 1. Introduction

According to the GSM Association, there were roughly 2 billon smartphones in use in 2019, and this number is expected to double in the next couple of years [1]. Such explosion in worldwide smartphone adoption presents unprecedented opportunities for the study of human behavior. Smartphones now contain multiple sensors to capture detailed, continuous, and objective measurements of human behavior, including on mobility and physical activity. Along with sufficient storage, powerful processors, and wireless transmission, such data can be obtained without additional hardware or instrumentation, which makes it feasible to study large cohorts of subjects over extended time periods. Importantly, smartphones are not a niche product, as appears to be the case with most wearable activity trackers [2], but instead they have become a globally available technology, increasingly adopted by users of all ages both in advanced and emerging economies [3,4]. While these technological developments make the task of data collection easier, analysis of the collected data is increasingly identified as the main bottleneck in research settings [5–7], and therefore it appears that the main challenge in human activity recognition (HAR) is now shifting from data collection to statistical methodology and pattern recognition.

This proliferation of smartphones has not gone unnoticed by the research community. At the time of writing, there were nearly 300 articles published on HAR methods using smartphones, a substantial increase from just a handful of articles published a few years earlier (Figure 1). This growing interest has taken place across various fields such as security and surveillance [8], personal navigation [9], and health monitoring [10]. Regardless of the motivation, the goal of HAR is to classify what activity was performed in a given

period of time. This task is particularly challenging due the physiological (e.g., weight, height, age) and habitual (e.g., posture, gait, walking speed) differences of smartphone users, but also due to differences in the built environment (e.g., buildings and green spaces) that provide the physical and social setting for human activity. Moreover, the data collection and statistical approach typically used in HAR may be affected by the variable location and orientation of the device [11], which complicates the transformation of collected data into meaningful and interpretable outputs.

To overcome these difficulties, researchers have proposed various algorithms which differ substantially in terms of their data specifications, signal manipulation techniques, and statistical classification



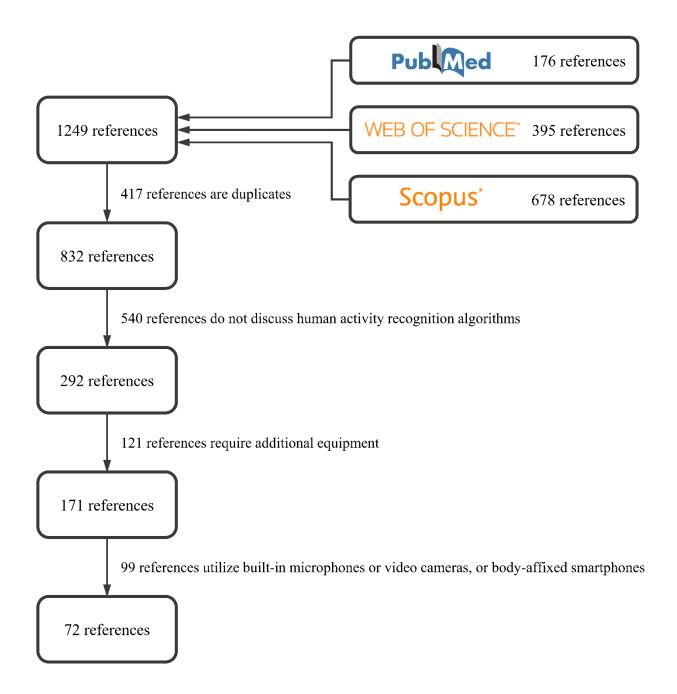
**Figure 1.** Cumulative number of articles on HAR using smartphones published between 2008 and middle 2019. The articles were collected from PubMed, Scopus and Web of Science databases, and then selected based on the relevance of their abstracts (for details, see Section 2 and Section 3).

approaches. The available studies both use existing methods and propose new methods for collection, processing, and classification of activities of daily living. Authors commonly discuss data filtering and feature selection techniques and compare the accuracy of various machine learning classifiers either on previously existing datasets or on datasets they have collected *de novo* for the purposes of the specific study.

The results are typically summarized using classification accuracy within different groups of activities like ambulation, locomotion, and exercise. This paper aims to summarize recent efforts in smartphone-based HAR research with the goal of providing an understanding of the contextual complexity and multidimensionality of the problem, the collected data, and the methods used to translate the digital measurements into human activities.

