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Review

Criterion validity of device-based motion sensors for monitoring free-living physical activity in community-dwelling manual wheelchair users: a systematic review

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Abstract: Community-dwelling manual wheelchair users (MWU) accumulate less physical activity (PA) and are more sedentary than their ambulatory peers. To promote PA and evaluate interventions, accurate PA monitoring methods in free-living circumstances are needed. Recent advances in device-based motion sensor (DBMS) technology and data analytics have raised the possibility that DBMS might be used – either individually or in combination – to provide accurate estimates of free-living PA in MWU. This study reviewed the evidence for existing DBMS for estimating energy expenditure (EE); self-propulsion (SP); activities other than SP; and wheelchair kinematics (WK) including time, distance and speed in MWU. Forty studies evaluating thirty-four devices were identified, analysed, and synthesized in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis Protocols (PRISMA-P) Statement and COSMIN Methodology for Systematic Reviews of Patient-Reported Outcome Measure. Sixteen devices (47%) were custom made and eighteen (53%) were commercially available devices. Of those commercially available, thirteen (72%) were research-based devices, and five (28%) were consumer-based devices. According to the assessment using COSMIN, twenty-six devices (76%) provided accurate estimates of the target outcome. The level of evidence was 'moderate' to 'high' for sixteen (47%) devices, 'very low' for eleven (32%), 'low' (24%) for eight, and 'low to high' for one (3%). Seventeen DBMS were body-worn and of those, tri-axial accelerometers secured to the upper-arm or wrist provided the most accurate estimate of EE and for differentiating SP from other daily activities. Fourteen DBMS were wheelchair mounted and of those, tri-axial accelerometers and inertial measurement units (IMU) provided accurate estimates of wheelchair movement time, distance, and speed. Devices with gyroscope sensor/s, also provided an accurate estimate of SP, upper body movement when doing activities such using an arm ergometer or playing wheelchair basketball, and distance travelled by the wheelchair. DBMS have the potential to monitor free-living PA in MWU. However, future research should be of higher methodological quality and aim to enhance accuracy and acceptability of DBMS through population specific algorithms and improved wearability.

Keywords: Accelerometer; accuracy; disability; gyroscope; inertial measurement unit; measuring

Introduction

There is strong, consistent evidence that manual wheelchair users (MWU) require a physically active lifestyle to achieve good health (Kawanishi & Greguol, 2013; Smith et al., 2022). Physical activity (PA) levels among MWU are typically insufficient for good health (Smith et al., 2022). Therefore, intervention studies promoting PA participation for MWU are vital (Kawanishi & Greguol, 2013). In order to evaluate whether these interventions successfully promote increased PA within this population, methods for accurate measurement of habitual PA in free-living environments are required (Kawanishi & Greguol, 2013).

Among the ambulatory population, the quantity of bi-pedal locomotor activity completed (e.g., walking, jogging, stair climbing, treadmill exercise) provides an indirect indication of free-living, habitual PA (Dowd et al., 2018; Tudor-Locke et al., 2004; Yang & Hsu, 2010). Bi-pedal locomotor activities are considered indirect as they either omit or do not accurately measure activities that are either non-locomotor or not bi-pedal such as swimming, cycling, skateboarding, and resistance training. However, as the vast majority of habitual activity accrued by the general population in free-living circumstances involves bi-pedal locomotion, these measures are considered an accurate indicator of habitual PA (Dowd et al., 2018; Yang & Hsu, 2010). Device-based motion sensors (DBMS), comprised of accelerometers, gyroscopes, and/or magnetometers, have been demonstrated to provide valid and reliable measures of bi-pedal locomotor activity in the general population (Dowd et al., 2018; Tudor-Locke et al., 2004; Yang & Hsu, 2010).

Among MWU the most widely accepted indicator of habitual free-living PA is self-propelled distance travelled by the wheelchair-user's day chair. Device based motion sensors have been demonstrated to provide accurate estimates of self-propelled distance travelled (Jörgensen et al., 2017; Nightingale et al., 2017; Oyster et al., 2011; Popp et al., 2018; Sonenblum et.al., 2012). However, compared to bi-pedal locomotor activity in the general population, it is likely that wheelchair distance travelled is a much less valid indicator of habitual free-living activity in MWU. For example, people who identify as MWU may not use a manual wheelchair for all mobility needs. MWU may use a wheelchair for community mobility but walk—with or without assistive devices—around their home or for short distances in the community. In these cases, wheelchair distance travelled will not capture this regular and potentially important component of PA (Jörgensen et al., 2017; Popp et al., 2018). Similarly, MWU may accrue a significant proportion of leisure time PA in sports. Sport is often played in a specific chair that is different from the chair used for daily activity. Unless the device is transferred or multiple devices are used, then the activity accrued during sports participation won't be captured (Nightingale et al., 2017). Furthermore, some MWU may accrue significant amounts of activity with no increase in wheelchair distance travelled when using common exercising modalities such as arm crank ergometers or wheelchair ergometers. They also won't accrue activity when performing physically demanding activities of daily living, such as transferring (e.g., from chair to bed, toilet, or car), lifting and carrying, or housework. Conversely, during activities such as downhill coasting or when being assisted by a personal support worker, wheelchair distance will increase with no associated increase in PA by the user (Hiremath et al., 2013; Nightingale et al., 2017).

Recent advances in the technology underpinning DBMS, together with advances in data analytics and machine learning techniques, have resulted in studies describing the use of DBMS to capture other components of PA, including but extending beyond wheelchair distance travelled (Lankhorst et al., 2020; Nightingale et al., 2017; Rast & Labruyère, 2020; Tsang et al., 2016). For example, arm worn devices with user-specified algorithms have been used to estimate energy expenditure (EE) of MWU and machine learning techniques have

been developed which can differentiate activities that will have different energy demands (e.g. self-propulsion activities compared with transferring, or household duties such as vacuuming and hanging out laundry) (Lankhorst et al., 2020; Nightingale et al., 2017; Rast & Labruyère, 2020; Shwetar et al., 2020; Tsang et al., 2016). These advances raise the possibility that DBMS might be used, either individually or in combination, to provide an index of free-living PA in MWU that is more valid than wheelchair distance travelled (Nightingale et al., 2017; Yang & Hsu, 2010). However, the investigation of such possibilities requires a comprehensive understanding of the types of DBMS available, the range of outcome measures that can be obtained, and the extent to which each is valid (Lankhorst et al., 2020; Rast & Labruyère, 2020; Tsang et al., 2016).

The overall aim of this review is to systematically identify, appraise, and synthesise evidence from scientific studies which have evaluated the accuracy of DBMS for estimating PA outcome measures in MWU with a view to provide guidance to researchers and clinicians who wish to measure free-living PA in this population. The specific aims of this review were to: 1) describe the types of DBMS evaluated and how they have been applied to estimate PA in MWU; 2) evaluate the methodological quality of included studies; and 3) evaluate the extent to which DBMS provide accurate estimates of the target outcomes (Dowd et al., 2018).

Materials and Methods

Protocol

The Preferred Reporting Items for Systematic Reviews and Meta-Analysis Protocols (PRISMA-P) Statement (Moher et al., 2015) and COSMIN Methodology for Systematic Reviews of Patient-Reported Outcome Measures (Mokkink et al., 2010; Mokkink et al., 2018a, 2018b; Prinsen et al., 2018; Terwee et al., 2018) were used as a guide for the analysis and reporting of the studies included in this review.

Identification of literature

A formal literature search using bibliographic search databases was the primary method of identifying relevant articles (Moher et al., 2015; Mokkink et al., 2018b.) A search of electronic literature databases including: PUBMED (1951-2024), SCOPUS (1966-2024), CINAHL via EBSCOHost (1982-2024), and PEDRO (-2024) was conducted on 25th November 2024, retrieving articles from database inception. These databases were identified as they represented comprehensive repositories of citations, abstracts, and full articles in fields relevant to the research questions.

Search strategy and criteria for article inclusion and exclusion

The complete search strategy used in this review can be found in Appendix 1. The PubMed searches were limited to journal articles and studies with human subjects. The keywords were also matched to the Medical Subject Headings (MeSH) index when available and searched as keywords. Additional records were identified through a manual search from the reference lists of included articles. The criteria for article inclusion and exclusion can be found in Table 1.

Screening and eligibility

All identified articles were exported to Endnote (Version X7.7, United States of America). Title and abstract screening were performed by two observers independently (KSK and NTNH) using the eligibility criteria. Two authors (KSK and SRG) then independently assessed full text articles for inclusion in the review. Conflicts were resolved by discussion with a third reviewer drawn from the authorship team (KC, SMT).

Table 1. Criteria for article inclusion and exclusion

Inclusion criteria	Exclusion criteria
The study evaluated the criterion validity of device-based motion sensors (DMBS) for measuring movement (e.g., distance, speed, duration), physical activity (PA), energy expenditure (EE), or activities of daily living in manual wheelchair users (MWU);	The validity of the measurement instrument was tested using non-human or mechanical mechanisms;
Participants were aged ≥ 18 years, with or without disabilities, and with any diagnosis	The study provided information on the validity and reliability of the measurement instrument, or used the measurement instrument to measure the outcomes of PA (e.g. intervention studies, systematic reviews) in MWU, but did not include primary research data on the outcome's measurement properties;
The protocol was conducted with wheelchair-based activities (e.g. wheelchair maneuvering or wheelchair propulsion).	Validated measurement instrument outcomes or criterion measures were based on physiological responses (e.g., heart rate, respiration, and skin temperature) instead of motion;
	A full-text of the study was not published in English or the study was considered grey literature (e.g. dissertations, conference abstracts, research reports, chapter(s) from a book, personal correspondence or commentaries, and policy documents).

Screening and eligibility

All identified articles were exported to Endnote (Version X7.7, United States of America). Title and abstract screening were performed by two observers independently (KSK and NTNH) using the eligibility criteria. Two authors (KSK and SRG) then independently assessed full text articles for inclusion in the review. Conflicts were resolved by discussion with a third reviewer drawn from the authorship team (KC, SMT).

Data extraction

Data extraction was completed by one reviewer (KSK) after all studies were screened and relevant studies selected. Microsoft Excel (Microsoft Office 365 ProPlus) was used to manage study data.

