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REVIEW

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Advanced analytical methods to assess physical activity behavior using accelerometer time series: A scoping review

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Physical activity (PA) is a complex human behavior, which implies that multiple dimensions need to be taken into account in order to reveal a complete picture of the PA behavior profile of an individual. This scoping review aimed to map advanced analytical methods and their summary variables, hereinafter referred to as wearable-specific indicators of PA behavior (WIPAB), used to assess PA behavior. The strengths and limitations of those indicators as well as potential associations with certain health-related factors were also investigated. Three databases (MEDLINE, Embase, and Web of Science) were screened for articles published in English between January 2010 and April 2020. Articles, which assessed the PA behavior, gathered objective measures of PA using tri-axial accelerometers, and investigated WIPAB, were selected. All studies reporting WIPAB in the context of PA monitoring were synthesized and presented in four summary tables: study characteristics, details of the WIPAB, strengths, and limitations, and measures of association between those indicators and health-related factors. In total, 7247 records were identified, of which 24 articles were included after assessing titles, abstracts, and full texts. Thirteen WIPAB were identified, which can be classified into three different categories specifically focusing on (1) the activity intensity distribution, (2) activity accumulation, and (3) the temporal correlation and regularity of the acceleration signal. Only five of the thirteen WIPAB identified in this review have been used in the literature so far to investigate the relationship between PA behavior and health, while they may provide useful additional information to the conventional PA variables.

KEYWORDS
accelerometry, algorithm, data processing, physical activity pattern, wearable sensors

1 | INTRODUCTION

Less sedentary behavior and more physical activity (PA) provide important health benefits and help mitigate health risks.[1] PA is a complex human behavior, which implies that multiple dimensions (e.g., the type, intensity, and duration) of PA need to be taken into account in order to reveal a complete picture of the PA behavior of an individual. The FITT framework (F = frequency, I = intensity, T = time, and T = type), developed by the American College of Sports Medicine, already referred to the multiple dimensions of PA and highlighted that each of those exclusion of a specific article were discussed in a team meeting, and discrepancies were resolved by consulting a third author (LM) when necessary.

2.6 | Data extraction process

In order to describe the different WIPAB, their interpretation, strengths, and limitations as well as their association with different health conditions, the data from the finally selected articles were extracted by two authors (TG and AB) separately by means of a data extraction form. The data extraction form was tested on five different studies to ensure their functionality. The extracted data were compared regularly to ensure consistency. The data extracted from each of the included articles relates to the following key information, providing the structure for the reported results. First, the study characteristics are presented, including the author(s), the year of publication, the study design, details on the study population (sample size, description of the population, sex, mean age, and age range), the device used, the wear location, the length of the follow-up period (measurement length), details on the periods analyzed and on the definition of valid data. Secondly, the identified WIPAB are described in detail, including the name of the indicator, a description, and an interpretation. An overview of the software used to determine the WIPAB can be found in the table in Appendix S2. Thirdly, the strengths and limitations of the identified WIPAB are pointed out, which are both based on those reported in the identified sources as well as on our expertise and critical evaluation. Lastly, the associations between the identified WIPAB and health-related factors are presented, including the name of the indicator, the population analyzed, the health-related factor, a specification on the analysis (statistical model and adjustment for potential confounders) used, and the outcome of the study (associations and their direction).

3 | RESULTS

The selection process is presented in the flow diagram (Figure 1). In total, 7247 records were identified through the database searches. Overall, 3838 duplicates were removed, resulting in 3409 records, which were included

