Device-based motion sensor brand or model	Sensor type and technical description	Available for purchase (YES/ NO)	Designed for MWU (YES/ NO)	Specification details	Validation study in this review: Author (year)
Actical (AC) activity monitor. Philips, Amsterdam, NL.	Omni-directional ACC that measures a subject's energy expenditure and step count.	No longer commercially available	NO	Commercially available research-based device – available for purchase by the general public and user has ready access to the raw data. http://www.ActiGraphy.com/solutions/actical	Conger et al. (2015)
ActiGraph GT3X. ActiGraph, LLC., Pensacola, FL, USA	3-axial ACC with integrated wear time and ambient light sensors. Captures and records continuous, high resolution physical activity and sleep/wake information.	YES	NO	Commercially available research-based device – available for purchase by the general public and user has ready access to the raw data. https://www.ActiGraphcorp.com/support/activity-monitors/gt3x/ https://www.actigraph.nl/en/product/70/wgt3x-bt-monitor.html	Garcia-Masso et al. (2013); Nightingale et al. (2014); Koojimans et al. (2014); Garcia-Masso et al. (2015); Nightingale et al. (2015); Learmonth et al. (2016); Chen & Morgan (2018);
ActiGraph GT9X	3-axial ACC with integrated wear time and ambient light sensors. Captures and records continuous, high resolution physical activity and sleep/wake information.	YES	NO	Commercially available research-based device – available for purchase by the general public and user has ready access to the raw data. https://s3.amazonaws.com/actigraphcorp.com/wp-content/uploads/2020/03/05155628/ActiGraph_Link_UserGuide_E.200.6001_Revision6_FINAL.pdf	Schwetar et al. (2020); Huang et al. (2024)
ActiWatch, Amserdam, NL.	A multidirectional piezoelectric ACC that measures degree and intensity of motion. http://www.usa.philips.com/healthcare/product/	YES	NO	Commercially available research-based device – available for purchase by the general public and user has ready access to the raw data. HC1046964/actiwatch-spectrum-activity-monitor https://www.camntech.com/motionware-mvpa/	Murphy et al. (2019)
Active 8 activity monitor. 2M Engineering ltd, NL.	3-axial ACC that measures body postures and motions and calculates related energy consumption.	YES	NO	Commercially available research-based device– available for purchase by the general public, includes features for consumers and user has ready access to the raw data. https://www.2mel.nl/project/activ8-validated-activity-monitor-that-recognizes-your-activities/	Leaving et al. (2019)
ActivPAL. ActvPaL Technologies Ltd., Glasgow, UK	A miniature electronic logger using an ACC to quantify free-living daily activities. The device contains a microprocessor, sensing element, recording element, associated electronics and power supply.	YES	NO	Commercially available research-based device – available for purchase by the general public and user has ready access to the raw data. http://www.palt.com/	Coulter et al. (2011)
ADXL202 ACC connected to Vitaport 3 data recorder. Analog Devices, Inc.Massachusetts, USA, adapted by Temec Instruments, Kerkrade, NL.	2- axial ACC.	No longer available.	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. https://www.analog.com/media/en/evaluation-boards-kits/evaluation-software/ADXL202EB_232A_c.pdf https://www.temec.com/	Postma et al. (2005)

ADXL345 Analog Devices. Norwood, Massachusetts, USA.	3-axial ACC.	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. https://www.analog.com/media/en/technical-documentation/data-sheets/ADXL345.pdf https://www.analog.com/en/products/adxl345.html	Popp et al. (2016)
Apple Watch® series 1,2, 4. Apple Inc. California, USA.	Wrist-worn smart watch that includes a ACC, a gyroscope and optical heart-rate sensors.	YES	YES	Commercially available consumer-based device – available for purchase by the general public, user doesn't have access to raw data. https://www.apple.com/lae/watch/	Karinharju et al. (2019); Benning et al. (2020); Benning et al. (2021); Glasheen et al. (2021); Danielsson (2024)
Blue Trident IMU (Vicon, Demver, USA)	Inertial measurement unit	YES	NO	Commercially available research-based device – available for purchase by the general public and user has ready access to the raw data. https://www.vicon.com/	Fasip et al. (2024)
BPMpro. 270 Vision. Chilbotlon, UK	Inertial measurement unit	YES	NO	Commercially available research-based device – available for purchase by the general public and user has ready access to the raw data. https://www.bpmpathway.com/about-270-vision/	Chen & Morgan (2018)
CSA (The Computer Science and Applications, Inc.). Model 7164. ActiGraph, LLC., Pensacola, FL, USA	1-axial ACC used extensively in PA research.	No longer available.	NO	Commercially available research-based device – available for purchase by the general public and user has ready access to the raw data. Specifications can not be found online. More information is described in the article of Washburn et al. (1999).	Washburn & Copay (1999)
Cateye (Boulder, CO)	Wireless Cycling Computer with magnet, reed switch, and a microcontroller.	YES	NO	Commercially available consumer-based device – available for purchase by the general public, user doesn't have access to raw data. https://www.cateye.com/intl/support/manual/data/doc/CC-RD310W-SPD01_HP_ENG_v7.pdf	Ohji et al.(2019); Karinharju et al. (2021)
Data logger (DL) integrated ACC.	Electronic device that use a microprocessor, an internal memory for data storage, and a sensor to collect data over time or in relation to location.	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. Brand details not available. https://en.wikipedia.org/wiki/Data_logger https://www.omega.com/en-us/resources/data-loggers	Sindall et al. (2013)
Emerald IMUs (APDM Inc., Oregon, USA)	3-axial ACC.	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. Specification details can not be found online. More information is described in the article of Fortune 2018. https://www.apdm.com/wearable-sensors/.	Fortune et al. (2018)
Fitbit Flex 2 (Fitbit Inc., California, USA)	3-axis ACC	YES	NO	Commercially available consumer-based device – available for purchase by the general public, user doesn't have access to raw data. https://canarywww.fitbit.com/sg/flex2 https://help.fitbit.com/manuals/manual_flex_2_en_US.pdf	Benning et al. (2020)