Quality assessment of the included studies and DBMS

Each included study was critically appraised for its methodological quality, measurement properties, and level of evidence by two reviewers (KSK and KC) using modified COSMIN checklists for criterion validity (Furlan et al., 2015; Mokkink et al., 2018a, 2018b; Prinsen et al., 2018; Terwee et al., 2018). The modified four step approach of the COSMIN checklist for methodological quality and level of evidence assessment can be found in Table 2. The COSMIN checklist for evaluating the methodical quality of the studies and measurement properties includes: 1) defining the measurement properties that are assessed; 2) evaluating the risk of bias by assessing the methodological quality of the included studies; 3) evaluating each measurement against criteria of good measurement properties; and 4) summarising and grading the quality of evidence (Mokkink et al., 2018b; Prinsen et al., 2018; Terwee et al., 2018). To rate the methodological quality of the included studies, a four-point scoring system (excellent; good; fair; and poor) was used and the lowest rating of any item in a box was taken ('worse score counts' method) according to the COSMIN guidelines (Mokkink et al., 2018a, 2018b; Prinsen et al., 2018; Terwee et al., 2018). The ratings for outcome measurement properties were qualified as: positive (+); indeterminate (?); and negative (-) (Mokkink et al., 2018a, 2018b; Prinsen et al., 2018; Terwee et al., 2018). To assess the quality of the evidence, each validated device was graded as having high, moderate, low, or very low evidence, referring to the confidence in the trustworthiness of the summarised measurement properties (Mokkink et al., 2018b; Prinsen et al., 2018; Terwee et al., 2018).

1 Table 2 The modified four step approach of COSMIN checklist for methodological quality and level of evidence assessment. (Mokkink et al., 2018a, 2018b; Prinsen et al.,
2 2018; Terwee et al., 2018)

<table>
<tr><td colspan="3">DEFINING THE MEASUREMENT PROPERTIES THAT ARE ASSESSED</td></tr>
<tr><td colspan="3">ASSESSING THE RISK OF BIAS (Standards evaluated with rating scores “excellent”, “good”, “fair”, “poor”)</td></tr>
<tr><td colspan="3">Standards evaluated include:
1. Whether the proposed criterion measure can be considered a reasonable “gold standard” based on the recommendations of COSMIN checklist (Criterion Validity Design Requirement 1). Studies were rated as “excellent” when criterion used could be considered “gold standard” (e.g., indirect calorimetry, direct observation.
2. Whether an appropriate time schedule for assessment of the PROM against the criterion measure was applied (Criterion Validity Design Requirement 3). Studies were rated as “excellent” when the PROM and criterion measure were administered at the same time.
3. Whether appropriate statistical methods were applied to continuous scores (Criterion Validity Statistical Methods 4) and dichotomous scores (Criterion Validity Statistical Methods 5). Studies were classified as “excellent” when appropriate statistical methods were applied for each score (e.g., correlations and AUC for continuous scores and sensitivity and specificity for dichotomous scores*).
4. Whether a clear description of how missing items were handled was provided (Criterion Validity Statistical Methods 6). Studies were classified as “excellent” when a clear description is provided.
Important methodological flaws that are not covered by the checklist but may bias results or conclusions were noted for items 1 – 4 above.</td></tr>
<tr><td colspan="3">CRITERIA FOR MEASUREMENT OUTCOME QUALITY RATING</td></tr>
<tr><td colspan="2">For continuous scores:
(+) Correlation with gold standard ≥ 0.70 OR AUC ≥ 0.70
(-) Correlation with gold standard < 0.70 OR AUC < 0.70
(?) Not all information for ‘+’ reported</td><td>For dichotomous scores*:
(+) >80%
(-) ≤80%
(?) Not all information for sensitivity and specificity or accuracy information</td></tr>
<tr><td colspan="3">LEVEL OF EVIDENCE QUALITY LEVEL</td></tr>
<tr><td></td><td>DEFINITION OF QUALITY LEVELS</td><td>CRITERIA</td></tr>
<tr><td>HIGH</td><td>Very confident that the true measurement property lies close to the estimate of the measurement property.</td><td>Consistent findings (>75%) in multiple studies of good methodological quality OR in one study of excellent methodological quality with measurement outcome quality rating: +++ or - - -</td></tr>
<tr><td>MODERATE</td><td>Moderately confident in the measurement property estimate: the true measurement property is likely to be close to the estimate of the measurement property, but there is a possibility that it is substantially different.</td><td>Consistent findings (>75%) in multiple studies of fair methodological quality OR in one study of good methodological quality with measurement outcome quality rating: ++ or - -</td></tr>
<tr><td>LOW</td><td>Confidence in the measurement property estimate is limited: the true measurement property may be substantially different from the estimate of the measurement property.</td><td>Limited information: One study of fair methodological quality with measurement outcome quality rating: + or – OR conflicting +/-</td></tr>
</table>

VERY LOW	We have very little confidence in the measurement property estimate: the true measurement property is likely to be substantially different from the estimate of the measurement property.	Only studies of poor methodological quality with measurement outcome quality rating: (?)

Abbreviations: AUC Area under curve; PROM Patient-Reported Outcome Measures *Current review applied the same scoring for studies involving dichotomous outcomes as a previous systematic review in this field. (Lankhorst et al., 2020)

This review focused only on studies that evaluated the validity of DBMS assessing motion using one or more of the following: accelerometers, gyroscopes, magnetometers, inertial measurement units (IMUs), and power meters. The term 'IMU' is used in this review when the validation study uses this definition of the estimation device. To streamline the findings and summarise practical considerations for device selection for researchers and clinicians, the studies were grouped into four physical activity (PA) variable categories. The categories were defined based on the PA outcome assessed: (1) studies estimating total energy expenditure (EE); (2) studies estimating self-propulsion (SP); (3) studies estimating activities other than SP; and (4) studies estimating wheelchair kinematics (WK). The PA variables are presented in Table 3.

Table 3. Physical activity variables evaluated for DBMS. The accuracy of custom-made, research-based devices, commercially available research-based devices, and commercially available consumer-based devices was reviewed relating to each PA variable.

Physical Activity Variable	Sub-Variable
Total Energy Expenditure (EE)	n/a
Self-propulsion (SP)	n/a
Activities other than SP	Grouped activities (evaluated all activities together).
	Sedentary activities (e.g., watching TV, computer work, lying down, passive propulsion).
	Household activities (e.g., folding laundry, mopping or sweeping, moving and carrying items).
	Body transfers (e.g., transferring to the wheelchair or from the wheelchair to another surface).
	Exercise (e.g., arm ergometer, hand cycling, resistance band exercises, playing wheelchair basketball).
Studies estimating wheelchair kinematics (WK)	Duration / time
	Distance.
	Speed.
	Activity classification of wheelchair movement periods and non-wheelchair movement periods.

The decision to distinguish wheelchair SP from other daily activities was made based on: 1) the understanding that wheelchair SP is the most common daily activity performed by MWU; and 2) the consistent presentation of this activity as a stand-alone variable in the studies evaluated (Jörgensen et al., 2017). The category of Activities other than SP was divided into five sub groups: 1) grouped activities (evaluated all activities together); 2) sedentary activities (e.g., watching TV, computer work, lying down, passive propulsion); 3) household activities (e.g., folding laundry, mopping or sweeping, moving and carrying items); 4) body transfers (e.g., transferring to the wheelchair or from the wheelchair to another surface); and 5) exercise (e.g., arm ergometer, hand cycling, resistance band exercises, playing wheelchair basketball). The category of WK was divided into four sub-groups of wheelchair movement: 1) duration/time; 2) distance; 3) speed; and 4) activity classification of wheelchair movement periods and non-wheelchair movement periods.

Included DBMS were classified into three groups based on their design purpose: 1) custom-made, research-based devices including sensors that were configured by researchers, that are not a commercialised product, and that allow users have access to the raw data; 2) commercially available research-based devices including sensors that are available for purchase by the general public and that allow users have access to the raw data; and 3) commercially available consumer-based devices including sensors that are available for purchase by the general public, where users don't have access to raw data. Lastly, DBMS were specified as either commercially available devices using default algorithms (where raw data are converted to PA outcomes using proprietary or pre-loaded algorithms) or custom

algorithms (where raw data are converted to PA outcomes using algorithms developed by individual research teams).

This review reports the most accurate commercially available research- and consumer-based devices and custom-made devices for each of the four PA outcome categories. The most accurate device was determined by considering its measurement outcome relative to the relevant criterion, together with the methodological quality scores and levels of evidence reported according to the COSMIN checklist. (Dowd et al., 2018; Mokkink et al., 2018a, 2018b; Prinsen et al., 2018; Terwee et al., 2018). The outcomes regarding DBMS, physical activity variables and estimation method, criterion measure, device positioning, study protocols and measurement properties mapped against the COSMIN checklist are presented in Appendices 3a-d.

Results

Literature search and selection of the studies

The search yielded 15,030 titles from four databases. After removing duplicates (n = 2,150) 12,880 studies were screened at title and abstract level, and five additional studies were identified by reviewing the reference lists of retrieved relevant papers. Two hundred and five studies were identified for full-text screening. At the end of the full-text selection and review process, 40 articles met the eligibility criteria. A flowchart describing article selection is shown in Figure 1.

An overview of the included studies is presented in Table 4 including: the bibliographic details (author, year, and study topic); the characteristics of the population (number of participants, gender, and diagnoses); the validated outcome and criterion measure; the specifications of the validated DBMS (brand, type, and output of the device); classification of the device's commercial availability and design purpose (research and/or consumer-based use); and the study's main findings.

Characteristics of the included study population

The studies comprised 747 participants in total, aged 18 to 71 years (65% male). Nine (15%) studies did not report participant sex. Sixteen studies (40%) included a sample of individuals with a spinal cord injury only. In total, there were 498 participants with SCI (67% of all participants). From the thirty-one studies that included participants with SCI, twenty-four reported the level or severity of the disability. Reporting of this information varied, using variables including neurological level of injury, complete or incomplete injury status, paraplegia, and tetraplegia. Some studies included this information for each individual participant while others presented a pooled total (e.g., 80% paraplegic). The double asterisks in Table 4 indicate the papers that reported the level of SCI.

Twelve studies (30%) included participants with disabilities other than SCI (for example amputation, Charcot-Marie-Tooth disease, and complex regional pain syndrome). A small number of studies (10%) did not report participant diagnosis. Seven studies (18%) included individuals who were both reliant and not reliant on a wheelchair for locomotion, and four studies (10%) included only individuals who were not reliant on a wheelchair for locomotion. However, all participants in these studies completed the protocol in a wheelchair.