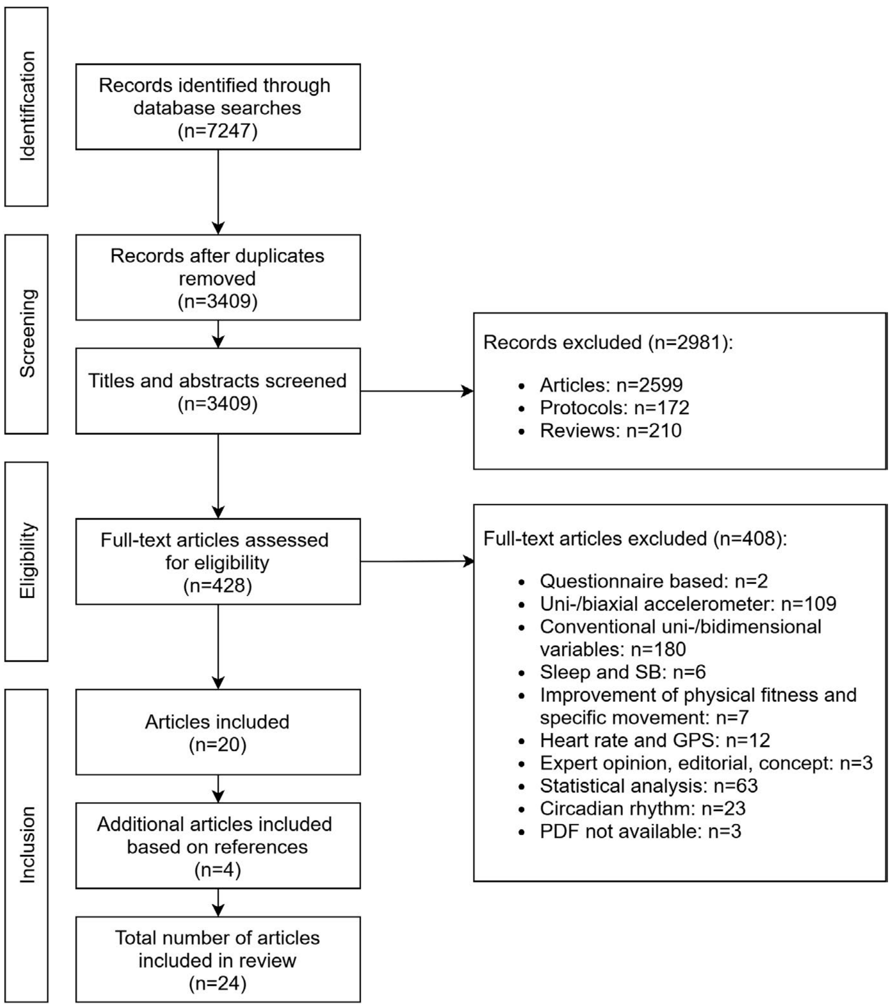

FIGURE 1 Flow-chart of the article selection

TABLE 3 Strengths and limitations of the identified wearable-specific indicators of physical activity behavior (WIPAB)

WIPAB	Strengths	Limitations	References
Intensity gradient	• Independence from cut points • Can be combined with the average acceleration to investigate independent, additive, or interactive associations of volume and intensity distribution with health • Captures time spent across the intensity spectrum without having to handle compositional challenges	• Only limited reference values in the literature • No information on temporal accumulation • Likely dependent on epoch length and acceleration metric choice • Magnitude of the intensity gradient dependent on the size of intensity bins used to summarize the acceleration signal	Buchan et al.[13] Fairclough et al.[9] Fairclough et al.[26] Rowlands, Dawkins et al.[38] Rowlands et al.[39] Rowlands, Fairclough et al.[40] Rowlands, Sherar et al.[41]
MX metric	• Independence from cut points • Post-hoc comparison with cut points	• Agreement on key MX metrics needed, so a decision needs to be made on time thresholds • No information on temporal accumulation	Fairclough et al.[26] Rowlands, Dawkins et al.[38] Rowlands, Fairclough et al.[40] Rowlands, Sherar et al.[41]
Power-law exponent alpha	• Information on bout length distribution • Identification of different PA behavior strategies (e.g., proportion of longer bout lengths in the accumulation of time spent at a specific intensity)	• Difficult to interpret in terms of typical (ie, subject or population preferred) bout length. Therefore, complementary metrics such as $x_{1/2}$ (median bout length) and $W_{1/2}$ (fraction of total time accumulated in bouts longer than $x_{1/2}$) were proposed	Barry et al.[33] Chastin and Granat[3] Fortune et al.[31] Keadle et al.[37]
Median bout length	• Information on the preferred bout length of a specific subject or population • Is directly related to the power-law exponent alpha	• Present only limited information on the bout length distribution	Chastin and Granat[3] Fortune et al.[31]
Proportion of total time accumulated in bouts longer than x	• Information on accumulation pattern of a specific activity intensity • Can be combined with the proportion of the number of bouts above a certain length x to form the Lorenz curves	• Present only limited information on the bout length distribution	Chastin and Granat[3] Fortune et al.[31] Keadle et al.[37]
Gini index	• Information on inequality in bout length distribution • Non-parametric	• Only limited reference values in the literature	Chastin and Granat[3] Dunton et al.[25] Fortune et al.[31] Keadle et al.[37]
Scaling exponent alpha	• Information on temporal correlations	• Requires that the time scales of interest occur in all recordings. No clear guidance on the selection of a suitable range of time scales • Originally developed for ECG analysis with long series of heartbeats, which may make it less suitable for relatively short series of behavior bouts per day • Not suitable for rare behaviors, for example, vigorous activity	Hu et al.[4] Li et al.[6] Pan et al.[36]