Fitbit Versa (Fitbit Inc., California, USA)	3-axis ACC and 3-axis gyroscope	YES	NO	Commercially available consumer-based device – available for purchase by the general public, user doesn't have access to raw data. Fitbit Versa User Manual	Danielsson et al. (2024)
Geneactiv (Activinsights Ltd., Cambridgeshire, UK)	3-axial ACC with physical activity intensity and sleep/wake measurements.	YES	NO	Commercially available research-based device – available for purchase by the general public and user has ready access to the raw data. https://www.activinsights.com/ActiGraphy/geneactiv-original/ https://www.geneactiv.org/products/	Nightingale et al. (2015)
G-WRM (Human Engineering Research Laboratories, VA Pittsburgh)	2-axial gyroscope with 6 reed switches. Device is self-enclosed, rechargeable, bluetooth-based device paired with an Android-based mobile application that measures angular velocity of the wheelchair wheel and distance traveled.	NO	YES	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. Specifications can not be found online. More information is described in the article of Hiremath et al. 2013.	Hiremath et al. (2013); Hiremath et al. (2015); Hiremath et al. (2016)
Instrumented treadmill (Bertec Cor poration; Columbus,Ohio, USA)	The instrumented treadmill with two 3-axial force platforms.	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. https://www.bertec.com/products/instrumented-treadmills	Gagnon et al. (2016)
ITG-3050 (InvenSense, TDK Corporation, Tokyo, Japan)	3-axial gyroscope.	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. https://www.invensense.com/products/motion-tracking/3-axial/itg-3050/	Popp et al. (2016)
LIS3DH (STMicroelectronics, Geneva, CH)	3-axial ACC.	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. https://www.st.com/content/st_com/en/products/mems-and-sensors/accelerometers/lis3dh.html https://www.st.com/resource/en/datasheet/lis3dh.pdf https://www.st.com/en/mems-and-sensors/lis3dh.html	Dowling et al. (2017)
MMA7260Q (Freescale Semiconductor, Inc Austin, Texas, USA [company defunct 2015])	3-axial ACC.	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. https://datasheet.octopart.com/MMA1260EG-Freescale-Semiconductor-datasheet-129446.pdf https://www.sparkfun.com/datasheets/ACCs/MMA7260Q-Rev1.pdf www.freescale.com/sensors	Sonenblum et al. (2012)

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Physical Activity Monitoring System (PAMS).	Combination of 2-axial gyroscope (G-WRM) and 3-axial ACC (Wocket).	NO	YES	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. Specification details can not be found online. More information is described in the article of Hiremath et al. (2015, 2016)	Hiremath et al. (2015); Hiremath et al. (2016)
PowerTap (Madison, Wisconsin, USA)	Power-measuring hub measures torque and wheel speed.	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. http://www.manualsdir.com/manuals/403783/powertap-sl-track-hub.html?page=3	Conger et al. (2014)
RT3 (StayHealthy, Inc., Monvoria, CA, USA)	3-axial ACC.	This model no longer available.	NO	Commercially available research-based device – available for purchase by the general public and user have ready access to the raw data. https://stayhealthy.com/	Hiremath & Ding (2011)
ReSense module (Leuenberger K, Gassert R. Zurich, CH)	Combination of 3-axial ACC (ADXL345, Analog Devices), a 3-axial gyroscope (ITG-3050, InvenSense), a 3-axial magnetometer (MAG3110, Freescale) and a barometric pressure sensor (BMP 085, BOSCH).	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. Specification details can not be found online. More information is described in the article of Leuenberger K, Gassert R. Low-power sensor module for long-term activity monitoring. Conf Proc IEEE Eng Med Biol Soc. 2011;2011:2237-2241. doi:10.1109/IEMBS.2011.6090424	Popp et al. (2016); Popp et al. (2018)
Smartphone (Xiaomi, Beijing, China),	MI A2 Android-based smartphone which featured an 8-core Qualcomm Snapdragon 660 and 4 GB of RAM, which featured an 8-core Qualcomm Snapdragon 660 and 4 GB of RAM, at a sampling rate of 50 Hz, using a dedicated mobile app, the Physics Toolbox Suite (Vieyra Software, Washington, DC, USA).	YES	NO	Commercially available consumer-based device – available for purchase by the general public, sensors are configured by researcher or research team, users have ready access to the raw data.	Marco-Ahulló et al. (2021)
Wheeleri (Finland)	Combination of data acquisition unit, a plastic disc containing an accelerometer,gyroscope, central processing unit, an internal clock and calendar and mobile application (Wheeleri App), which connects to the data acquisition unit via Bluetooth.	NO	YES	Custom made consumer-based and research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product.	Karinharju et al. (2021)
Wocket	3-axial ACC	Specifications can not be found online.	Specifications can not be found online.	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product.	Hiremath et al. (2015); Hiremath et al. (2016)

x-IMU (x-io-Technologies Bristol, UK)	Inertial sensors based upon miniature MEMS inertial sensor technology, combination of 3-axial gyroscope, 3-axial ACC and 3-axial magnetometer.	No longer available.	NO	Commercially available research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. https://x-io.co.uk/x-imu/ https://www.x-io.co.uk/downloads/x-IMU-User-Manual-v5.2.pdf	Van der Sikke et al. (2015)
Xsens^{TN} DOT (Netherlands)	IMU with combination of 3-axial gyroscope, 3-axial ACC and 3-axial magnetometer.	YES	NO	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, commercialized product. Specification details can be found online https://www.movella.com/products/xsens.	Klimstra et al. (2023)
Specification and brand details were not explained in the study.	3-axial ACC.	NR	NR	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. More information is described in the study of Ojenda & Ding (2014).	Ojenda & Ding (2014)
Specification and brand details were not explained in the study. Microstone Corporation, Nagano, Japan.	Combination of triaxial ACC with gyro sensor.	NR	NR	Custom made research-based device – sensors are configured by researcher or research team, users have access to the raw data, not commercialized product. More information is described in the article of Kiuchi et al. (2014)	Kiuchi et al. (2014)