### 2. Methods

Our systematic review was conducted by searching for articles published by June 30, 2019, on PubMed, Scopus, and Web of Science databases. The databases were screened for titles, abstracts, and keywords containing phrases "activity" AND ("recognition" OR "estimation" OR "classification") AND ("smartphone" OR "cell phone" OR "mobile phone"). The search was limited to full-length journal articles written in English. After removing duplicates, we read titles and abstracts of the remaining publications. References that did not investigate HAR approaches were excluded from further screening. In the following step, we filtered out studies that employed auxiliary equipment, like wearable or ambient devices, and studies that required carrying multiple smartphones. Only studies that made use of commercially available consumer grade devices (either personal or loaner devices) were read in full. We excluded papers that used smartphone microphone or video camera for activity classification as they might record information about an individual's surrounding, including information about unconsented individuals, and thus hinder large-scale application of the approach due to privacy concerns. Finally, to best understand studies that mimic free-living settings, we neglected papers that utilized devices strapped or glued to the body in a fixed position.



**Figure 2.** Flowchart of the literature search process.

# 3. Results

Our search resulted in a total of 1249 hits for the specified search criteria, including 176 references in PubMed, 395 references in Web of Science, and 678 references in Scopus (Figure 2). After duplicate removal, we read the abstracts of 832 publications, which revealed that 540 articles did not discuss HAR

algorithms. Therefore, only 292 references were assigned for full reading, of which 121 references that employed additional hardware were excluded together with an additional 99 references that utilized built-in microphones or video cameras. Additionally, we excluded studies with smartphones affixed to the human body. The remaining 72 references were read in detail.

Most HAR approaches consist of four stages, namely data acquisition, data preprocessing, feature extraction, and activity classification. In the following, we provide an overview of these steps and briefly point to significant methodological differences among the studies. Table 1 summarizes specific aspects of each study: we have decomposed data acquisition process to sensor type, experimental environment, investigated activities, and selected smartphone location; we have also indicated which studies preprocess collected measurements using signal correction methods, sensor orientation-invariant transformations, and noise filtering techniques; we have marked investigations due to types of signal features they extract, as well as due to the feature selection approaches; finally, we have indicated the adopted activity classification principles, utilized classifiers, and practices for accuracy reporting. Figure 3 displays the most frequent terms used in the included studies.

### 3.1. Data acquisition

We use the term data acquisition to refer to a process of collecting and storing raw sub-second level smartphone measurements for the purpose of HAR. The data are typically collected by a program or application that runs on the device and samples data from built-in smartphone sensors within predefined time intervals. The process is carried out on a group of individuals enrolled in a given study, who typically perform various activities while carrying the device at different body locations. The selected data acquisition scheme defines the scope of research and has a significant impact on generalizability of the proposed methodology to other studies. Therefore, we carefully examined the literature for details on the investigated population, measurement environment, performed activities, and smartphone settings.

We found that data acquisition is typically conducted on a small cohort of less than 30 subjects. Such cohorts often include healthy adults in their twenties and thirties, and occasionally involve a handful of older

Table 1. Summary of HAR systems using smartphones. Marked cells indicate aspects present in particular studies.

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# data acquisition controlled measurement free-living environment mobility investigated activity accelerometer gyroscope magnetometer sensor lower body upper body purse/bag/backpack smartphone body location data preprocessing repair denoising transformation feature extraction signal fixed segmentation feature time-domain frequency-domain type feature manual selection automatic activity classification simple classifier ensemble classification single step scheme offline computation platform online between cohorts cross-validation between body locations confusion matrix performance computation time battery drain

**Figure 3.** Word cloud of the most frequent terms used in the included studies.

individuals. Less effort has been devoted to investigate populations with different demographic and disease characteristics, such as elders [12] and subjects with Parkinson's disease [10]. As an example of a larger study, Kelishomi et al. [13] analyzed data from 480 healthy individuals.

In the reviewed papers, data collection typically takes place in a research facility and/or nearby outdoor surroundings. In such environments, study participants are asked to perform a series of activities along predefined routes and to interact with predefined objects. The duration and order of performed activities are usually determined by the study protocol and the subject is supervised by a research team member. A less popular approach involves observation conducted in free-living environments, where participants perform activities without specific constraints. Such studies are likely to provide more insight into diverse activity patterns due to individual habits and unpredictable real-life conditions. Compared to a single laboratory visit, it also allows investigators to monitor behavioral patterns over many weeks [14] or months [15].