(Continues)

TABLE 3 (Continued)

WIPAB	Strengths	Limitations	References
Autocorrelation coefficient at lag *k*	• Information on temporal correlations	• Strength of correlation potentially specific to sensor location, and signal processing steps	Autocorrelation at lag 1 min: Krane-Gartiser et al.[28] Scott et al.[29] Autocorrelation at lag 24 h: Chen et al.[34] Merilahti et al.[32] Taibi et al.[30]
Fourier analysis	• Information on the variance of different frequency spectrum components	• Does not capture temporal structure • Less suitable for rare behaviors, especially when these rare behaviors have a low signal magnitude	Hauge et al.[35] Krane-Gartiser et al.[28] Scott et al.[29]
Sample entropy	• Information of the regularity of the time series • Independence from time series length • Robustness regarding outliers	• Resting periods can skew the results	Hauge et al.[35] Krane-Gartiser et al.[28] Krane-Gartiser et al.[27] Scott et al.[29]
Lempel-Ziv complexity	• Information on diversity of states and dynamics of change between different states (variability of the time series) • If applied to PA states: quantity and quality dimension of daily activities are taken into account	• Transformation of the original signal into a finite sequence with only binary elements (coarse-graining process) • Dependency from the resolution of the time series • Susceptible to noise, due to sensitivity to the amplitude distribution • Sensitive to the length of the sequence	Paraschiv-Ionescu et al.[14] Zhang et al.[15]
Permutation Lempel-Ziv complexity	• Information on diversity of states and dynamics of change between different states (variability of the time series) • If applied to PA states: quantity and quality dimension of daily activities are taken into account • Use of permutations (motifs) of a chosen length (instead of a coarse-graining process) to estimate complexity • Robustness to noise as it only considers the order relations between the values in the time series	• Sensitive to the length of the sequence	Paraschiv-Ionescu et al.[14]
Symbolic dynamics	• Information on the variability of the time series	• Depends on prior classification of the time series in symbolic patterns	Krane-Gartiser et al.[28]

The MX metric can be compared to cut points post-hoc, enabling the maintenance of the continuous nature of the variable and the comparison to any cut-point or acceleration indicative of a standard activity. By plotting the MX metric, visual comparisons of within and between-group differences can be made, thus allowing the generation of data-driven norms.[38] However, the MX metric depends on the wear location and may differ between monitor brands, which could hinder the comparability between studies. Furthermore, there is still no consensus on the key MX metrics to analyze with respect to health conditions. Hence, a decision on time thresholds (i.e., most active *x* minutes) needs to be made. Finally, as the MX metric and the intensity gradient ignore the temporal activity accumulation, a combination with PA accumulation indicators should be envisaged.[38]

4.1.2 | Activity accumulation

The power-law exponent alpha and the Gini index are measures that quantify how sedentary or active time has been accumulated. The power-law exponent alpha provides for example information on the distribution of the