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Device-based motion sensors estimating EE	Device name and motion sensor/s used	Author	Criterion measure	Method of estimating the EE	Protocol of activities performed to quantify the EE	Number of devices used and positioning	Validation outcome of estimating the EE	Methodological quality (poor, fair, good, excellent; positive [+], indeterminate [?] and negative [-])	Level of evidence: (very low, low, moderate, excellent)
Devices estimating EE / commercially available	Actical (omni directional activity monitor)	Conger et al. (2015)	IC	CA calculated from acceleration signals (acceleration and frequency of movement)	Linear wheelchair propulsion with different speeds and surface in semi-natural settings	1 device on right wrist	Agreement between estimate and criterion: No difference across 5 wheelchair-based activities $p < .001$ (detailed numbers for results not reported in the paper)	Poor (?)	Very Low
	ActiGraph GT3X (3-axial ACC)	Garcia-Masso et al. (2013)	IC	CA calculated from ACC counts (counts s-¹) (sampling frequency 1Hz/sec)	10 daily activities –including lying down, body transfers, moving items, mopping, working on a computer, watching TV, arm-ergometer exercise, passive propulsion, slow propulsion and fast propulsion; environment NR	1 device on non-dominant wrist	Agreement between estimate and criterion: #r = .86, MSE = 4.98, MAE = 1.65, RMSE = 2.23	Good (+)	High
						1 device on dominant wrist	Agreement between estimate and criterion: r = .86, MSE = 5.16, MAE = 1.67, RMSE= 2.27	Good (+)	
						1 device on waist	Agreement between estimate and criterion: r = .67, MSE = 10.65, MAE = 2.39, RMSE = 3.26	Good (-)	
						1 device on chest	Agreement between estimate and criterion: r = .68, MSE = 10.43, MAE = 2.41, RMSE = 3.23	Good (-)	
		Nightingale et al. (2014)	IC	CA calculated from acceleration signals converted to PAC (sampling frequency 30Hz)	Linear wheelchair propulsion and computer work; environment NR	1 device on right wrist	Agreement between estimate and criterion: r = .93 (absolute bias ±95% limits of agreement 0 ± 6.5kJ*min^{-1})	Excellent (+)	
						1 device on right upper arm	Agreement between estimate and criterion: r = .87 (absolute bias ±95% limits of agreement 0 ± 8.5kJ*min^{-1})	Excellent (+)	
						1 device on waist	Agreement between estimate and criterion: r = .73 (absolute bias ±95% limits of agreement 0 ± 11.8kJ*min^{-1})	Excellent (+)	
		Nightingale et al. (2015)	IC	CA calculated from acceleration signals converted to PAC (sampling frequency 30Hz)	Linear wheelchair propulsion + household activity in controlled settings	1 device on right wrist	Agreement between estimate and criterion: r = .82 ($p < .01$) Mean ± SD PAEE estimation errors 14 ± 50%	Excellent (+)	
						1 device on right upper arm	Agreement between estimate and criterion: r = .68 ($p < .01$) Mean ± SD PAEE estimation errors 15 ± 45%	Excellent (+)	

	Learmonth et al. (2016)	IC	DA calculated from ACC counts (VM)	Linear wheelchair propulsion in controlled settings	1 device on right wrist	Agreement between estimate and criterion: r = .95, SD = .37; R^2 = .90, SD = .14	Excellent (+)	
					1 device on left wrist	Agreement between estimate and criterion: r = .93, SD = .44; R^2 = .87, SD = .19	Excellent (+)	
					2 devices: 1 on right wrist + 1on left wrist	Agreement between estimate and criterion: r = .94, SD = .38; R^2 = .88, SD = .15	Excellent (+)	
ActGraph GT9X (3-axial ACC)	Shwetar et al. (2020)	IC	CA from acceleration signals converted to PAEE	Linear wheelchair propulsion with different speeds and surfaces + ADL + exercise; environment NR	1 device on dominant wrist	Agreement between estimate and criterion for all five predictive equations across 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 = −0.11–0.89 kcal min^{-1}	Excellent (-)	High
	Huang et al. (2024)	Doubly labelled water	CA	Seven days all time monitoring in free living (home) circumstances	1 device on dominant wrist	Agreement Between Estimate and Criterion in Field Validation All models: MAE = 136–1141 kcal/day; MAPE = 6.1%–50.2% RF: 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%) Model 3: MAE = 1025 (SD = 274) kcal/day; MAPE = 43.4% (SD = 7.6%) Model 4: MAE = 1141 (SD = 465) kcal/day; MAPE = 50.2% (SD = 23.5%)	Poor (?)	
Apple Watch Series 4	Danielsson et al. (2024)	IC	DA using EE values provided from device converted to kcal/min	Linear wheelchair propulsion with different treadmill incline-speed combinations in controlled settings	1 device on nondominant wrist	MAPE (All Inclines and Stages Combined): wheelchair users 27.4% (SD = 16.7%); people without disability 32.1% (SD = 14.4%)	Poor (?)	Very low
CSA (1-axial ACC, model 7164)	Washburn & Copay (1999)	IC	DA calculated from acceleration counts (count/min^{-1})	Linear wheelchair propulsion in semi-natural settings	1 device on left wrist	Agreement between estimate and criterion: r = .67 ($p < .01$)	Fair (-)	Low
					1 device on right wrist	Agreement between estimate and criterion: r = .52 ($p < .01$)	Fair (-)	

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	Fitbit Versa	Danielsson et al. (2024)	IC	DA using EE values provided from device converted to kcal/min	Linear wheelchair propulsion with different treadmill incline-speed combinations in controlled settings	1 device on nondominant wrist	MAPE (all inclines and stages combined): wheelchair users 73.9% (SD = 7%); people without disability 44% (SD = 38%)	Poor (?)	Very low
	Geneactiv (3-axial ACC)	Nightingale et al. (2015)	IC	CA calculated from PAC compared with PAEE	Linear wheelchair propulsion + household activities in controlled settings	1 device on upper arm	Agreement between estimate and criterion: r = .87 (*p* < .01); mean PAEE estimation error = 3% (SD = 25%)	Excellent (+)	High
						1 device on wrist	Agreement between estimate and criterion: *r* = .88 (p < .01); mean PAEE estimation error = 4% (SD = 26%)	Excellent (+)	
	RT3 (3-axial ACC)	Hiremath & Ding (2011)	IC	DA calculated from activity counts and EE in kcal/minute at 1 Hz/sec	4 daily activities + exercise in semi-natural settings	1 device on waist	Agreement between estimate and criterion for all activities ICC (3,1) =0.64 (LB = 0.51, UB = 0.73), p < .05, Spearman rho, r = .72, p < .0	Fair (-)	Low
							Agreement between estimate and criterion for deskwork ICC (3,1) = 0.60 (LB = 0.12, UB = 0.85), *p* < .05, Spearman rho, *r* = .66, *p* < .05	Fair (-)	
							Agreement between estimate and criterion for arm-ergometry ICC (3,1) = 0.40 (LB = 0.12, UB = 0.62), p < .05, Spearman rho, r = .52, p < .05	Fair (-)	
							Agreement between estimate and criterion for propulsion ICC (3,1) = 0.52 (LB = 0.26, UB = 0.70), *p* < .05, Spearman rho, *r* = .44, *p* < .05	Fair (-)	
							Agreement between estimate and criterion for resting ICC (3,1) = 0.53 (LB = 0.02, UB = 0.82), p < .05, Spearman rho, r = .53	Fair (-)	
	Xiaomi android-based smartphone (built-in accelerometer)	Marco-Ahulló et al. (2021)	IC	CA calculated from acceleration signals	10 upper limb ADL; Environment NR	1 device on the non-dominant arm	Agreement between estimate and criterion using model with all variables: *r* = .72; MSE = 6.16; MAE = 1.76	Excellent (+)	High
							Agreement between estimate and criterion using model with linear variables: r = .72; MSE = 6.16; MAE = 1.76	Excellent (+)	
							Agreement between estimate and criterion using model with non-linear variables: r = 0.71; MSE = 6.48; MAE = 1.85	Excellent (+)	
Devices predicting EE / custom made	Physical Activity Monitoring System (PAMS) (2 separate units: one 3-axial ACC and one 2-axial gyroscope)	Hiremath et al. (2016)	IC	CA calculated from angular velocity (s^{-1}) and acceleration signals	10 daily activities –including: propelling wheelchair at various surfaces, up and down a ramp; being pushed wheelchair; wheelchair basketball or darts; folding laundry; performing deskwork; using a resistance	2 devices: 3-axial ACC on upper-arm and gyroscope on spokes of the right wheelchair wheel	Agreement between estimate and criterion for all activities: ICC (3,1) = 0.82, 95% CI [0.79, 0.85], *p* < .05; average error = -9.82% (SD = 37.03%)	Excellent (+)	High
							Agreement between estimate and criterion for propulsion: ICC (3,1) = 0.69, 95% CI [0.57, 0.78], p < .05	Excellent (-)	