Activity selection is one of the key aspects of HAR. The studies considered here tend to focus on a small set of activities, including sitting, standing, walking, running, and stair climbing. The less common activities involve various types of mobility, locomotion, fitness, and household routines. For instance, Wu et al. [16] differentiate between slow, normal, and brisk walking; Guvensan et al. [17] investigate multiple transportation modes, like car, bus, tram, train, metro, and ferry; Pei et al. [18] recognize sharp body-turns; and Della Mea et al. [19] look into household activities, like sweeping a floor or walking with a shopping bag. In Table 1, "posture" refers to lying, sitting, standing, or any pair of these activities; "mobility" refers to walking, stair climbing, body turns, riding elevator, or escalator, running, cycling, or any pair of these activities; "locomotion" refers to motorized activities; and "other" refers to various household and fitness activities or singular actions beyond the described groups.

The spectrum of investigated activities determines the choice of sensors used in data acquisition. At the time of writing, a standard smartphone is equipped with a number of built-in sensors and protocols that can be used for activity monitoring, including accelerometer, gyroscope, magnetometer, barometer, GPS, proximity sensor, light sensor, as well as the information on calls/texts and on-screen activity. The literature suggests that the most commonly used sensors for HAR are accelerometer, gyroscope, and magnetometer,

which is possibly due to the temporally dense, high-resolution measurements they provide for distinguishing among activity classes. The inertial sensors are often used synchronously providing more insight into the dynamic state of the device. Some studies show that the use of a single sensor can yield similar activity recognition results [20]. To alleviate the impact of sensor position, researchers collect data using built-in barometer and GPS sensors to investigate changes in altitude and geographic location [21,22]. Certain approaches benefit from the broader set of capabilities of smartphones, and the researchers may additionally exploit proximity and light sensors which allow the recognition of a measurement's context, e.g., the distance between smartphone and subject's body, and changes between in-pocket and out-of-pocket locations based on changing illumination [23,24]. The selection of sensors is also affected by secondary research goals, like simplicity of classification and minimization of battery drain. In such approaches, data collection is carried out on a single sensor (e.g. accelerometer [14]), a small group of sensors (e.g., accelerometer and GPS [25]), or with purposely modified sampling frequency to reduce the amount of data collected and processed [26].

The sampling frequency describes how many observations are collected by a particular sensor in one second. The selection of sampling frequency is usually performed as a trade-off between measurement accuracy and battery drain. In a typical data acquisition setting, the sampling frequency ranges between 20 to 30Hz for inertial sensors and 1 to 10Hz for barometer and GPS. The most significant variations from this description are required for inertial sensors if limited energy consumption is a priority (e.g., accelerometer sampled at 1Hz [27]) or if the investigators use advanced signal processing methods (e.g., accelerometer sampled at 100Hz [28]).

A crucial parameter in the data acquisition process is the smartphone's body location. This is important mainly because of the nonstationary nature of real-life conditions and the strong effect it has on the smartphone's inertial sensors. The main challenge in HAR is due to the fact that the data recorded by accelerometer, gyroscope, and magnetometer differ between upper and lower body as the device is not affixed to any specific location or orientation in uncontrolled free-living conditions [29]. Therefore, it is essential that studies collect data from as many body locations as possible to ensure generalizability of

results. In the reviewed literature, subjects were often instructed to carry the device in pants pocket (either front or back), although a number of studies also considered other placements, such as jacket pocket [30], bag or backpack [31], and holding the smartphone in hand [32].

To establish the ground truth for physical activity in HAR studies, the data are usually annotated manually by trained research personnel or by subjects themselves [33,34]. However, we also encountered several approaches that automate this process both in controlled and free-living conditions. For instance, in [14] the data were labelled using a designated smartphone application. A different approach was proposed in [35], where authors used a built-in step counter to produce "weak" labels. Also, the annotation can be done using built-in microphone [36] and video camera [12].

Finally, the data acquisition process is carried out on purposely designed applications which capture and transmit data to the external server using cellular, Wi-Fi, Bluetooth, or wired connection. In online activity classification, the collected data do not leave the device but instead the entire HAR pipeline is implemented on the smartphone.

## 3.2. Data preprocessing

We use the term data preprocessing to refer to a collection of procedures aimed at repairing, cleaning, and transforming measurements recorded for HAR. The need for such step is threefold: (1) measurement systems embedded in smartphones are often less stable than research-grade data acquisition units, and the data might therefore be sampled unevenly or there might be missingness or sudden spikes that are unrelated to subject's actual behavior; (2) the temporal orientation of the device influences tri-axial measurements of inertial sensors, thus potentially degrading the performance of the HAR system; and (3) despite careful planning and execution of the data acquisition stage, data quality may be compromised due to other unpredictable factors, e.g., lack of compliance by the study participants, unequal duration of activities in the measurement (i.e., dataset imbalance), or technological issues.