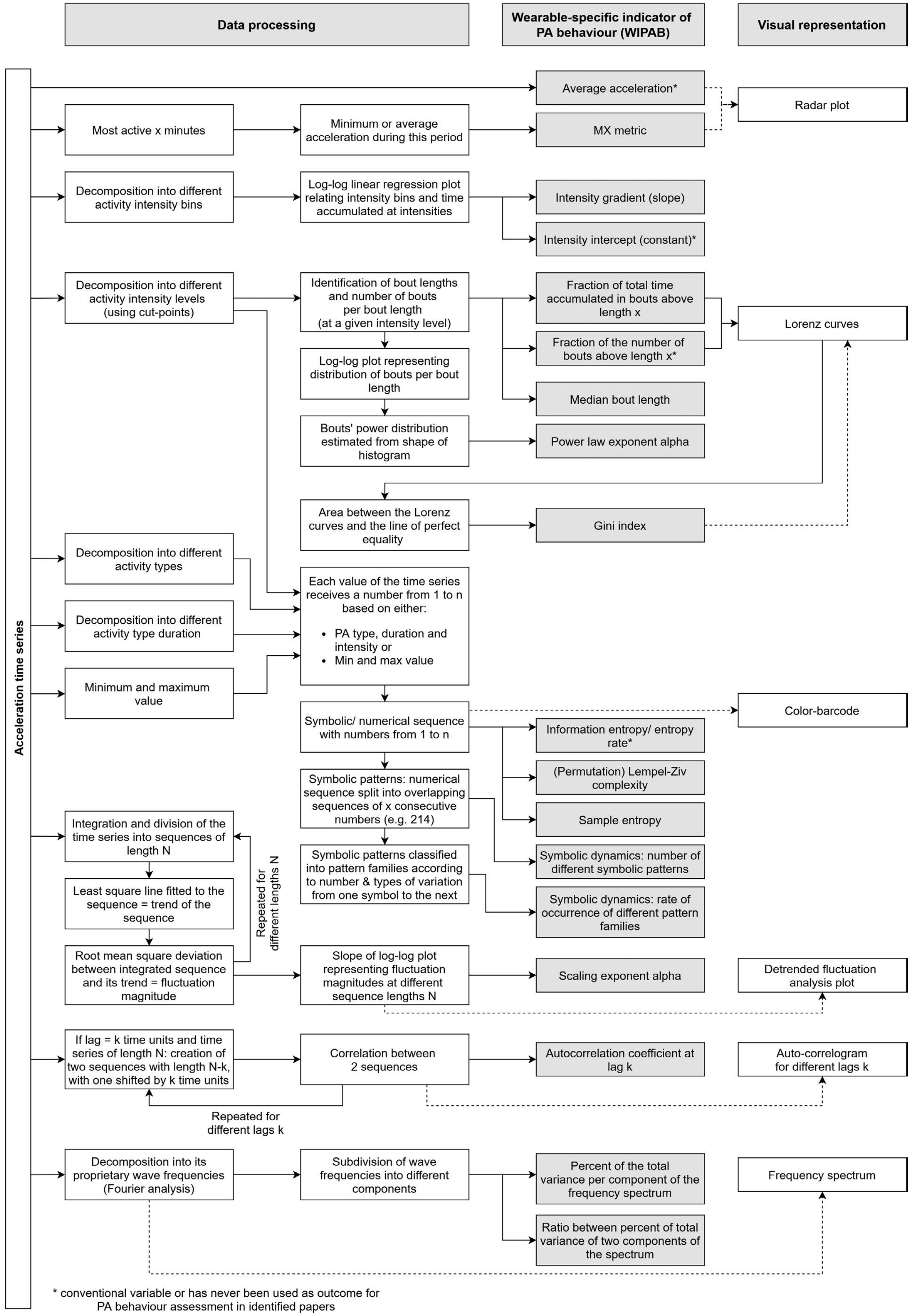

FIGURE 2 Overview of the identified wearable-specific indicators of physical activity behavior (WIPAB)

TABLE 4 Correlations and measures of association between the wearable-specific indicators of physical activity behavior (WIPAB) and health-related factors

WIPAB	Reference	Population	Health-related factor
Intensity gradient	Buchan et al.[13]	Children	BMI z-score
	Fairclough et al.[9]	Children	BMI z-score
			Waist-to-height ratio
			Cardiorespiratory fitness
			Metabolic syndrome score
			Health-related quality of life
	Rowlands, Fairclough et al.[40]	Children (9–10 years)	BMI z-score
		Adolescent girls (11–12 years)	Percent body fat
		Adolescent girls (13–14 years)	Percent body fat
		Adult office workers	Percent body fat
		Premenopausal women	Percent body fat
			Bone density T-score
		Postmenopausal women	Percent body fat
			Bone density T-score

TABLE 4 (Continued)