					deskwork, using a resistance band; and performing arm ergometry in semi-natural settings		Agreement between estimate and criterion for basketball: ICC (3,1) = 0.84, 95% CI [0.56, 0.94], p < .05	Excellent (+)	
							Agreement between estimate and criterion for arm ergometry: ICC (3,1) = 0.47, 95% CI [0.19, 0.66], p < .05	Excellent (-)	
							The activity-specific model underestimated EE for physical activities involving wheelchair movement		
						2 devices: 3-axial ACC on right wrist and gyroscope on spokes of the right wheelchair wheel	Agreement between estimate and criterion for all activities: ICC (3,1) = 0.89, 95% CI [0.87, 0.91], $p < .05$; average error = -5.65% (SD = 32.61%)	Excellent (+)	
							Agreement between estimate and criterion for propulsion: ICC (3,1) = 0.84, 95% CI [0.78, 0.89], p < .05	Excellent (+)	
							Agreement between estimate and criterion for basketball: ICC (3,1) = 0.91, 95% CI [0.75, 0.97], p < .05	Excellent (+)	
							Agreement between estimate and criterion for arm ergometry: ICC (3,1) = 0.85, 95% CI [0.77, 0.90], p < .05	Excellent (+)	
							The activity-specific model underestimated EE for physical activities involving wheelchair movement.		
	PowerTap (Power meter)	Conger et al. (2014)	IC	CA calculated from power (W)	Linear wheelchair propulsion with different speeds and surfaces in semi-natural settings	1 device on right wheel of the wheelchair	Agreement between estimate and criterion: $r = .694$, $p < .01$	Excellent (-)	High
							Model 1 (power): $R^2 = .48$ (SEE = .97, RMSE = .97, prediction bias = -0.21)	Excellent (-)	
							Model 2 (power, speed): $R^2 = .70$ (SEE = .74, RMSE = .82, prediction bias = 0.00)	Excellent (+)	
	The ReSense IMU (3-axial ACC, 3-axial gyroscope, 3-axial magnetometer)	Popp et al. (2018)	IC	CA calculated from acceleration signals	Linear continuous wheelchair propulsion in semi-natural settings	4 devices: one on each wrist, one at the chest and one on the right wheel of the wheelchair	The overall classification accuracy of the EE estimation model 97.9% The Sensitivity for the individual activities 81.8-100% (Median of 100%) The mean estimation error 14,4%	Excellent (+)	High
	3-axial ACC with gyro sensor (brand not available)	Kiuchi et al. (2014)	IC	CA calculated from acceleration signals and angular velocity (s^{-1})	Linear continuous wheelchair propulsion in controlled settings	4 devices: 1 on left wrist, 1on right wrist, 1 on left upper arm and 1 on right upper arm	Agreement between estimate and criterion: Model 1based on acceleration $R^2 = .64- .82$ (SEE .003-.005)	Poor (?)	Very low
							Agreement between estimate and criterion: Model 2 based on angular velocity: $R^2 = .50- .83$ (SEE .003-.005)	Poor (?)	

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							Agreement between estimate and criterion: Model 3 based on acceleration + angular velocity R^2 = .68- .87 (SEE .003-.004)	Poor (?)		

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Device-based motion sensors estimating self-propulsion	Device name and motion sensor/s used	Author	Criterion measure	Method of estimating self-propulsion	Protocol of activities performed to quantify the self-propulsion	Number of devices used and positioning	Validation outcome of estimating self-propulsion	Methodological quality (poor, fair, good, excellent; positive [+], indeterminate [?] and negative [-])	Level of evidence: (very low, low, moderate, excellent)
Devices predicting self-propulsion / commercially available	ActiGraph GT3X (3-axial ACC)	Koojimans et al. (2014)	VR	CA to identify time spent (s) in SP and in other activities calculated from vector counts	26 daily activities –including treadmill propulsion with 4 different speeds, flat ground propulsion with 3 different speeds, propulsion and maneuvering during activities and hand biking in controlled settings	2 devices: 1 on wrist and 1 on spokes of the wheelchair wheel (side not reported)	Identifying SP from other activities: Overall agreement 85.2 (76.7–92.3) %, Sensitivity 88 (83.1–93.0) %, Specificity 83.3 (72.6–91.2) %	Good (+)	Moderate
							For ACC data, the accuracy of self-propelled wheelchair driving duration was 80%–90%, with an average overestimation of 5.5 s (SD = 34 s, p = .60)	Good (+)	
		Chen & Morgan (2018)	DO	Different CAs to estimate SP calculated from arm acceleration signals	Wheelchair propulsion patterns with a stationary roller system: single loop over semicircle and double loop over propulsion on two different surfaces in controlled settings	2 devices: 1 on the dominant upper-arm and 1 on the dominant wrist	The support vector machine algorithm built from 3-axis ACC data predicted wheelchair propulsion with 99.7% accuracy.	Fair (+)	
		Garcia-Masso et al. (2015)	DO	CAs to identify slow and fast SP calculated from ACC counts (counts s^{-1})	10 daily activities –including linear SP of the wheelchair over the floor at a moderate and fast speed, environment NR	2 devices: 1 on both wrists	Accuracy for identifying slow self-propulsion 66.6%	Good (-)	
							Accuracy for identifying fast self-propulsion 93.75%	Good (+)	
	Active 8 activity monitor (3-axial ACC)	Leving et al. (2018)	VR	CA to differentiate SP from other activities calculated from activity counts and relative duration (s) of performed	16 daily activities –including treadmill propulsion with 4 different velocity and at 2 different slopes and flat surface propulsion at 3 different velocity in controlled	2 devices: 1 on right forearm and 1 on the right wheel	Differentiating the SP from other activities: Agreement 82.1% (SD: 4.3; range 73.1-88.4%)	Excellent (+)	High
							Sensitivity 77.7%	Excellent (-)	
							Positive predictive value 78.2%	Excellent (-)	
	ActiWatch (multidirectional ACC)	Murphy et al. (2019)	ProDiary ACC	DA to estimate SP calculated from average acceleration counts /minute (counts/min)	8 daily activities –including slow and brisk forward SP in controlled settings	1 device on the non-dominant wrist	Agreement for estimating slow SP ICC= 0.82, (p < .01)	Fair (+)	Low
							Agreement for estimating brisk SP ICC= 0.86, (p < .01)	Fair (+)	
	Apple Watch series 1 (ACC + gyroscope)	Karinharju et al. (2019)	VR	DA to estimate SP calculated from push counts	21 daily activities –including discontinuous linear wheelchair propulsion with different speeds, continuous wheelchair propulsion with turning, wheelchair propulsion with maneuvering, confined space maneuvering and stationary activities in semi-natural settings	1 device on the dominant wrist	Accuracy of estimating SP ICC 0.77, r = .84 (MD = -103 pushes, Upper LoA = 217, Lower LoA = -423 pushes)	Excellent (+)	High