Table 4 The overview of identified studies including: the bibliographic details, the characteristics of the population, the validated outcome and criterion measure; the characteristics of the validated device-based motion sensors, classification of the devices commercial availability and design purpose and the main results reported

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Washburn & Copay (1999)	Assessing PA during wheelchair pushing: validity of portable ACC	21 (9F / 12M)	SCI=11 SB= 7 Other=3	EE (ml· $kg^{-}1min^{-1}$)	Indirect calorimetry	CSA (1-axis ACC, model 7164) using acceleration counts (count/min^{-1})	C1	Significant associations between EE derived from each wrist-worn CSA monitor and indirect calorimetry r = .52 -.67 (p <.01)
Postma et al. (2005)	Validity of the detection of wheelchair propulsion as measured with an Activity Monitor in patients with spinal cord injury	10 (3F / 7M)	SCI = 10	SP	Video recordings	ADXL202 (2-axial ACC connected to Vitaport 3 data recorder) using ACC signals	C2	Detection of wheelchair propulsion agreement 92% (range 87-96%), sensitivity 87% (range 76-99%) and specificity 92% (range 85-98%) Sensitivity for the detection of wheelchair propulsion with: poor triceps strength 81% (range 76– 89%), (p < .01), good triceps strength 95% (range 89–99%), (p < .01) Mean overestimation in duration of wheelchair propulsion 3.9% (p < .05)
Hiremath et al. (2011)	Evaluation of activity monitors in manual wheelchair users with paraplegia	24 (5F / 19M)	SCI = 24	EE (kcal/min)	Indirect calorimetry	RT3 (3-axial ACC) using activity counts	C1	All activities: ICC (3,1) = .64, 95% CI [0.51, 0.73], p < .05; Spearman rho, r = .72, p < .05 Deskwork: ICC (3,1) = .60, 95% CI [0.12, 0.85], p < .05; Spearman rho, r = .66, p < .05 Arm ergometry: ICC (3,1) = .40, 95% CI [0.12, 0.62], p < .05; Spearman rho, r = .52, p < .05

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
								Propulsion: ICC (3,1) = .52, 95% CI [0.26, 0.70], $p < .05$; Spearman rho, $r = .44$, $p < .05$. Resting: ICC (3,1) = .53, 95% CI [0.02, 0.82], $p < .05$; Spearman rho, $r = .53$ EE estimation errors varied from 22.0 to 52.8%
Coulter et al. (2011)	Development and validation of a PA monitor for use on a wheelchair	14 (9F / 5M)	SCI = 14	Wheelchair kinematics (distance travelled and wheelchair moving time)	Video recordings	ActivPAL (3-axial ACC) using the radial and tangential acceleration [Absolute angle (˚), number of wheel revolutions and duration of movement(s)]	C1	Wheel revolution: ICC = 1.00, 95% CI [1.00, 1.00], mean difference = 0.002 (SD = 0.016), MAPE = 0.59% Absolute angle: ICC = 0.999, 95% CI [0.999, 0.999], mean difference = 0.0006 (SD = 3.853) Duration of movement: ICC = 0.981, 95% CI [0.669, 0.994]
Sonenblum et al. (2012)	Validation of an ACC-based method to measure the use of manual wheelchairs	5 (2M / 3NR)	SCI = 2 AB = 3	Wheelchair kinematics (wheelchair moving time and distance)	Video recording and measured distance	MMA7260Q Freescale Semiconductor (3-axial ACC connected to a custom data logging system) using acceleration (g's), wheel revolutions and speed (m/s)	C2	Wheelchair movement time accuracy 91-96%. Wheelchair movement distance accuracy 96% (SD = 2%)

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Garcia-Masso et al. (2013)	Validation of the use of Actigraph GT3X ACCs to estimate energy expenditure in full time manual wheelchair users with spinal cord injury	20 (NR)	SCI = 20	EE (ml·kg-1·min-1)	Indirect calorimetry	ActiGraph GT3X (3-axial ACC) using ACC counts (counts s-1)	C1	The accuracy using four ActiGraph GT3X ACC placed on four different locations varied r = .67-.86
Sindall et al. (2013)	Criterion validity and accuracy of global positioning satellite and data logging devices for wheelchair tennis court movement	15 (4F/11M)	NR	Wheelchair kinematics (distance travelled)	Measured distance and Data logger (concurrent validity)	Data logger (DL) (integrated ACC) using distance (m) calculated from wheel revolutions	C2	Distance in moving forward estimated with DL on left wheel was lower compared with measured distance and distance estimated with DL on the right wheel. Distance in reversing drill estimated with DL right was lower than measured distance and distance estimated with DL on the left wheel.
Hiremath et al. (2013)	Development and evaluation of a gyroscope-based wheel rotation monitor for manual wheelchair users	1 (NR)	AB = 1	Wheelchair kinematics (distance travelled)	Measured distance via a tape measure and Smartwheel/ Three-dimensional passive motion capture system	G-WRM (2-axial gyroscope) using angular velocities (s^{-1}) converted to distance traveled	C2	Distance travelled: ICC (3,1) varied from 0.000-1.000 (Lower: 0.997-1.000 and upper: 1.000-1.000). MAPE forward and backward trials with camper 2.5 = 0.58% camper 15.5 = 0.88% Handcycling distance error: G-WRM 1 = 1.06% G-WRM 2 = 0.04% G-WRM 3 = -0.88%

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Nightingale et al. (2014)	Predicting PA EE in manual wheelchair users	15 (NR)	SCI = 9 SB = 2 Other = 2 AB = 2	EE*	Indirect calorimetry	ActiGraph GT3X (3-axial ACC) using PAC	C1	PAC correlation Waist r = .73 (absolute bias ±95% limits of agreement 0.0 ± 11.8kJ*min^{-1}) Upper arm r = 0.87 (absolute bias ± 95% limits of agreement 0.0 ± 8.5kJ*min^{-1}) Wrist r = .93 (absolute bias ± 95% limits of agreement 0.0 ± 6.5kJ*min^{-1})
Kooijmans et al. (2014)	Valid detection of self-propelled wheelchair driving with two ACCs	10 (10M)	SCI = 10	SP	Video recordings	ActiGraph GT3X (3-axial ACC) using vector counts	C1	Detection of self-propelled wheelchair driving: Overall agreement 85.2% (range 76.7-92.3%), sensitivity 88% (range 83.1-93.0%), specificity 83.3% (range 72.6-91.2%) Accuracy for self-propelled wheelchair driving duration 0.80%, average overestimation 5.5 s (SD 34 s, p-value = .60) Accuracy for other activities - 0.90%

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Ojeda and Ding (2014)	Temporal parameters estimation for wheelchair propulsion using wearable sensors	26 (6F /20M)	SCI = 26	SP	Video recordings and SmartWheel®	3- axial ACC (brand NR) using stroke number and push frequency, (stroke / sec)	C2	Accuracy for estimating the stroke number: upper arm ICC = 0.994, 95% CI [0.998, 0.997], p = .001, MAPE = 8.0% (SD = 7.1%); wrist ICC = .990, 95% CI [0.980, 0.995], p < .001, MAPE = 10.8% (SD = 9.8%); seat ICC = .984, 95% CI [0.972, 0.991], p < .001, MAPE = 13.4% (SD = 15.6%) Accuracy for estimating the push frequency: upper arm ICC = 0.916, 95% CI [0.843, 0.953], p < .001, MAPE = 12.9% (SD = 15.1%); wrist ICC = 0.889, 95% CI [0.802, 0.936], p < .001, MAPE = 17.2% (SD = 19.3%); seat ICC = 0.690, 95% CI [0.071, 0.868], p < .001, MAPE = 24.2% (SD = 16.6%)
Kiuchi et al. (2014)	Preliminary study for the assessment of PA using a triaxial ACC with a gyro sensor on the upper limbs of subjects with paraplegia driving a wheelchair on a treadmill	6 (6M)	SCI = 6	EE (kcal kg^{-1} min^{-1})	Indirect calorimetry	3-axial ACC with gyro sensor (brand not available) using acceleration signals and angular velocity (s^{-1})	C2	Coefficient of determination for Model 1 (acceleration data): R^2 = .64–.82 (SEE = 0.003–0.005) Model 2 (angular velocity): R^2 = .50–.83 (SEE = 0.003–0.005) Model 3 (acceleration data and angular velocity): R^2 = .68–.87 (SEE = 0.003–0.004)

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Conger et al. (2014)	Estimating EE through hand rim propulsion power output in individuals who use wheelchairs	14 (3F /11M)	SCI = 7 SB = 4 Other = 3	EE (kcal kg^{-1} hr^{-1})	Indirect calorimetry	PowerTap (Power meter) using Power (W)	C2	Correlation between power and EE: r = .694, p < .01 No significant differences were found between EE and prediction models Model 1 (power): R^2 = .48 (SEE = 0.97, RMSE = 0.97, prediction bias = -0.21) Model 2 (power, speed): R^2 = .70 (SEE = 0.74, RMSE = 0.82, prediction bias = 0.00)
García-Massó et al. (2015)	Identifying PA type in manual wheelchair users with spinal cord injury by means of ACCs	20 (NR)	SCI = 20	SP and daily activities (other than SP)	Human observation	ActiGraph GT3X (3-axial ACC) using ACC counts (counts s-1)	C1	Accuracy for classifiers of individual activity: Range 55–72.5% Non-dominant wrist 61.5-63.3% Dominant wrist 55.0-61.4% Combination of non-dominant and dominant wrist 62.9-68.9% Combination of 4 sensors 65.9-72.5% Accuracy for classifiers of grouped activity classifiers: Range: 83.2–93.6% Non-dominant wrist 83.9-87.0%. Dominant wrist 83.2-85.9% Combination of non-dominant and dominant wrist 86.8-87.1% Combination of 4 sensors = 89.4-93.6%

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Nightingale et al. (2015)	Influence of ACC type and placement on PA EE prediction in manual wheelchair users	17 (NR)	SCI = 9 SB = 2 Other = 2 AB = 2	EE*	Indirect calorimetry	ActiGraph GT3X (3-axial ACC) using PAC	C1	ACC outputs compared to criterion: upper arm r = .68 ($p < .01$); wrist r = .82 ($p < .01$) Mean PAEE estimation error for all activities combined: upper arm = 15% (SD = 45%), wrist = 14% (SD = 50%)
					Indirect calorimetry	Geneactiv (3-axial ACC) using PAC	C1	ACC outputs compared to criterion: upper arm r = .87 ($p < .01$); wrist r = .88 ($p < .01$) Mean PAEE estimation error for all activities combined: upper arm = 3% (SD = 25%), wrist = 4% (SD = 26%)
Conger et al. (2015)	Validity of PA monitors for estimating EE during wheelchair propulsion	14 (3F /11M)	SCI = 7 SB = 4 Other = 3	EE (kcal kg^{-1} hr^{-1})	Indirect calorimetry	Actical (AC) (omni directional activity monitor) using acceleration signals	C1	No difference between criterion method and Actical across 5 activities $p < .001$ (detailed numbers for results not reported)
Hiremath et al. (2015)	Detection of physical activities using a Physical Activity Monitor System for wheelchair users	45 (6 F/ 39M)	SCI = 45	SP and daily activities (other than SP)	Video recordings	Physical Activity Monitoring System (PAMS) (2-axial gyroscope and 3-axial ACC) using angular velocity (s^{-1}) and acceleration (m/s^2)	C2	Overall accuracy for physical activities: PAMS-Arm 89.26%, PAMS-Wrist 88.47%
						Wocket (3-axial ACC) using angular acceleration		Overall accuracy for physical activities: Arm-wocket 70.38%, Wrist wocket 74.55%