The first group of obstacles is typically addressed using signal processing techniques (in Table 1, see "repair"). For instance, in order to alleviate the mismatch between requested and effective sampling

frequency, Derawi and Bours [8] propose the use of linear interpolation, while Gu et al. [37] utilize spline interpolation. Such procedures are imposed on a range of affected sensors, typically including accelerometer, gyroscope, magnetometer, and barometer. Further time-domain preprocessing considers data trimming, carried out to remove unwanted data components. For this purpose, the beginning and end of each activity bout are clipped as nonrepresentative for the given activity [30], where a bout refers to a short period of activity of a specified kind. During this stage the researchers also deal with dataset imbalance. The imbalance occurs when observations of one activity significantly dominate over others. Such situation makes the classifier susceptible to overfitting in favor of the larger class; however, the issue might be solved by up- or downsampling of data [13,38]. Additionally, the measurements are processed for high-frequency noise cancellation (in Table 1, see "denoising"). The literature identifies several methods suitable for serving this task, including the use of low-pass finite impulse response filters (with cut-off frequency typically equal to 10Hz for inertial sensors and 0.1Hz for barometers) [39,40], weighted moving average [8], moving median [29], and singular value decomposition [41].

Another element of data preprocessing considers device orientation (in Table 1, see "transformation"). Smartphone measurements are sensitive to device orientation, which may be due to personal choices, clothing, body shape, and movement during dynamic activities [38]. One of the popular solutions is to transform the three-dimensional signal into univariate vector magnitude which is invariant to rotations and more robust to translations. This procedure is often applied to accelerometer, gyroscope, and magnetometer data. Accelerometer data can also be subjected to digital filtering by separating the signal into linear (related to body) and gravitational (related to orientation) acceleration [42]. This separation is typically performed using high-pass Butterworth filter of low order (e.g., order 3) with cut-off frequency below 1Hz. Other approaches transform tri-axial measurement into bi-axial with horizontal and vertical axes [32], or project the data from the device coordinate system into fixed coordinate system using a rotation matrix (Euler angle-based [43] or quaternion [31]).

#### 3.3. Feature extraction

We use the term feature extraction to refer to a process of selecting and computing meaningful summaries of smartphone data for the goal of activity classification. A typical extraction scheme includes data visualization, data segmentation, feature selection, and feature calculation. A careful feature extraction step allows investigators not only to understand the physical nature of activities and its manifestation in digital measurements, but more importantly also helps uncover hidden structures and patterns in the data. The identified differences are later quantified through various statistical measures to distinguish among activities. In an alternative approach, the entire process of feature extraction is automated using deep learning, which handles both segmentation and feature selection. On the other hand, and as with most applications of deep learning, this often results in loss of interpretability and limited control over the process.

The conventional approach to feature extraction begins with data exploration. For this purpose, researchers employ various graphical techniques, like scatter plots, lag plots, autocorrelations plots, histograms, and power spectra [44]. The choice of tools is often dictated by the study objectives and methods. For example, research on inertial sensors typically presents raw three-dimensional data from accelerometers, gyroscopes, and magnetometers plotted for the corresponding activities of standing, walking, stair climbing, etc. A similar approach is used for barometric pressure data. Acceleration data are often inspected in the frequency-domain, particularly to observe periodic motions of walking, running, and cycling [29], and the impact of external environment, like natural vibration frequencies of a bus or a subway [45]. Locomotion and mobility are investigated using estimates of speed derived from GPS. In such settings, the investigators calculate the average speed of the device and associate it with either the group of motorized (car, bus, train, etc.) or non-motorized (walking, cycling, etc.) modes of transportation.

The established differences are then processed to render them amenable computer processing. This is accomplished by dividing the measurements into smaller fragments (also, segments or epochs) and calculating signal features for each fragment. This segmentation is typically conducted using a windowing technique that allows consecutive windows to overlap. The window size has usually a fixed duration or length that varies from 1 to 5s, while the overlap is often set to 50%. Several studies investigate how to

select the optimal window size, which emphasizes the importance of this parameter to the performance of HAR systems [46–48]. This calibration aims to closely match the window size with the duration of a single instance of the activity. Similar motivation leads researchers to seek more adaptable segmentation methods. One idea is to segment data based on specific time-domain events, like zero-cross points, peak points, or valley points, which represent the start and end points of a particular activity bout [8,38]. This allows for segments to have different lengths corresponding to a single fundamental period of the activity in question. Such approach is typically used to recognize quasiperiodic activities like walking, running, stair climbing, and sitting and standing [41].