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	Apple Watch series 1 (ACC + gyroscope)	Glasheen et al. (2021)	DO	DA to estimate SP calculated from push counts	Wheelchair propulsion on treadmill + an overground obstacle course and hand cycling with arm cycle ergometer (figure 8s around 2 cones) in controlled and semi-natural settings	1 device on the dominant wrist	Accuracy of estimating SP for: Low cadence: Treadmill ICC = -0.18; MAPE 22%	Excellent (-)	
							Arm ergometry ICC = 0.88; MAPE 1%	Excellent (+)	
							Moderate cadence: Treadmill ICC = 0.47; MAPE 3%	Excellent (-)	
							Arm ergometry ICC =0.95; MAPE = 1%	Excellent (+)	
							High cadence: Treadmill ICC = 0.98; MAPE 1%	Excellent (+)	
							Arm ergometry ICC = 0.88; MAPE 1%	Excellent (+)	
							Variable cadence: Treadmill ICC = 0.22; MAPE 6%	Excellent (-)	
							Arm ergometry ICC = 0.97; MAPE 4%	Excellent (+)	
							Overground tasks: Casual pace ICC = 0.90; MAPE = 15%	Excellent (+)	
							Fast pace ICC = 0.79; MAPE 18%	Excellent (+)	
							Figure 8 ICC = 0.82; MAPE = 21%	Excellent (-)	
	Apple Watch series 4 (ACC + gyroscope)	Benning et al. (2020)	DO	DA to estimate SP calculated from push counts	Driving wheelchair on outdoor test course with right and left turns in semi-natural settings	1 device on nondominant wrist	Accuracy of estimating SP: Calibrated Apple Watch percentage of error = 13.9% (MD = 13.55 pushes; 95% LoA [−8.09, 35.19] pushes);	Poor (?)	
							Uncalibrated Apple Watch percentage of error = 22.8% (MD = 19.05 pushes; 95% LoA [−9.96, 48.06] pushes)	Poor (?)	
		Benning et al. (2021)	DO	DA to estimate SP calculated from push counts	Driving wheelchair in two different courses in semi-natural settings	1 device on nondominant wrist	Accuracy of estimating SP: MAPE = 9.20% (MD = 12.33 pushes; 95% LoA [−5.99, 30.66] pushes)	Poor (?)	
	BPMpro IMU (with 3-axial ACCs) + Actigraph GT3X (3-axial ACC)	Chen & Morgan (2018)	DO	CA to estimate SP from other activities calculated from arm acceleration signals and rotation data	1 participant performed two different wheelchair propulsion patterns in controlled settings and one participant performed 8 daily activities in semi-natural settings	2 devices: 1 on the dominant upper-arm and 1 on the dominant wrist	Accuracy of support vector machine algorithm built from ACC and IMU rotation data predicting wheelchair propulsion: F1= .968	Fair (+)	Low
	Fitbit Flex 2	Benning et al. (2020)	DO	Wheelchair Propulsion to estimating SP calculated from push counts	Driving wheelchair on outdoor test course with right and left turns in semi-natural settings	1 device on nondominant wrist	Accuracy of estimating SP: 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)	Poor (?)	Very low

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Devices predicting self-propulsion / custom made	ADXL202 (2-axial ACC)	Postma et al. (2005)	VR	CA to identify SP calculated from acceleration(gravitational + inertial) signals and duration /time (s) (with sampling frequency 32Hz) of performed activities	24 daily activities –including forward wheelchair propulsion and propulsion with maneuvering (activity duration >5s) in semi-natural settings	6 devices: 1 on the left thigh,1 on the right thigh, 1 on the left wrist, 1 on the right wrist, 2 on the sternum	The accuracy of detecting wheelchair propulsion: Agreement 92 (87-96) %, Sensitivity 87 (76-99) %, Specificity 92 (85-98) % Sensitivity: poor triceps strength 81 (76– 89) %, ($p < .01$), good triceps strength 95 (89–99) % ($p < .01$)	Good (+)	Moderate
							Mean overestimation in duration of wheelchair propulsion = 3.9% ($p < .05$)	Good (+)	
	Emerald IMUs (3-axial ACC)	Fortune et al. (2019)	VR	CAs to identify SP calculated from acceleration (g) and angular velocity data	6 daily activities –including level and simulated ramp propulsion in controlled settings	3 devices: 1 on the both upper arms and 1 on the chest	The accuracy, specificity and area under the curve of identifying SP activities = 99%	Excellent (+)	High
	G-WRM (2-axial gyroscope)	Hiremath et al. (2015)	VR	CA to identify SP calculated from angular velocity (s^{-1}) (converted into wheelchair velocity and distance travelled)	10 daily activities –including active and passive wheelchair propulsion at different speeds and surfaces, folding laundry, performing deskwork, playing basketball and darts, using a resistance band and exercising on an arm ergometer in controlled and semi-natural settings	1 device on the right wheel of the wheelchair	Accuracy of detecting wheelchair propulsion 95.03% Sensitivity of detecting wheelchair propulsion 90% Specificity of detecting wheelchair propulsion 97%	Excellent (+)	High
	Instrumented treadmill with two 3-axial force platforms	Gagnon et al. (2016)	SMARTWheel™	CA to estimate SP calculated from push phase time (s), recovery phase time (s) and propulsive moments (Mz)	Linear continuous wheelchair propulsion with steady speed on treadmill, controlled settings	Treadmill equipped with 2 devices underneath a right and a left treadmill rubber band	Associations between treadmill and the instrumented pushrim: Mean duration of the push phase $r = .98$	Good (+)	Moderate
							Mean duration of the recovery phase $r = .99$	Good (+)	
							Mean propulsive moment $r = .97$	Good (+)	
							Peak propulsive moment $r = .96$	Good (+)	
	LIS3DH (tri-axial ACC)	Dowling et al. (2017)	SMARTWheel™	CA to estimate SP calculated from push counts based on acceleration signals	Wheelchair propulsion on 50m flat track, 3 SP trials and 3 assisted propulsion trials in semi-natural settings	1 device on the frame of the wheelchair	Accuracy of estimating push counts 97.7%	Poor (?)	Very low
	Physical Activity Monitoring System (PAMS) (2 separate units: one 3	Hiremath et al. (2015)	VR	CA to identify SP calculated from angular velocity (s^{-1}) converted into wheelchair velocity and distance travelled; and	10 daily activities –including active and passive wheelchair propulsion at different speeds and surfaces, folding laundry, performing deskwork, playing basketball and darts, using a resistance band and exercising	1 device: 3-axial ACC on upper-arm and gyroscope on spokes of the right wheelchair wheel	Accuracy of detecting the wheelchair propulsion 98.41% Sensitivity of detecting the wheelchair propulsion 99% Specificity of detecting the wheelchair propulsion 98%	Excellent (+)	High