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
						G-WRM (2-axial gyroscope) using angular velocity (s^{-1})		Overall accuracy for physical activities: 65.41%
Van der Slikke et al. (2015)	Opportunities for measuring wheelchair kinematics in match settings; reliability of a three inertial sensor configuration	20 (3F / 13M)	NR	Wheelchair kinematics (speed)	Optical 3D system	X-IMU (3-axial gyroscope, 3-axial ACC and 3-axial magnetometer) using wheel acceleration signals (WhA) and wheel gyroscope (WhG) signals	C2	Correlations between IMU data and Optical 3D system: Linear speed (ICC > 0.90), Rotational speed (ICC> 0.99), Instantaneous Rotation Centre (IRC) (ICC > 0.90)
Learmonth et al. (2016)	ACC output and its association with EE during manual wheelchair propulsion	24 (9F / 15M)	SCI = 10 SB = 5 Other = 9	EE (ml·kg-1·min-1)	Indirect calorimetry	ActiGraph GT3X (3-axial ACC) using ACC counts (VM)	C1	Association between VO_2 and ACC counts: left wrist r = .93 (SD = .44), R^2 = .87 (SD = 0.19), p < .01; right wrist r = .95 (SD = 0.37), R^2 = .90 (SD = 0.14), p < .01; combined left and right wrist r = .94 (SD = 0.38), R^2 = .88 (SD = 0.15), p < .01
Popp et al. (2016)	A novel algorithm for detecting active propulsion in wheelchair users following spinal cord injury	21 (3F / 18M)	SCI = 21	SP	Video recordings	TheReSense (3-axial ACC, 3-axial gyroscope, 3-axial magnetometer) using unspecified output	C2	Overall accuracy of presented algorithm varied from 82.07 - 93.29%. Overall accuracy of: modules with gyroscope 83.77 - 93.29%, modules without gyroscope 82.07 - 91.12%

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
		2 (2M)	AB = 2	Wheelchair kinematics (distance travelled and is the wheelchair moving)	Video recordings	ADXL345 (2-axial ACC) using angular velocity and distance (m)	C2	Estimating wheelchair movement: sensitivity = 94.69% (SD = 3.01%), specificity = 99.25% (SD = 0.43%) Estimated distance accuracy = 99.2–99.8%
		2 (2M)	AB = 2	Wheelchair kinematics (distance travelled and is wheelchair moving)	Video recordings	ITG-3050 (3-axis gyroscope) using angular velocity and distance (m)	C2	Estimating wheelchair movement: sensitivity = 95.80% (SD = 1.91%), specificity = 99.58% (SD = 0.29%) Estimated distance accuracy = 97.7–99.9%
Gagnon et al. (2016)	Estimating pushrim temporal and kinetic measures using an instrumented treadmill during wheelchair propulsion: A concurrent validity study	16 (3F / 13M)	Other = 13	SP	SMARTWheel™	Instrumented treadmill with two 3-axial force platforms using time (s) of push phase, recovery phase and propulsive moments (Mz)	C2	Associations between treadmill and the instrumented pushrim: Mean duration of the push phase: r = .98 Mean duration of the push phase: recovery phase: r = .99 Mean propulsive moment: r = .97 Peak propulsive moment: r = .96
Hiremath et al. (2016)	Estimation of EE for wheelchair users using a Physical Activity Monitoring System	45 (6F / 39M)	SCI = 45	EE (kcal/min)	Indirect calorimetry	Physical Activity Monitoring System (PAMS) (2-axial gyroscope and 3-axial ACC) using angular velocity (s^{-1}) and acceleration signals	C2	EE estimation: PAMS arm: ICC (3,1) = 0.82, $p < .05$; average error = -9.82% (SD = 37.03%) PAMS wrist: ICC (3,1) = 0.89, $p < .05$; average error = -5.65% (SD = 32.61%)

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Dowling et al. (2017)	Telehealth monitor to measure PA and pressure relief maneuver performance in wheelchair users	10 (10M)	SCI = 10	SP	SMARTWheel™	LIS3DH (tri-axial ACC) using SP pushes	C2	Accuracy of activity monitor for SP pushes: 97.7%
Chen & Morgan (2018)	Toward community-based wheelchair evaluation with machine learning methods	1 (NR)	TM =1	SP	Direct observation	ActiGraph GT3X (3-axial ACC) using acceleration signals	C1	Accuracy of arm acceleration of wheelchair propulsion (Study 1): 99.7%
			TM =1	SP	Direct observation	BPMpro (3-axial ACC) using arm acceleration signals and rotation data	C1	Accuracy of arm acceleration and additional rotation data for wheelchair propulsion (Study 2): F1 = .968
Popp et al. (2018)	Estimation of EE in wheelchair-bound spinal cord injured individuals using IMU	30 (3F / 27M)	SCI = 30	EE (ml·kg-1·min-1)	Indirect calorimetry	ReSense IMU (3-axial ACC, 3-axial gyroscope, 3-axial magnetometer) using acceleration	C2	Overall classification accuracy of the EE estimation model 97.9% Sensitivity for individual activities: 81.8-100% (median of 100%) Mean estimation error 14.4%
Leving et al. (2018)	Validity of consumer-grade activity monitor to identify manual wheelchair propulsion in standardized activities of daily living	16 (8F / 8M)	AB = 16	SP and ALD	Video recordings	Active 8 activity monitor (3-axial ACC) using vector counts	C1 + includes features for consumers	Overall agreement for activities in 2 classes = 82.1% (SD = 4.3%; range = 73.1–88.4%), sensitivity = 77.7%, positive predictive value = 78.2% Overall agreement for activities in 5 classes = 56.6% (SD = 4.5%; range = 48.8–65.6%), sensitivity = 52.8%, positive predictive value = 51.9%

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
								Agreement for total duration of all tasks = 84.5%
Murphy et al. (2019)	Estimating PA in spinal cord injury using wrist-worn ACCs	38 (about one third were females)	SCI =19 AB = 19	SP and daily activities (other than SP)	ProDiary ACC	Actiwatch (multidirectional ACC) using acceleration counts (counts/min)	C1	Agreement between Actiwatch and ProDiary across 8 activities ICC = .81-92, $p < .01$
Karinharju et al. (2019)	Validity of the Apple Watch® for monitoring push counts in people using manual wheelchairs	26 (6F / 20M)	SCI = 15 SB = 3 Other = 8	SP	Video recordings	Apple Watch series 2 (ACC, gyroscope and optical heart-rate sensor) using push counts	C3 + includes features for wheelchairs users	Accuracy of estimating SP: ICC = 0.77, r = .84 (MD = -103 pushes; 95% LoA [−423, 217] pushes)
Fortune et al. (2019)	Estimation of manual wheelchair-based activities in the free-living environment using a neural network model with inertial body-worn sensors	10 (1F / 9M)	SCI =10	SP and daily activities (other than SP)	Video recordings	Emerald IMUs (3-axial ACC) using acceleration (g) and time (hours)	C2	Differentiating non-propulsion activity: accuracy 0.94%, specificity 0.97%, area under the curve 0.97% Differentiating non-propulsion activity: accuracy = 0.94, specificity = 0.97, area under the curve (AUC) = 0.97 Differentiating propulsion activity: accuracy = 0.99, specificity = 0.99, AUC = 0.99 Differentiating static time: accuracy = 0.95, specificity = 0.92, AUC = 0.98
Benning et al. (2020)	Comparison of accuracy of activity measurements with wearable activity	20 (2F /18M)	AB = 20	SP	Digital tally counter	Apple Watch series 4 (ACC, gyroscope and optical heart-rate sensor) using push counts	C3 + includes features for wheelchairs users	Estimating SP: calibrated Apple Watch percentage of error = 13.9% (MD = 13.55 pushes; 95% LoA [−8.09, 35.19] pushes); uncalibrated Apple

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
	trackers in wheelchair users					Fitbit Flex 2 (ACC)using step counts		Watch percentage of error = 22.8% (MD = 19.05 pushes; 95% LoA [−9.96, 48.06] pushes) Fitbit Flex 2 percentage of error = 59.7% (reported in text) and 148.4% (reported in results table) (MD = 144.5 pushes; 95% LoA [−95.56, 193.56] pushes) EE estimates from five sets of predictive equations for all activities (including sedentary, light, and MVPA): MAE = 0.87–6.41 kcal min^{-1}; MAPE = 31%–206%; ICC (3,1) = 0.06–0.59; LoA range = 4.70–25.09 kcal min^{-1}
Shwetar et al. (2020)	Comparative validity of energy expenditure prediction algorithms using wearable devices for people with spinal cord injury	29 (6F /23M)	SCI = 29	EE (kcal min−1)	Indirect calorimetry	ActiGraph GT9X using acceleration signals with five sets of predictive EE equations	C1	EE estimates from five sets of predictive equations for all activities (including sedentary, light, and MVPA): MAE = 0.87–6.41 kcal min^{-1}; MAPE = 31%–206%; ICC (3,1) = 0.06–0.59; LoA range = 4.70–25.09 kcal min^{-1}

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Benning et al. (2021)	Measurement performance of activity measurements with newer generation of Apple Watch in wheelchair users with spinal cord injury.	15 (3F / 12M)	SCI = 15	SP	Direct observation	Apple Watch series 4 (ACC, gyroscope and optical heart-rate sensor) using push counts	C3 + includes features for wheelchairs users	Push counts: MAPE = 9.20% (MD = 12.33 pushes; 95% LoA [−5.99, 30.66] pushes)
Marco-Ahulló et al. (2021)	Validation of using smartphone built-In accelerometers to estimate the active energy expenditures of full-time manual wheelchair users with spinal cord injury.	20 (NR)	SCI = 20	EE (ml·kg1·min1)	Indirect calorimetry	Xiaomi MI A2 Android-based smartphone (accelerometer) using a dedicated mobile app Toolbox suite)	C4 (access to the raw data requires research-based app)	Estimating EE using model with all variables: r = .72; MSE = 6.16; MAE = 1.76 Estimating EE using model with linear variables: r = .72; MSE = 6.16; MAE = 1.76 Estimating EE using model with non-linear variables: r = .71; MSE = 6.48; MAE = 1.85
Ohji et al. (2021)	Measurement of self-propulsion distance of wheelchair using cycle computer excluding assistance distance by touch switch	1 (NR)	AB = 1	Wheelchair kinematics		Cycle computer (CC-VL 820 velo9, CAT EYE) with the touch switch (AD00018)	C3	Accuracy for estimating wheelchair distance in the rectangular facility was 180m compared to criterion 181m: the error was 1 m. Accuracy for estimating wheelchair distance with caregiver assisted was 100% (20m) and without caregiver assisted was 100% (30m)