The literature offers a large variety of signal features used for HAR. Such features can be divided into several categories based on the initial signal processing procedure. This enables one to distinguish between activity templates (i.e., raw signal), time-domain features, and frequency-domain features. The most popular features in the reviewed papers are calculated from time-domain signals as descriptive statistics, such as local mean, variance, minimum and maximum, interquartile range, energy, and higher order statistics. Other time-domain features include mean absolute deviation, mean (or zero) crossing rate, regression coefficients, and autocorrelation. Some studies describe novel and customized time-domain features, like histogram of gradients [49], magnitude of standard deviations [50], number of local maxima and minima, their amplitude and temporal distance between them [26]. The described time-domain features are typically calculated over each axis of the three-dimensional measurement or orientation-invariant vector magnitude. Studies that use GPS also calculate average speed [51], while studies that use barometer observe pressure derivative [52].

Signals transformed to the frequency domain appear to be less exploited in the literature. A commonly performed signal decomposition uses the Fast Fourier Transform (FFT). The essential advantage of frequency-domain features over time-domain features is their ability to identify and isolate certain periodic components of the performed activities. This enables researchers to estimate energy within particular frequency bands associated with human activities, like gait and running [33], as well as with different ways of locomotion [45]. Other frequency-domain features include spectral entropy and parameters of the dominant peak, e.g., its frequency and amplitude.

Activity templates function essentially as blueprints for different types of physical activity. In HAR systems, these templates are compared to patterns of observed raw measurements using various distance metrics [25]. Given the heterogeneous nature of human activity, activity templates are often enhanced using techniques similar to dynamic time warping [38]. As an alternative to raw measurements, some studies use signal symbolic approximations created by discretization functions that transform data segments into symbols [53,54].

In the reviewed articles, the number of extracted features typically varies from a few to a dozen. However, some studies purposely calculate too many features (sometimes hundreds) and let the analytical method identify those that are most relevant and informative to HAR. Support vector machines [52], gain ratio [55], recursive feature elimination [25], correlation-based feature selection [33], and principal component analysis [56] are among popular feature selection/dimension reduction methods. A comparison of feature selection methods is provided by Saeedi and El-Sheimy [57].

## 3.4. Activity classification

We use the term activity classification to refer to a process of associating extracted features with particular activity classes based on the adopted classification principle. The classification is typically performed by a supervised learning algorithm that has been trained to recognize patterns between features and labeled physical activities. The fitted model is then validated on separate observations, usually using data from the same cohort. The comparison between predictions made by the model and the known true labels allow one to assess the generalizable accuracy of the approach. This section summarizes the methods used in classification and validation, and also provides some insights into reporting on HAR performance.

The choice of classifier aims to identify a method that has the highest classification accuracy for the collected datasets and for the given data processing environment (e.g., online vs. offline). The literature examines a broad range of classifiers from simple decision trees [12], k-nearest neighbors [42], support vector machines [58], logistic regression [10] and naïve Bayes [9] to ensemble classifiers such as random forest [47], AdaBoost [29], bagging [16] and convolutional neural networks [39,59]. Simple classifiers are

frequently compared to find the best solution in the given measurement scenario [35,55,60]. Similar type of analysis is implemented for ensemble classifiers [51]. Incremental learning techniques are proposed to adapt the classification model to new data streams and unseen activities [61,62]. To increase the effectiveness of HAR, some studies use a hierarchical approach, where the classification is performed in separate stages and each stage can use a different classifier. The multi-stage technique is used for gradual decomposition of activities (coarse-grained first, then fine-grained) [14,24,34,39] and to handle the predicaments of changing sensor location (body location first, then activity) [58]. Classification accuracy can also by improved using post-processing, which relies on modifying the initially assigned label using the rules of logic and probability. The correction is typically performed based on activity duration [45], activity sequence [17], and activity transition probability and classification confidence [63].

The selected method is typically cross-validated, which splits the collected dataset into two parts, training and testing, and only uses the part of the data for testing that was not used for training. The literature mentions a few cross-validation procedures, k-fold and leave-one-out cross-validation being the most common [64]. Popular train-test proportions are 90-10, 70-30, and 60-40. A validation is especially valuable if it is performed using cohorts with different demographics and smartphone use habits. Such approach allows one to understand the generalizability of the HAR system to real-life conditions and populations. We found a few studies that follow this validation approach [10,12,44].