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	units: one 3-axial ACC and one 2-axial gyroscope)			travelled, and angular acceleration (m/s²) of body motion	resistance band and exercising on an arm ergometer in controlled and semi-natural settings	1 device: 3-axial ACC on right wrist and gyroscope on spokes of the right wheelchair wheel	Accuracy of detecting the wheelchair propulsion 97.61% Sensitivity of detecting the wheelchair propulsion 97% Specificity of detecting the wheelchair propulsion 98%	Excellent (+)	
	ReSense IMU's (3-axial ACC, 3-axial gyroscope, 3-axial magnetometer)	Popp et al.(2016)	VR	CA to identify SP calculated from unspecified ACC and gyroscope data	Linear continuous wheelchair propulsion forward and backward in semi-natural settings	4 devices: 1 on each wrist, the chest and between the spokes of the wheelchair	Accuracy of detecting SP with gyroscope-based module >93.29%	Fair (+)	Low
							Accuracy of detecting SP with module without gyroscope 82.07%	Fair (+)	
	Wocket (3-axial ACC)	Hiremath et al. (2015)	VR	CA to identify SP calculated from angular acceleration (m/s²) of body motion	10 daily activities –including active and passive wheelchair propulsion at different speeds and surfaces, folding laundry, performing deskwork, playing basketball and darts, using a resistance band and exercising on an arm ergometer in controlled and semi-natural settings	1 device on the right upper-arm	Accuracy to detect wheelchair propulsion 88.47% Sensitivity to detect wheelchair propulsion 65% Specificity to detect wheelchair propulsion 97%	Excellent (+)	High
						1 device on the right wrist	Accuracy to detect wheelchair propulsion 95.83% Sensitivity to detect wheelchair propulsion 86% Specificity to detect wheelchair propulsion 99%	Excellent (+)	
	3- axial ACC (brand not available)	Ojenda & Ding (2014)	VR and SMARTWheel™	CA to estimate SP calculated from stroke number and push frequency (stroke / sec)	24 level-surface trials of wheelchair propelling at self-selected speed, low speed, and fast speed, and 12 sloped-surface trials at a self-selected speed; Environment NR	1 device on dominant upper arm	Agreement for estimating stroke number: ICC = 0.994, 95% CI [0.998, 0.997], $p < .001$, MAPE = 8.0% (SD = 7.1%)	Fair (+)	Low
							Agreement for estimating push frequency: ICC = 0.916, 95% CI [0.843, 0.953], $p < .001$, MAPE = 12.9% (SD = 15.1%)	Fair (+)	
						1 device on dominant wrist	Agreement for estimating stroke number: ICC = .990, 95% CI [0.980, 0.995], $p < .001$, MAPE = 10.8% (SD = 9.8%)	Fair (+)	
							Agreement for estimating push frequency: ICC = 0.889, 95% CI [0.802, 0.936], $p < .001$, MAPE = 17.2% (SD = 19.3%)	Fair (+)	
						1 device underneath the wheelchair seat	Agreement for estimating stroke number: ICC = .984, 95% CI [0.972, 0.991], $p < .001$, MAPE = 13.4% (SD = 15.6%)	Fair (+)	

							Agreement for estimating push frequency: ICC = 0.690, 95% CI [0.071, 0.868], p < .001, MAPE = 24.2% (SD = 16.6%)	Fair (-)	

Device-based motion sensors estimating daily activities (other than SP)	Device name and motion sensor/s used	Author	Criterion measure	Method of estimating the daily activities (other than SP)	Protocol of activities performed to quantify the daily activities (other than SP)	Number of devices used and positioning	Validation outcome of estimating the daily activities (other than SP)	Methodological quality (poor, fair, good, excellent; positive [+], indeterminate [?] and negative [-])	Level of evidence: (very low, low, moderate, excellent)
Devices predicting daily activities (other than SP) / commercially available	ActiGraph GT3X (3-axial ACC)	Garcia-Masso et al. (2015)	DO	CAs to identify individual and grouped activities calculated from ACC counts (counts s^{-1})	10 daily activities –including lying down, body transfers, moving items, mopping, working on a computer, watching TV, arm-ergometer exercise, passive propulsion, slow propulsion and fast propulsion. Environment not reported	1 device on the non-dominant wrist	Accuracy to identify activity type with the individual activity classifiers 61.5-63.3%	Good (-)	Moderate
							Accuracy to identify activity type with the grouped activity classifiers 83.9-87.0%	Good (+)	
						1 device on the dominant wrist	Accuracy to identify activity type with the individual activity classifiers 55.0-61.4%	Good (-)	
							Accuracy to identify activity type with the grouped activity classifiers 83.2-85.9%	Good (+)	
						2 devices: 1 on each wrist	Accuracy for identifying activity type with the individual activity classifiers 62.9-68.9%	Good (-)	
							Accuracy for identifying activity type with the grouped activity classifiers 86.6-90.4%	Good (+)	

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							Accuracy for identifying the sedentary activities accuracy 93.75-100%	Good (+)	
							Accuracy for identifying the household activities 85.94-90.56%	Good (+)	
							Accuracy for identifying the body transfers 85.59%	Good (+)	
							Accuracy for identifying the arm ergometer 100%	Good (+)	
						4 devices: 1 on each wrist, 1 on the waist and 1 on the chest	Accuracy for identifying activity type with the individual activity classifiers 65.9-72.5%	Good (-)	
							Accuracy for identifying activity type with the grouped activity classifiers 89.4-93.6%	Good (+)	
	Active 8 activity monitor (3-axial ACC)	Leving et al. (2018)	VR	CA to identify upper body activities divided into 5 activity classes calculated from activity counts and duration (s) per performed task	16 daily activities—including sedentary activities, household activities, SP and assisted propulsion and wheelchair basketball in controlled settings	2 devices: 1 on right forearm and 1 on the right wheel	Agreement of total duration of all tasks 84.5%	Excellent (+)	Moderate
							Overall agreement of 5 activity classes 56.6% (SD: 4.5; range 48.8-65.6%), sensitivity 52.8%, positive predictive value 51.9%	Excellent (-)	
	Actiwatch (multidirectional ACC)	Murphy et al. (2019)	ProDiary ACC	DA to identify upper body activity type calculated from	8 daily activities—including sedentary activities,	1 device on the non-dominant wrist	The accuracy identifying activity type:	Fair (+)	Low