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Glasheen et al. (2021)	Accuracy of Apple Watch fitness tracker for wheelchair use varies according to movement frequency and task.	30 (12F /18M)	SCI = 8 SB = 1 Other = 6 AB = 15	SP	Direct observation	Apple Watch series 4 (ACC, gyroscope and optical heart-rate sensor) using push counts	C3 + includes features for wheelchairs users	SP accuracy for low cadence: treadmill ICC = -0.18, MAPE = 22%; arm ergometry ICC = 0.88, MAPE = 1% SP accuracy for moderate cadence: treadmill ICC = 0.47, MAPE = 3%; arm ergometry ICC = 0.95, MAPE = 1% SP accuracy for high cadence: treadmill ICC = 0.98, MAPE = 1%; arm ergometry ICC = 0.88, MAPE = 1% SP accuracy for variable cadence: treadmill ICC = 0.22, MAPE = 6%; arm ergometry ICC = 0.97, MAPE = 4% SP accuracy for overground tasks: casual pace ICC = 0.90, MAPE = 15%; fast pace ICC = 0.79, MAPE = 18%; figure 8 ICC = 0.82, MAPE = 21%
Karinharju et al. (2021)	Validity of two wheelchair-mounted devices for estimating wheelchair speed and distance traveled.	25 (5F / 20M)	SCI = 14 SB = 3 Other = 8	Wheelchair kinematics (distance travelled)	Measured distance	Cateye Strada Wireless Cycling Computer (magnet, reed switch, micro-controller) using distance travelled (m) Wheeleri (accelerometer,gyroscope, central processing unit and mobile application)	C3 C4 + includes features for wheelchairs users	Accuracy for estimating distance Cateye: total distance MAPE = 4.7% (mean bias = −23.9 m; 95% LoA [−41.5, −6.3] m); continuous forward propulsion MAPE = 6.0%; linear discontinuous propulsion MAPE = 53.4%; propulsion with maneuvering MAPE =

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
						using distance travelled (m)		80.9%; maneuvering within confined spaces MAPE = 77.9% Wheeleri: total distance MAPE = 5.6% (mean bias = 48.0 m; 95% LoA [40.9, 55.1] m); linear discontinuous propulsion MAPE = 1.3%; continuous forward propulsion MAPE = 5.3%; propulsion with maneuvering MAPE = 9.6%; maneuvering within confined spaces MAPE = 28.4%
Klimstra et al. (2023)	A Simple and Valid Method to Calculate Wheelchair Frame Rotation Using One Wheel-Mounted IMU	9 (NR)	NR	WK (speed)	Wheelchair-frame-mounted IMU	XsensTM DOT IMU (3-axial gyroscope, 3-axial ACC and 3-axial magnetometer)	C1	Accuracy for estimating speed IMU left wheel: r^2 mean = .996 (SD = .005) RMSE (rad/s) mean = .067 (SD = .029) MAE (rad/s) = .049 (SD = .022)IMU right wheel: r^2 mean = .995 (SD = .003) RMSE (rad/s) mean = .074 (SD = .024) MAE (rad/s) = .055 (SD = .018)

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Danielsson et al. (2024)	Accuracy of the Apple Watch Series 4 and Fitbit Versa for Assessing Energy Expenditure and Heart Rate of Wheelchair Users During Treadmill Wheelchair Propulsion: Cross-sectional Study	40 (18F / 22M)	SCI=11 SB=2 Other=7 AB=20	EE (kcal/min)	Indirect calorimetry	Apple Watch series 4 (ACC, gyroscope and optical heart-rate sensor) using activity setting outdoor push walking pace Fitbit Versa (ACC and gyroscope) using activity setting treadmill running	C3 + includes features for wheelchairs users C3	Accuracy for estimating EE (with all inclines and stages combined): Apple Watch underestimated EE: MAPE 29.2% (SD = 22%) in wheelchair users and 30% (SD = 12%) in people without disability; differences increased negatively with higher exercise intensity The Fitbit overestimated EE: MAPE 73.9% (SD = 7%) in wheelchair users and 44.7% (SD = 38%) in people without disability; differences increased negatively with higher exercise intensity
Huang et al. (2024)	Preliminary field validity of ActiGraph-based energy expenditure estimation in wheelchair users with spinal cord injury	10 (1F / 9M)	SCI=10**	EE (kcal/day)	Doubly Labelled Water	ActiGraph GT9X using acceleration signals with five sets of predictive EE equations	C1	Three validated models showed good preliminary field validity for assessing total energy expenditure in MWUs with SCI: RF-model: MAE = 167 (SD = 99) kcal/day, MAPE = 7.4% (SD = 5.1%); Model 1: MAE = 190 (SD = 120) kcal/day, MAPE = 8.2% (SD = 5.0%); Model 2: MAE = 136 (SD = 96) kcal/day, MAPE = 6.1% (SD = 4.7%)

Reference	Topic of the study	Number of participants (F/ M/ NR)	Diagnoses	PA Outcome Validated	Criterion measure	Device-based motion sensor type and output	Class (C1 - C4)	Main results
Fasipe et al. (2024)	Inertial Measurement Unit and Heart Rate Monitoring to Assess Cardiovascular Fitness of Manual Wheelchair Users during the Six-Minute Push Test	10 (3F / 7M)	SCI=6** SB=3 Other=1	WK (distance speed)	Direct observation	Blue Trident IMU using linear acceleration and angular velocity	C1	Strong correlations found between the IMU and the criterion for calculated laps r = .964, distances r = .971, and speed r = .970

Abbreviations: AB able bodied, ACC accelerometer, EE energy expenditure, F female, ICC Intraclass correlation, IMU inertial measurement unit, LB lower bound, LoA limits of agreement, M male, MAE mean absolute error, MSE mean square error, MAPE mean absolute percentage error, NR not reported, PA physical activity, PAC physical activity counts, PAEE physical activity energy expenditure, rMSE Root mean square error, SB Spina Bifida, SCI spinal cord injury, SEE standard error of estimate, SD standard deviation, SP self-propulsion, TM transverse myelitis, UB upper bound, WK wheelchair kinematics. *All studies estimating EE used total EE of measured period. Asterisk indicates the papers that are using PAEE (Physical activity energy expenditure). ** Asterisk indicates the papers that reported the level of SCI. C1= Commercially available research-based device– available for purchase by the general public and user has ready access to the raw data; C2= Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product; C3= Commercially available consumer-based device – available for purchase by the general public, user doesn't have access to raw data; C4= Custom made consumer and research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product

Characteristics of the included measurement instruments

Thirty-four DBMS for estimating PA participation in MWU were identified. Appendix 2 details the specifications, technical details, and availability of the devices. Most (56%) were accelerometer-based motion sensors; the others were gyroscope-based motion sensors (9%), IMU's comprised of accelerometers (6%), devices that used a combination of sensors (21%), and one was a powermeter (3%).

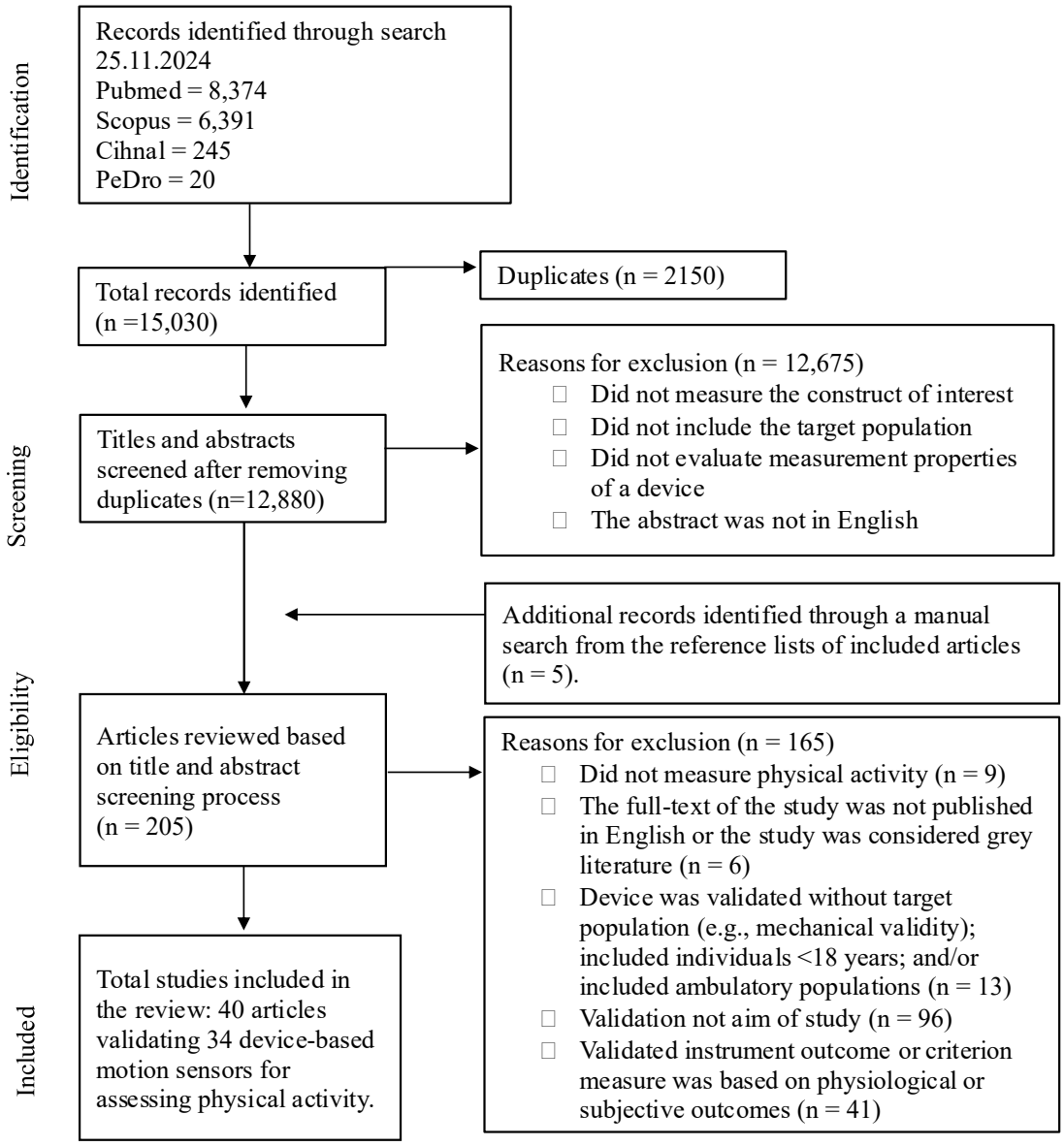

Figure 1. Flowchart of the search strategy and selection of literature. Modified from: COSMIN Risk of Bias checklist manual for systematic reviews of PROMs (Mokkink et al., 2010). The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement (Moher et al., 2015).