WIPAB	Reference	Population	Health-related factor
		Adults with type 2 diabetes	Percent body fat
			Short Physical Performance Battery score
	Rowlands et al.[39]	Adolescent girls	BMI z-score
			Percent body fat
		Adults with type 2 diabetes	BMI
			Percent body fat
			Average grip strength
			Sit-to-stand test (60 repetitions)
			Short Physical Performance Battery score
Scaling exponent alpha	Hu et al.[4] *Activity correlations (alpha) at small time scales (<1.5 h)*	Elderly with dementia	Mini-Mental State Examination score (cognition)
			Multidimensional observation scale for elderly: social withdrawal behavior score
			Cornell Scale for Depression in Dementia score (mood)
	Li et al.[6] *Per 1-SD decrease in alpha*	Elderly without mild cognitive impairment at baseline	Incident mild cognitive impairment
		Elderly without dementia at baseline	Incident Alzheimer's dementia

TABLE 4 (Continued)

WIPAB	Reference	Population	Health-related factor
24-h autocorrelation	Chen et al.[34]	Lung cancer patients	Total sleep time Sleep efficiency Sleep-onset latency
	Merilahti and Korhonen[32]	Elderly without dementia	Activities of daily living score
Lempel-Ziv complexity	Paraschiv-Ionescu et al.[14]	Community-dwelling older adults	Fall-related psychological concerns (Falls Efficacy scale)
	Zhang et al.[15] *Original PA time series*	Younger older adults	Community Balance and Mobility Scale score
	Zhang et al.[15] *Smoothed PA time series*	Younger older adults	Community Balance and Mobility Scale score
Permutation Lempel-Ziv complexity	Paraschiv-Ionescu et al.[14]	Community-dwelling older adults	Fall-related psychological concerns (Falls Efficacy scale) Functional mobility status (Timed up-and-go test)

Abbreviations: (–), no association; (↗), positive association; (↘), negative association; Cox, Cox-proportional hazard regression model; GLM, generalized linear model; LME, linear mixed effects model; MLRM, multiple linear regression model.

bout durations, which can be used to identify different PA behavior pattern (e.g., if a person tends to accumulate sedentary time with a higher proportion of longer bouts compared to shorter bouts).[3,31] As the power-law exponent alpha is a unit-less parameter, the interpretation might be more difficult. Therefore, Chastin et al.[3] proposed two additional metrics: the median bout length ($x_{1/2}$), which provides information on the preferred bout length for a specific subject or population, and $W_{1/2}$, which is the proportion of the total time at a specific intensity that is accumulated in bouts longer than the median bout length ($x_{1/2}$). The generalization of the latter (W_x, proportion of the total time at a specific intensity that is accumulated in bouts longer than x) further contributes to the calculation of the Gini index. By plotting W_x against the proportion of the number of bouts of length x, we get the Lorenz curves, which are used to calculate the Gini index.[3,42] Hence, the Gini index, a non-parametric measure, describes the inequality in bout durations. However, similar to the intensity gradient, there is also a lack of reference values for the Gini index in the literature. As already stated above, metrics describing both the activity intensity distribution and the activity accumulation are complementary.

4.1.3 | Temporal correlation and regularity

The scaling exponent alpha, the autocorrelation at lag k (e.g., lag 24 h or lag 1 min), and the Fourier analysis are measures that investigate temporal correlations (self-similarities) between values to find repeating patterns. The sample entropy, the (permutation) Lempel-Ziv complexity, and the symbolic dynamics approach quantify the amount of regularity in a time series. The particular feature of these metrics is that they take the chronological aspect into account. It should be noted that the term "Fourier analysis" and "symbolic dynamics approach" were kept in the present review, even though that they describe rather the method than the specific outcome metric, in order to be consistent with the cited papers as well as because they can have more than one outcome.

To determine the amount of regularity in an acceleration time series, specific pre-processing (i.e., data reduction) techniques may be needed to convert the raw signal into a new numerical or symbolic sequence. In the context of the symbolic dynamics approach, the acceleration time series is divided into n equal portions based on the acceleration value range, and each value receives then a number from 1 to n. Another pre-processing technique was applied before the use of the (permutation) Lempel-Ziv complexity,[14,15] where a symbolic sequence was composed of different PA states. PA states are created from the combination of the PA type, intensity, and duration categories. This approach presents the advantage that both the quantity and quality dimensions of daily activities are taken into account, providing important information on the PA behavior.[14,15]

In a subsequent step, entropy measures can be used to quantify the information embedded in the symbolic/numerical sequence. The Lempel-Ziv complexity, for