Activity classification is the last stage of HAR. Analysis results are typically reported in terms of the classification accuracy using various standard metrics like precision, recall, and F-score. More nuanced summaries use the confusion matrix, which allows one to examine which activities are more likely to be mistaken. Such approach is particularly useful for visualizing classification differences between similar activities, such as normal and fast walking or bus and train riding. Additional statistics are usually provided in context of HAR systems designed to operate on the device. In this case activity classification needs to be balanced among acceptable classifier performance, processing time, and battery drain [65]. The desired performance optimum is obtained by making use of dataset remodeling (e.g., by replacing the oldest observations with the newest ones), low-cost classification algorithms, limited preprocessing, and

conscientious feature selection [29,54]. Computation time is sometimes reported for complex methods, such as deep neural networks [66], extreme learning machine [67], or symbolic representation [53,54,68], as well as in comparative analyses [30]. Nevertheless, a comprehensive comparison of results is difficult or impossible as discussed next.

### 4. Discussion

Over the past few years many studies have investigated HAR using smartphones. The reviewed literature provides detailed descriptions of essential aspects of data collection, data processing, and activity classification. The studies have been conducted with one or more objectives, e.g., to limit technological imperfections (e.g., no GPS signal reception indoors), to minimize computational requirements (e.g., online systems), and to maximize classification accuracy (all studies). Our review summarizes most frequently used methods and offers available alternatives. We do not however identify any one ultimate activity recognition procedure, and we doubt that one even exists. This results in part from the complexity of the task. Different studies use different activities, signal processing techniques, and classifiers, and each likely suffers from specific potential drawbacks.

Some of our concerns relate to the quality of the collected data. While datasets are usually collected in laboratory settings, there is little evidence that algorithms trained using data from these controlled settings generalize to free-living conditions [69,70]. In free-living settings, such aspects as duration, frequency, and the specific ways of performing any activity are subject to individual choice and capability, and these degrees of freedom therefore need to be considered in the development of HAR systems. Further, some studies are conducted with a small number of able-bodied volunteers. This substantially eases the process of data handling and classification but also likely limits the generalizability of the approach to larger and more diverse populations. The latter point is well demonstrated by del Rosario et al. [12] and Albert et al. [10]. In the first study, the authors observe that the performance of a classifier trained on a young cohort significantly decreases once validated on the older cohort. Similar conclusions can be drawn from the second study, where the observations on healthy individuals do not replicate in individuals with Parkinson's disease.

We observed that the majority of studies utilize smartphones positioned stationary at a single body position (i.e., a specific pants pocket), and sometimes even with fixed orientation. Such scenarios are however rarely observed in real-life settings, and these types of studies should therefore be considered more as proofs of concept rather than HAR systems that generalize to free-living settings. Other data quality considerations relate to the description of the experiment and study protocol, including demographic details of the enrolled cohort, environmental context, and details of the performed activities. Such information should be reported as fully and as accurately as possible.

Only a few papers consider classification in a context that involves activities outside the defined research scope, i.e., activities that the HAR system was not trained on. The designed classifiers were instead tasked to associate every movement with one of the prespecified set of activities. Real-life activities are however not limited to any particular set of behaviors, i.e., we do not only sit still, stand still, walk, and climb stairs. These classifiers, when applied to free-living conditions, will naturally miss the activities they were not trained on but will also likely overestimate others. An improved recognition scheme could assume that the observed activities are a sample from a broader spectrum of possible behaviors or assess the uncertainty associated with the classification of each event.

Despite meeting the technical and practical requirements for human activity monitoring, a lack of standardized procedures makes an apples-to-apples comparison of the studies difficult. The research also suffers from deficits in publicly available datasets, source code, and trained classification models. Although some efforts have been made in this area [71], the recommended course of action assumes collecting and analyzing data from a large spectrum of sensors on diverse and under-studied populations and validating classifiers against widely accepted gold standards.

Our paper serves as an overview of the field of smartphone-based HAR. Although we conducted the literature search in a systematic manner, this review does not include technical papers and conference proceedings. Despite this limitation, we hope that the provided analysis might help consolidate knowledge on the use of smartphones to measure human behavior, provide insights into the complexity and

multidimensionality of smartphone measurement and data analysis, and offer guidelines and direction to anyone interested in this challenging but important topic.

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