Seventeen (50%) of the thirty-four DBMS that were assessed in validation studies were custom-made devices. The remaining (n = 17, 50%) were commercially available devices, from which just over 30% (n = 35) were research-based devices. Two (6%) commercially available DBMS are no longer available for purchase. Of the seventeen commercially available devices, five (15%) were consumer-based devices, from which two were specifically designed for people using wheelchairs.

Characteristics of the device positioning and study protocols

Twenty-two studies (55%) used DBMS attached to the participants' bodies, with six studies (15%) using a combination of two or more attachment locations. Five attachment sites were used: right wrist, left wrist, upper-arm, and chest. The next most common were DBMS attached to the individual's wheelchair (28%, 11 studies) including the wheel spoke, frame, tipping lever, or under the seat of the wheelchair, with a further three studies using a combination of multiple devices in different wheelchair locations. The remaining studies used a combination of participant body and wheelchair-mounted devices (20%).

The validity of the DBMS were assessed in a variety of settings including controlled laboratory settings (n = 6, 15%), or semi-natural settings such as gyms, running tracks, and simulated home environments (n = 22, 55%). Three studies (8%) validated sensors in both controlled and semi-natural settings , two studies (5%) in both controlled settings and in the participant's home environment, and one (3%) in free-living circumstances. Five studies (13%) did not report the environment in which the protocol was conducted.

Twenty-one studies (53%) included a combination of different daily activities common to people using wheelchairs such as sedentary activities, household activities, and exercising in their protocol, whereas eighteen studies (45%) included variations of wheelchair propulsion. Just over 10% (n = 5) included different types of upper-limb exercise such as hand-cycling, resistance training, and playing wheelchair basketball.

Quality of the included studies

For the thirty-four studies reviewed, the methodological quality ranged from poor to excellent, with most scoring excellent (37%). Thirty-one (91%) DBMS were assessed for criterion validity, two (6%) were assessed for concurrent validity, and one (3%) was assessed for both criterion and concurrent validity. The mean sample size of the studies was 17 (*SD* = 11) and varied from one to 45 participants. Two studies reported using a sample size calculation, and only 22 (55%) reported inclusion and exclusion criteria for participant recruitment. Fourteen studies (35%) reported the small sample recruited for their study as a limitation. The heterogeneity of statistical methods used in the studies resulted in an inability to pool the results for the DBMS and therefore, the best level of evidence method was used (Mokkink et al., 2018b; Prinsen et al., 2018; Terwee et al., 2018). The level of evidence, based on the methodological quality and confidence level of truthfulness of DBMS measuring PA, ranged from very low (32%) to high (29%).

Criterion validity and level of evidence of DBMS for estimating EE in people using manual wheelchairs

Outcomes relating to the validity of DBMS for estimating EE are reported in Appendix 3a. Fifteen studies (38%) evaluated the validity of thirteen different DBMS for estimating EE for MWU. Twelve of these devices were validated using indirect calorimetry as the criterion measure, and one device was validated using the doubly labelled water method.

Twelve studies (80%) used one DBMS to estimate EE, and three studies (20%) used a combination of two or more DBMS. One study (7%) used both one DBMS and a combination of two DBMS in their protocol. Attachment sites included the body, the wheelchair wheel, or a combination of body and wheelchair attachments. Of the thirteen DBMS used to estimate EE, nine (70%) were commercially available devices, and four (30%) were custom-made devices. Of the commercially available devices, six (67%) were research-based devices, and three (33%) were consumer-based devices.

The most accurate commercially available research-based device for estimating EE was the ActiGraph GT3X (Garcia-Masso et al., 2013; Learmonth et al., 2016; Nightingale et al., 2014; Nightingale et al., 2015). The highest accuracy for estimating EE with the ActiGraph

GT3X was achieved using one device attached to the right wrist, with an accuracy of $r = .95$ (Learmonth et al., 2016) using a default algorithm from the device software. The methodological quality of the studies that validated the ActiGraph GT3X for estimating EE was good to moderate, with positive measurement outcome quality. The level of evidence was high (+) as there were multiple studies with good to moderate quality and consistent results.

The most accurate commercially available consumer-based device for estimating EE was the Xiaomi MI A2 Smartphone (Marco-Ahulló et al., 2021). The highest accuracy for estimating EE with the Xiaomi MI A2 was measured from the non-dominant arm ($r = .72$) using a default algorithm (dedicated mobile app). The methodological quality of the study that validated the Xiaomi MI A2 for estimating EE was excellent, with positive measurement outcome quality. The level of evidence was high (+) as there was one study with excellent quality and consistent results.

The most accurate custom-made devices for estimating EE were the Physical Activity Monitoring System (PAMS) (Hiremath et al., 2016) and the ReSense (Popp et al., 2018). The highest accuracy for estimating EE with the PAMS was achieved with the accelerometer sensor attached on the right wrist and the gyroscope sensor attached on the right wheelchair wheel (ICC = .89, $p < .05$). The accuracy and sensitivity for the ReSense estimates of EE were 97.9% and 81.8-100%, respectively, which was determined using a combination of four devices: one attached on each wrist, one on the chest, and one on the right wheel of the wheelchair. The methodological quality of the studies that validated the PAMS and the ReSense for estimating EE were excellent, with positive measurement outcome quality. The level of evidence was high as there was one study for both devices with excellent (+) quality available.

Criterion validity and level of evidence of DBMS for estimating self-propulsion and daily activities, other than self-propulsion common to MWU

Sixteen studies (40%), utilising sixteen different DBMS, evaluated the validity of devices for estimating SP and daily activities (other than SP) common to MWU. All studies assessed the validity of DBMS for estimating SP, while six evaluated their validity for estimating daily activities other than SP.

Self-propulsion

Outcomes regarding the validity for estimating SP are reported in Appendix 3b. All studies in this review included SP activities in their research protocol. Criterion measures for estimating SP included direct observation with video recording or human observation, the SMARTWheel™, and a Pro Diary activity monitor. In seven studies (44%) SP was assessed with one DBMS, and in eight studies (50%) with a combination of two or more DBMS.

One study (6%) used both one DBMS and a combination of multiple DBMS in their protocol. Devices were attached either to the body, the wheelchair, or both. Of the sixteen DBMS estimating SP, six (38%) were commercially available devices, four (67%) of which were research-based devices and two (33%) consumer-based devices. Ten (62%) were customised devices made by the researchers.

The most accurate commercially available research-based device for estimating SP was the ActiGraph GT3X (Chen & Morgan, 2018; García-Massó et al., 2015; Kooijmans et al., 2014). The highest accuracy for estimating SP was achieved with a combination of two devices, with one attached on the dominant upper-arm and one on the dominant wrist (accuracy = 99.7%), and using a custom algorithm (Chen & Morgan, 2018). The methodological quality of the studies that validated the ActiGraph GT3X for estimating SP

were fair to good, with positive measurement outcome quality. The level of evidence was moderate (+) as there were multiple studies with fair to good quality and consistent results available.

The most accurate commercially available consumer-based device for estimating SP was the Apple Watch (Glasheen et al., 2021; Karinharju et al., 2019). The highest accuracy for the Apple Watch estimating SP was achieved when worn on the dominant wrist (ICC = .98), using a default algorithm (Glasheen et al., 2021). The methodological quality of the studies that validated the Apple Watch for estimating SP were poor to excellent, with positive measurement outcome quality. The level of evidence was high (+) as there were two studies with excellent (+) quality and consistent results available.

The most accurate custom-made devices for estimating SP were the Emerald inertial measurement unit system (Emerald IMU) (Fortune et al., 2019) and the PAMS (Hiremath et al., 2015). The highest accuracy for estimating SP with the Emerald IMU was achieved using a combination of three devices: one attached on each upper arm, and one on the chest (accuracy 99%, specificity 99%, area under the curve 99%). For estimating SP with the PAMS, the highest accuracy was achieved using one device attached on the upper arm, and one on a wheelchair wheel (accuracy 98.41%, sensitivity 99%, specificity 98%). The methodological quality of the studies that validated the Emerald IMU and PAMS for estimating SP was excellent, with positive measurement outcome quality. The level of evidence was high (+) as there was one study with excellent quality and consistent results available for both devices.

Daily activities (other than SP)

Outcomes regarding the validity for estimating daily activities (other than SP) are reported in Appendix 3c. Of the thirteen studies that evaluated the validity of DBMS for estimating various daily activities, five studies (38%) validated them for estimating grouped activities, sedentary activities, household activities, body transfers, and exercise. Criterion measures for estimating daily activities (other than SP) included direct observation via video recordings or human observation, and the ProDiary activity monitor. In one study (20%), daily activities were assessed with one DBMS, and in two studies (40%) with a combination of two or more DBMS. Two studies (40%) used both one DBMS and a combination of multiple sensors in their protocol.

Devices were attached either to the body, the wheelchair wheel, or a combination of the body and wheelchair. Of the seven DBMS estimating daily activities (other than SP), three (43%) were commercially available research-based devices and four (57%) were custom-made devices.

All commercially available devices estimating daily activities (other than SP) were research-based devices. The most accurate commercially available research-based device for estimating daily activities (other than SP), was the ActiGraph GT3X (García-Massó et al., 2015). The highest accuracy for estimating grouped activities with the ActiGraph GT3X was achieved using a combination of four devices, with one attached on each wrist, one on the waist, and one on the chest (accuracy = 89-94%), and using a custom algorithm. The highest accuracy using the ActiGraph GT3X to estimate sedentary activities (accuracy = 94-100%), household activities (accuracy = 86-91%), body transfers (accuracy = 86%) and upper body exercising with an arm ergometer (accuracy = 100%) was achieved using a combination of two devices, with one attached on each wrist. The methodological quality of the study that validated the ActiGraph GT3X for estimating daily activities (other than SP) was good, with positive measurement outcome quality. The level of evidence was moderate (+) as there were good quality and consistent results available.