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				average acceleration counts / minute (counts/min)	housework activities, propulsion activities, handcycling and resistance band exercising in controlled settings		All activities together ICC = 0.81-0.92 (p < .01)	Fair (+)	
							Sedentary activities ICC = 0.89-0.91 (p < .01)	Fair (+)	
							Household activities ICC = 0.81-0.89 (p < .01)	Fair (+)	
							Handcycling ICC = 0.88 (p < .01)	Fair (+)	
							Resistance band exercising ICC = 0.92 (p < .01)	Fair (+)	
Devices predicting upper body activities / custom made	Emerald IMUs (3-axial ACC)	Fortune et al. (2019)	VR	CA to identify non-propulsion activities and time spent stationary (static time) from other activities with activity classification model calculated from the lab-based IMU acceleration (g) and angular velocity data	6 daily activities—including counter height and overhead reaching, crossbody lift, propulsion and transfers	3 devices: 1 on each upper arm and 1 on the chest	Accuracy of identifying non-propulsion activity 0.94% Specificity of identifying non-propulsion activity = 0.97% Area under the curve of identifying non-propulsion activity = 0.97%.	Excellent (+)	High
							Accuracy of identifying static time = 0.95% Specificity of identifying static time = 0.92% Area under the curve for identifying static time = 0.98%	Excellent (+)	
	G-WRM (2-axial gyroscope)	Hiremath et al. (2015)	VR	CA to identify upper body activities calculated from angular velocity (s^{-1}) converted into wheelchair velocity and distance travelled	10 daily activities—including active and passive wheelchair propulsion at different speeds and surfaces, folding laundry, performing	1 device on the right wheel of the wheelchair	Accuracy of detecting grouped activities (all activities together) 65.41%	Excellent (-)	High

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				and distance travelled	laundry, performing deskwork, playing basketball and darts, using a resistance band and exercising on an arm ergometer in controlled and semi-natural settings		Accuracy of detecting sedentary activities 90.66-98.21%	Excellent (+)	
							Accuracy of detecting the household activities 72.56%	Excellent (-)	
							Accuracy of detecting the arm ergometer 81.71%	Excellent (+)	
							Accuracy of detecting the wheelchair basketball 95.43%	Excellent (+)	
	Physical Activity Monitoring System (PAMS) (2 separate units: one 3-axial ACC and one 2-axial gyroscope)	Hiremath et al. (2015)	VR	CA to identify upper body activities calculated from angular velocity (s^{-1}) converted into wheelchair velocity and distance travelled and angular acceleration (m/s^2) of body motion	10 daily activities—including active and passive wheelchair propulsion at different speeds and surfaces, folding laundry, performing deskwork, playing basketball and darts, using a resistance band and exercising on an arm ergometer in controlled and semi-natural settings	2 devices: tri-axial ACC on upper-arm and gyroscope on spokes of the right wheelchair wheel	Accuracy of detecting grouped activities (all activities together) 89.26%	Excellent (+)	High
							Accuracy of detecting the sedentary activities 94.43-99.01%	Excellent (+)	
							Accuracy of detecting the household activities 92.84%	Excellent (+)	
							Accuracy of detecting the arm ergometer 98.21%	Excellent (+)	
							Accuracy of detecting the wheelchair basketball 97.42%	Excellent (+)	

						2 devices: tri-axial ACC on right wrist and gyroscope on spokes of the right wheelchair wheel	Accuracy of detecting grouped activities (all activities together) 88.47%	Excellent (+)	
							Accuracy of detecting sedentary activities 94.83-99.01%	Excellent (+)	
							Accuracy of detecting the household activities 93.04%	Excellent (+)	
							Accuracy of detecting the arm ergometer 97.22%	Excellent (+)	
							Accuracy of detecting the wheelchair basketball 97.02%	Excellent (+)	
	Wocket (3-axial ACC)	Hiremath et al. (2015)	VR	CA to identify upper body activities calculated from angular acceleration (m/s^2) of body motion.	10 daily activities including active and passive wheelchair propulsion at different speeds and surfaces, folding laundry, performing deskwork, playing basketball and darts, using a resistance band and exercising on an arm ergometer in controlled and semi-natural settings	1 device on the right upper arm	Accuracy of detecting grouped activities (all activities together) 70.38%	Excellent (-)	High
							Accuracy of detecting the sedentary activities 92.25-94.43%	Excellent (+)	
							Accuracy of detecting the household activities 81.51%	Excellent (+)	
							Accuracy of detecting the arm ergometer 94.23%	Excellent (+)	

							Accuracy of detecting wheelchair basketball 96.62%	Excellent (+)	
						1 device on the right wrist	Accuracy of all activities together 74.55%	Excellent (-)	
							Accuracy of the sedentary activities' accuracy 87.67-93.64%	Excellent (+)	
							Accuracy of the household activities 88.27%	Excellent (+)	
							Accuracy of the arm ergometer 98.21%	Excellent (+)	
							Accuracy of the wheelchair basketball 95.23%	Excellent (+)	