The most accurate custom-made devices for estimating daily activities (other than SP) were the Emerald IMU (Fortune et al., 2019) and the PAMS (Hiremath et al., 2015). The highest accuracy for detecting the grouped activities was achieved with a combination of three Emerald IMU devices: one attached on each upper arm, and one on the chest (accuracy = 94%, specificity = 97%, area under the curve = 97%). The highest accuracy for detecting sedentary time (accuracy 95-99%), household activities (accuracy 93%), arm ergometer (accuracy 97%), and wheelchair basketball (accuracy 97%) was achieved with PAMS, and using a combination of two devices: one attached on the right wrist, and one on the wheelchair wheel. The methodological quality of the studies validating the Emerald IMU and PAMS for estimating activities (other than SP) was excellent, with positive measurement outcome quality. The level of evidence was high (+) as there was one study with excellent quality and consistent results available for both devices.

Criterion validity and level of evidence of DBMS for estimating wheelchair kinematics in MWU

Outcomes regarding the validity of estimating wheelchair kinematics are reported in Appendix 3d. Twelve studies (30%) evaluated the validity of eleven DBMS for estimating wheelchair kinematics.

Seven studies validated devices for estimating wheelchair movement distance: two studies measured wheelchair movement duration; three studies measured wheelchair movement speed; and one study differentiating wheelchair movement from no movement. Criterion measures included measured distance, direct observation via video recordings, a 3D motion capture system, the SMARTWheel™, and the Xsens™. Device attachment sites included the spokes of the wheelchair wheel, wheelchair frame, a hand cycle, a combination of spokes of the wheelchair wheel and the frame, and a tipping lever of the wheelchair. Of eleven DBMS estimating wheelchair kinematics, five (45%) were commercially available devices and six (55%) were custom-made devices.

The most accurate commercially available research-based devices for estimating wheelchair kinematics were the ActivPAL (Coulter et al., 2011) and the Blue Trident IMU (Fasipe et al., 2024). The highest accuracy for ActivPAL for estimating wheelchair movement speed and moving time (ICC = 1.00, .981, respectively), was achieved using a combination of two devices, with one attached on each wheelchair wheel, and using a custom algorithm. The highest accuracy for Blue Trident IMU for estimating wheelchair movement distance and speed (r =.97, r =.97, respectively), was achieved using a combination of two devices, with one attached on the bottom of the wheelchair and on the participant's right wrist, and using a custom algorithm. The methodological quality of the studies that validated the ActivPAL and Blue Trident IMU was both excellent, with positive measurement outcome quality. The level of evidence was high as there was one study with excellent (+) quality available for each device.

The only commercially available consumer-based device for estimating wheelchair kinematics was the Cateye Strada Wireless Cycling Computer (magnet, reed switch, and a microcontroller) (Karinharju et al., 2021; Ohji et al., 2021). The highest accuracy for the Cateye for estimating wheelchair movement distance was achieved with placement on the right wheelchair wheel (MAPE = 4.7%), using a default algorithm (Karinharju et al., 2021). The methodological quality of the studies validating the Cateye for estimating wheelchair kinematics was poor, with questionable measurement outcome quality. The level of evidence was very low (?) as there were two studies with poor (?) quality available.

The most accurate custom-made devices to estimate wheelchair movement distance, classification of wheelchair movement, and wheelchair movement speed were the G-WRM (Hiremath et al., 2013) and the ITG-3050 (Popp et al., 2016). The G-WRM had the highest

accuracy for estimating wheelchair movement distance (ICC = .999-1), using three devices attached to the right wheelchair wheel. The ITG-3050 provided high accuracy for estimating if the wheelchair was moving (sensitivity = 95.80%, specificity = 99.58%), using a combination of five ITG-3050 devices attached on the right wheel of the wheelchair. The methodological quality of the study that validated the G-WRM for estimating WK was good. The level of evidence was moderate (+) as there was one study with good (+) quality available. The methodological quality of the study that validated the ITG-3050 for estimating WK was fair, with positive measurement outcome quality. The level of evidence was low as there was one study with fair (+) quality available.

Summary of device characteristics

Table 5 summarises the device characteristics important for assessment of free-living PA of MWU. Devices included are those that are currently available for purchase by the general public and have positive outcome measurement properties according to the COSMIN assessment.

Table 5. Summary of device characteristics important for assessment of free-living PA in MWU. Devices are currently available for purchase by the general public and have a minimum fair rating of methodological quality with positive outcome measurement properties, compared to gold standard.

Characteristics		Body worn							Wheelchair			Both		
Device		A	B	C	D	E	F	J	G	K	H	E	I	L
Outcome of interest														
	Energy expenditure	+	+	-	-	-	-	-	-	-	-	-	-	+
	Self-propulsion	-	-	+	+	+	+	+				+	-	+
	Grouped activities of daily living	+	-	+	-	+	-	+	-	-	-	-	-	-
	Sedentary activities	-	-	+	-	+	-	-	-	-	-	-	-	-
	Static time	-	-	-	-	-	-	+	-	-	-	-	-	-
	Household activities	-	-	+	-	+	-	-	-	-	-	-	-	-
	Body transfers	-	-	-	-	+	-	-	-	-	-	-	-	-
	Arm ergometer/hand cycling	-	-	+	-	+	-	-	-	-	-	-	-	-
	Resistance training	-	-	+	-	-	-	-	-	-	-	-	-	-
	Wheelchair movement distance	-	-	-	-	-	-	-	-	-		-	+	-
	Wheelchair movement speed	-	-	-	-	-	-	-	+	+	+	-	+	-
	Wheelchair movement time	-	-	-	-	-	-	-	+	-	-	-	-	-
Considerations														
	Commercially available device	+	+	+	+	+	+	-	+	-	+	+	+	+
	Custom-made device	-	-	-	-	-	-	-	-	+	-	-	-	+
	Provides raw data	+	+	+	-	+	+	+	+	+	+	+	+	+
	PA output generated using default (proprietary or pre-loaded) algorithm	+*	-	+	+	-	-	-	-	-	-	-	-	-
	Device output can be blinded to the user	+	+	+	-	+	+	+	+	+	+	+	+	+
	Designed for everyday use in MWU	-	-	-	-	-	-	-	-	-	-	-	-	-
	Consumer-based device	-	+	-	+	-	-	-	-	-	-	-	-	-
	Allow self-monitoring (user access to their data)	-	+	+	+	-	-	-	-	-	-	-	-	-

Abbreviations: 1 Devices (A = ActiGraph GT3X; B = Xiaomi MI; C = ActiWatch; D = AppleWatch); 2 Devices (E = ActiGraph GT3X ; F = BMPpro IMU; G = ActivPAL; H = Xsens IMU; I = Blue Trident IMU); 3 Devices (J = Emrald IMU; K = X-IMU); 4 Devices (L = ReSense IMU); IMU = inertial measurement unit, MWU = manual wheelchair users. Plus sign (+) indicates a positive answer; minus sign (–) indicates that no information available. Energy expenditure was estimated with one device with default algorithm, grouped activities of daily living with custom algorithm.

Discussion

The use of DBMS to measure PA participation in people using wheelchairs has gained increased prominence over the past twenty years, with a twofold increase in studies published since 2014 (Lankhorst et al., 2020; Tsang et al., 2016). The current review

provides a comprehensive, systematic synthesis of research describing the range, accuracy, and current use of DBMS for measuring four distinct PA outcomes relevant to estimating free-living PA among MWU: 1) EE; 2) SP; 3) daily activities (other than SP); and 4) WK including wheelchair movement distance, time, and speed. The current review extends the results of two previous systematic reviews relating to PA measurement in MWU (Lankhorst et al., 2019; Tsang et al., 2016) by: including both commercial and custom-made devices; synthesising evidence available over a longer time period (1999 to 2024); and including studies that evaluate four common types of PA participation for MWU in individuals who both do, and do not, utilise a wheelchair for ambulation in the research protocol. Subsequently, in this review an additional twenty-two papers validating DBMS with twenty-three different DBMS were identified. Expanding on previous reviews, this study examines SP as a PA variable, separately from other types of daily activities.

Numerous factors need to be considered when selecting a DBMS for the measurement of PA participation including cost, access, specialist training, and participant burden. To assist clinicians and researchers to select an appropriate device, this paper divided the DBMS into custom-made and commercially available devices, and evaluated each group of devices against the four physical outcomes of interest. In total, the review provided eight distinct recommendations, summarised in Table 6. Whilst additional work is required to improve the methodological rigour of protocols used to evaluate DBMS, the synthesis of available studies demonstrates that EE, SP, and daily activities (other than SP) such as sedentary activities, household activities, body transfers and arm ergometer exercising, can be accurately measured with body worn tri-axial accelerometers or with a combination of body worn tri-axial accelerometers and wheelchair-based gyroscope sensors. However, the utility of these devices is limited by lack of wheelchair-specific design features, specific application to research-based settings, and restricted access to participant data.

The ActiGraph GT3X and ActivPAL are two of the most frequently used commercially available accelerometers for measuring PA in ambulatory populations. However, these devices are specifically designed to collect data in research contexts and require proprietary software for initialising and downloading, expertise to guide decision making for analysis, and typically blind participants to their real-time data, limiting their utility in day-to-day practice. From all 31 validated devices, the Apple Watch, Cateye cycling computer, and Xiaomi MI smartphone were the only commercially available consumer-based devices that allow users access to their data and therefore have the most utility for participant self-monitoring outside of a research context (Benning et al., 2020; Benning et al., 2021; Danielsson, et al, 2024; Glasheen et al., 2021; Karinharju et al., 2019; Marco-Ahulló et al., 2021). Smartphones with embedded triaxial accelerometers could provide a low-cost alternative to estimate free-living PA in MWU where participants do not need to be blinded to their behaviour (Marco-Ahulló et al., 2021).

To date, the Apple Watch is the only validated consumer-based device that has features specifically designed for the measurement of PA for people using wheelchairs, which increases its utility as a self-monitoring device in community-dwelling MWU (Benning et al., 2020; Benning et al., 2021; Danielsson, et al, 2024; Glasheen et al., 2021; Karinharju et al., 2019). For research purposes, the Apple Watch provides accurate estimates of average push counts in large samples, which may be useful in determining the public health benefits of PA in MWU. Recently, the technology company Garmin has released a new Venu 3 series watch that includes wheelchair mode to track indoor and outdoor push and handcycling activities. However, the validity of Venu 3 for estimating PA in MWU has not yet been evaluated.

Table 6. Recommendations for researchers and clinicians: commercially available research and consumer-based devices to measure energy expenditure (EE), self-propulsion (SP), daily activities (other than SP), and wheelchair kinematics.

Device and physical activity variable	Recommendation
Recommendation 1: Commercially available, research-based device to measure EE	ActiGraph GT3X. One device on right wrist analysed using algorithm device software.
Recommendation 2: Commercially available, consumer-based device to measure EE	Xiaomi MI A3 smartphone. One device on non-dominant arm using default algorithm from dedicated mobile application.
Recommendation 3: Commercially available, research-based device to measure SP	ActiGraph GT3X. Two devices, one on wrist and one on upper-arm or wheelchair, using custom algorithm.
Recommendation 4: Commercially available, consumer-based device to measure SP	Apple Watch. One device on dominant wrist using default algorithm from Apple Watch smartwatch.
Recommendation 5: Commercially available, research-based device to measure daily activities (other than SP)	ActiGraph GT3X. Four devices, one attached on each wrist, one on the waist and one on the chest, using a custom algorithm.
Recommendation 6: Commercially available, research-based device to measure wheelchair movement speed and moving time.	ActivPAL. Two devices, one attached on each wheelchair wheel, using a custom algorithm.
Recommendation 7: Commercially available, research-based device to measure wheelchair movement speed and distance.	Blue Trident. Two devices, one attached on the bottom of the wheelchair and on right wrist, using a custom algorithm.
Recommendation 8: Commercially available, consumer-based device to measure wheelchair movement distance.	Cateye Strada Wireless Cycling Computer. One device on the right wheelchair wheel using a default algorithm.

The application of accelerometers including the ActiGraph GT3X and ActivPAL in free-living settings among MWU requires consideration due to the need to use assistive devices like elastic bands, medical tape, and straps to attach the units to the participant's upper limb or wheelchair (Coulter et al., 2011; Garcia-Masso et al., 2013; García-Massó et al., 2015; Kooijmans et al., 2014; Nightingale et al., 2014). ActiGraph has now released the ActiGraph GT9X Link (3-axial ACC), a wrist worn activity monitor, which has the potential to address some of the feasibility considerations for MWU. One study in this review evaluated the validity of this monitor, however, the findings reported that the validity was not sufficient for clinical and research use in MWU, and that more studies are needed (Shwetar et al., 2020).

Interpreting study findings

When interpreting the study findings, it is important to consider the assessment of the methodological quality of the included studies: 45% were classified as poor or fair and 55% were classified as good or excellent. The statistical methods utilised by the studies limit their methodological quality, in particular, those used to evaluate the relationship between the estimation measure and the reference measure. As a result of the variability in the statistical methods used, statistical comparison and pooling of the results between the monitors included in this review was challenging, or not possible. Therefore, this review used the method of best level of evidence to determine the quality of the summarised results for the included measurement properties (Lankhorst et al., 2020; Mokkink et al., 2018b; Prinsen et al., 2018; Terwee et al., 2018). Nonetheless, this approach is consistent with a similar review in the field and still offers valuable insights into the utility and accuracy of DBMS for MWU (Lankhorst et al., 2020).

It is important to note that two modifications were made to the COSMIN checklist guidelines during the quality review process. Firstly, the requirement relating to the minimum sample size (n = 30) was removed. This requirement is based on patient reported outcome measures and does not necessarily apply to validation studies of objective measures, where a smaller sample size for evaluation of criterion validity is appropriate and common (Mokkink et al., 2018b; Prinsen et al., 2018; Terwee et al., 2018). Secondly, the COSMIN checklist provides recommendations for rating the quality of statistical methods of studies reporting continuous data, however, ratings for statistical methods involving dichotomous outcomes are not defined (Mokkink et al., 2018a, 2018b; Prinsen et al., 2018; Terwee et al., 2018). Therefore, this review used the same scoring for studies involving dichotomous outcomes as a previous systematic review in this field (Lankhorst et al., 2020).

Generalisability of study findings and future recommendations

There are two main factors that limit the generalisability of the findings of this review. In 35% of the studies, details of participant eligibility were not reported. In studies that reported participant characteristics, the sample was highly homogeneous with 66% of participants diagnosed with spinal cord injury. Eight (33%) of these studies did not report participant's lesion level, limiting the ability to compare device accuracy for individuals with tetraplegia to individuals with paraplegia. In this review, only two studies reported performing a sample size calculation (Benning et al., 2020; Hiremath & Ding, 2011). In addition, evaluation of the studies demonstrated a discrepancy between the number of participants recruited to the study, and the number of participants who were able to successfully complete the testing protocol. Moreover, in 35% of the studies, the missing data was not clearly reported.

Secondly, the activities included in the protocols, and the environment where the studies were conducted, limits the generalisability of the results for the estimation of free-living PA participation. In this review, 84% of the study protocols were conducted in controlled and semi-controlled settings. It is proposed that the use of a controlled environment and structured activities instead of activities that better replicate daily living (e.g. continuous vs non-continuous linear pushing) reduces the external validity of the results and may not reflect the everyday life of MWU (Tsang et al., 2016). In addition, it is proposed that the accuracy of the algorithms used in estimating PA in MWU may depend on the types of activities performed (Shwetar et al., 2020). To increase the generalisability of the results, and to avoid bias in interpreting the results, future studies exploring the validity of device-based PA monitors in MWU should ensure that they: are adequately powered with respect to their sample size; recruit a large variety of participants with different diagnoses, impairments, and levels of ability to perform wheelchair-based activities; and include a wide variety of different daily wheelchair-based activities in semi-controlled and/or free-living settings.

Limitations of this review

This review has limitations worth noting. Firstly, it limited studies with adult populations (≥18 years), and were published in peer-reviewed journals that were available in English. Therefore, relevant research may have been excluded if examining validity in children and young people or if reported in a language other than English, limiting the ability to apply the results to paediatric populations. Secondly, to be able to evaluate the use of existing DBMS for the measurement of PA participation in community-dwelling MWU, only studies that evaluated DBMS in wheelchair-based activities were included. Therefore, studies that measured mechanical validity with an unoccupied wheelchair or study results with ambulatory activities were not included. Finally, this study was not able to report the

validity of DBMS for people with different types of disabilities and injury levels, as inconsistent methods were used to report the participant characteristics. Additionally, the majority of studies did not report their results by disability or injury level, with only a few studies discussing the influence of impairment in their paper. Future research should consider the influence of impairment and functionality when evaluating the validity of DBMS among MWU. This information would increase the likelihood of selecting the most appropriate DBMS, mounting location, and analysis methods when measuring PA in free-living circumstances.

Strengths of this review

The limitations of this review are offset by a number of strengths. In contrast to previous reviews in the field (Lankhorst et al., 2020; Tsang et al., 2016), studies that included ambulatory participants completing activities in a manual wheelchair were included in the current review. MWU are a very heterogeneous population with variability in functional abilities and capacity for wheelchair movements including pushing and manoeuvring (Jörgensen et al., 2017). Therefore, including ambulatory populations completing activities in wheelchairs introduces a level of variability in participant's performance and abilities that are proposed to increase the external validity and generalisability of the study results (Nightingale et al., 2017).

Studies evaluating both commercially available and/or custom-made devices were included in the current review, as well as those evaluating criterion and/or concurrent validity. This information could be beneficial for those developing new methods for measuring PA in MWU. Most importantly, unlike previous studies in the field, this review makes important distinctions between different daily activities performed by MWU by reporting the results for SP, other daily activities, and WK separately. This distinction provides important information for stakeholders implementing PA monitors in the field and allows researchers to select the device that best represents the intended activity of the participant.

Conclusions

Despite the growing interest in the field of PA measurement in MWU, the outcome of this review reinforces the fact that currently, there is no single device available that can accurately monitor the variety of free-living, daily activities in MWU, while simultaneously providing information relating to the principles of PA participation (e.g. intensity, frequency, duration, and activity type). This outcome is consistent with the ambulant population and identifies important avenues for future research. The results of this review demonstrate that DBMS can provide indirect, accurate measurements of PA in community-dwelling MWU, by using a combination of two devices including one attached on the right wrist (e.g., Actigraph GT3X, ActiWatch or Apple Watch) and one on the wheelchair wheel (e.g., ActiPAL). However, the recommendations provided are limited by the methodological quality of the studies included. Therefore, in relation to capturing free-living PA in community-dwelling MWU, more studies focusing on the development, evaluation, and acceptability of PA monitors are needed. Specifically, more attention needs to be paid to the algorithms and device settings to better suit different MWU with different abilities and body functions.

Perspectives

This paper provides comprehensive and up to date information on commercially available and custom-made DBMS for researchers and clinicians who wish to promote and/or monitor daily habitual PA in free-living community dwelling MWU. This information can also be beneficial for those developing new methods for measuring PA in MWU and for

individuals who are looking for a suitable consumer-based PA monitor for their daily habitual activities (e.g. for self-monitoring or goal setting purposes).Authors should discuss the results and how they can be interpreted in perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible, including how the findings relate to a European perspective. Future research directions may also be highlighted. The study limitations are also included in this section.

Supplementary Materials: Large tables and figures can be added at the end of the manuscript. Using the same format of tables as those in the text. See Appendix section.

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Availability of data and materials: The data that supports the findings of this study are available in the supplementary material (Appendix 1-3) of this article.

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Conflicts of Interest: One DBMS included in this study (Wheeleri) was developed by the Accessibility and Welfare Technology Research group at Satakunta University of Applied Sciences, Finland. The corresponding author was a member of this group and provided ad hoc advice to the device development process but received no funding support (direct or indirect) or public acknowledgment for her advice. The other authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Appendices

Appendix 1. Systematic review search string

Search string PubMed:

25.11.2024

("physical activity" OR "physical activities" OR "Motor Activity"[Mesh] OR "activity energy expenditure" AND "wheelchairs"[MeSH Terms] OR "wheelchairs"[All Fields] OR "wheelchair"[All Fields] OR "Wheelchairs/utilization"[Mesh]) Filters: Journal Article, Humans, English, from 1000/1/1 – 2024/11/24

Search string CHINAHL EBSCOhost:

25.11.2024

((MM "Physical Activity") OR (MH "Leisure Activities")) AND ((MM "Wheelchairs") OR (MH "Wheelchair Sports") Published Date: 20160301-20251124 Research Article; Human

Search string Scopus:

25.11.2024
"physical activity" OR "physical activities" OR "Motor Activity" OR "activity energy expenditure" AND wheelchair OR wheelchairs AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (PUBYEAR , 2024) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017))

Search string Pedro:

25.11.2024
Physical activity wheelchair

Other appendices on supplementary file

Appendix 2 Specifications and technical details of the device-based motion sensors included on this study.

Appendix 3a. Validity of device-based motion sensors estimating energy expenditure.

Appendix 3b. Validity of device-based motion sensors estimating self-propulsion.

Appendix 3c. Validity of device-based motion sensors estimating daily activities (other than self-propulsion).

Appendix 3d. Validity of device-based motion sensors estimating wheelchair kinematics.

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