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Device-based motion sensors estimating wheelchair kinematics	Device name and motion sensor/s used	Author	Criterion measure	Method of estimating the wheelchair kinematics	Protocol of activities performed to quantify the wheelchair kinematics	Number of devices used and positioning	Validation outcome of estimating the wheelchair kinematics	Methodological quality (poor, fair, good, excellent; positive [+], indeterminate [?] and negative [-])	Level of evidence: (very low, low, moderate, excellent)
Devices predicting wheelchair kinematics / commercially available	ActivPAL (3-axial ACC)	Coulter et al. (2011)	VR	CA for estimating wheelchair moving duration calculated from the radial and tangential acceleration (Absolute angle[˚], number of wheel revolutions and duration of movement [s])	Continuous propulsion on indoor track with self-selected speed, and outdoor wheelchair skills course with ramp and obstacle manoeuvres, left and right turns, gravel path and kerbs in semi-natural settings	2 devices: One in spokes of each wheel	Accuracy of wheel revolution: ICC = 1.00, 95% CI [1.00, 1.00], mean difference = 0.002 (SD = 0.016), MAPE = 0.59%	Fair (+)	Low
							Accuracy of absolute angle: ICC = 0.999, 95% CI [0.999, 0.999], mean difference = 0.0006 (SD = 3.853)	Fair (+)	
							Accuracy of duration of movement: ICC = 0.981, 95% CI [0.669, 0.994]	Fair (+)	
	Blue Trident IMU (accelerometer, gyroscope integrated with the same coordinated axes)	Fasipe et al. (2024)	MD and DO	CA for estimating wheelchair laps, distance and speed	Continuous six minutes propulsion on hallway between two cones positioned 32.1 m apart from each other in semi-controlled settings	2 devices: one on the bottom of the wheelchair and one on the right wrist	Accuracy estimating wheelchair movement: IMU laps: r = .947	Excellent (+)	High
							IMU distance: r = .97	Excellent (+)	
							Mean speed: r = .97	Excellent (+)	
	The Cateye Strada Wireless Cycling Computer (magnet, reed switch, and a microcontroller)	Karinharju et al. (2021)	MD	Accuracy of the cycling computer estimating wheelchair moving distance	Discontinuous linear wheelchair propulsion with different speeds, continuous wheelchair propulsion with turning, wheelchair propulsion with maneuvering, confined space maneuvering in semi-natural settings	1 device in spokes of the right wheel	Accuracy estimating wheelchair movement distance: Total distance MAPE = 4.7% (mean bias [±95% LoA] = −23.9 [−41.5 to −6.3] m) Continuous forward propulsion MAPE = 6.0% (mean bias [±95% LoA] = -0.1 [-1.6 to 1.4] m) Linear discontinuous propulsion MAPE = 53.4% (mean bias [±95% LoA] = -10.3 [-10.8 to -9.7] m) Propulsion with maneuvering MAPE = 80.9% (mean bias [±95% LoA] = 2.0 [1.3 to 2.7] m) Maneuvering within confined spaces MAPE = 77.9% (mean bias [±95% LoA] = 2.3 [1.5 to 3.2] m)	Poor (?)	Very Low

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		Ohji et al. (2021)	MD	Accuracy of the cycling computer estimating wheelchair moving distance and self-propulsion distance and with touch switch	Wheelchair driving on 180m rectangular facility (10 laps) and 50-m straight runway alternately propelled by the volunteer and caregiver in controlled settings	1 device attached to the right tipping lever of the manual wheelchair	Accuracy for estimating wheelchair distance in the rectangular facility was 180m compared to criterion 181m: the error was 1 m.	Poor (?)	
							Accuracy for estimating wheelchair distance with caregiver assisted was 100% (20m) and without caregiver assisted was 100% (30m)	Poor (?)	
	X-IMU (3-axial gyroscope, 3-axial ACC and 3-axial magnetometer)	Van der Slikke et al. (2015)	Optical 3D system	CA for estimating wheelchair movement speed calculated from wheel acceleration signals (WhA) and wheel gyroscope (WhG) signals	9 activities of wheelchair maneuvering in semi-controlled settings	3 devices: two on the right wheel and one on frame of the wheelchair	Accuracy for estimating wheelchair movement speed between estimate and criterion: Linear speed: ICC > .90	Fair (+)	Low
							Rotational speed: ICC > .99	Fair (+)	
							Instantaneous rotation centre (IRC): ICC > .90	Fair (+)	
	XsensTM (3-axial gyroscope, 3-axial ACC and 3-axial magnetometer)	Klimstra et al. (2023)	Xsens IMU in wheelchair frame	CA for estimating wheelchair speed (frame rotation) with single wheel-mounted IMU (red/s)	Continuous wheelchair driving 10m, discontinuous wheelchair driving forward, backward, left and right in semi-controlled settings	2 devices, one attached to the left and right wheel of the wheelchair	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) MD = .016 rad/s; LoA = −.067 to .10	Fair (+)	Low
							IMU right wheel: r^2 mean = .995 (SD = .003) RMSE (rad/s) mean = .074 (SD = .024) MAE (rad/s) = .055 (SD = .018) MD = .002 rad/s; LoA = −.059 to .064 rad/s	Fair (+)	
Devices predicting wheelchair kinematics/ custom made	ADXL345 (3-axial ACC)	Popp et al. (2016)	VR	CA for estimating the wheelchair movement and moving distance calculated from angular velocity and distance (m)	Linear continuous wheelchair propulsion in semi-natural settings.	5 devices on the right wheel of the wheelchair	Detecting wheelchair movement: sensitivity = 94.69% (SD = 3.01%), specificity = 99.25% (SD = 0.43%)	Fair (+)	Low
							Indoor track wheelchair moving distance accuracy = 99.2%–99.6%	Fair (+)	
							Outdoor track wheelchair distance accuracy = 99.3%–99.8%	Fair (+)	
							Overall distance (indoor + outdoor) accuracy = 99.2%–99.8%	Fair (+)	

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	Data logger (integrated ACC)	Sindall et al. (2013)	MD	CA for estimating wheelchair movement distance (m) calculated from wheel revolutions (distance, speed and direction)	Linear continuous wheelchair propulsion in semi-natural settings.	2 devices: 1 on each wheel	Accuracy for Tennis-field test: Distance in moving forward estimated with DL on left wheel was lower compared with MD and distance estimated with DL on the right wheel Distance in reversing drill estimated with DL right was lower than MD and distance estimated with DL on the left wheel Accuracy for linear track test: data logger on the left wheel reported lower values than the criterion value ($p = .001$) and the data logger on the right wheel ($p = .006$) Data logger on the left and right wheels both significantly overestimated the criterion distance at 800 m ($p = .0001$ and $p = .040$, respectively)	Poor (?)	Very low
	G-WRM (2-axial gyroscope)	Hiremath et al. (2013)	MD, Smartwheel and 3-D motion capture system	CA for estimating wheelchair movement calculated from angular velocities (s^{-1}) converted to distance traveled (sampling frequency 64Hz)	Linear continuous wheelchair propulsion in controlled settings	3 devices on the right wheel of wheelchair	Accuracy for distance travelled ICC=0.999-1.000, MAPE = 0.58-0.88%	Fair (+)	Low
		Hiremath et al. (2013)	MD	CA for estimating wheelchair movement distance with CA calculated from angular velocities (s^{-1}) converted to distance traveled	Linear continuous handcycling in seminatural settings	3 devices on the wheel of the handcycle	Accuracy > 95%	Fair (+)	
	ITG-3050 (3-axial gyroscope)	Popp et al. (2016)	VR	CA for estimating detection of wheelchair movement and moving distance with CA calculated from angular velocity (m/s) and distance (m)	Linear continuous wheelchair propulsion in semi-natural settings	5 devices on the right wheel of the wheelchair	Accuracy for estimating if wheelchair is moving: Sensitivity 95.80±1.91% Specificity 99.58±0.29%	Fair (+)	Low
							Accuracy for estimating wheelchair moving distance on indoor track 97.7-99.8%	Fair (+)	
							Accuracy for estimating wheelchair moving distance on outdoor track 98.5-99.9%	Fair (+)	

							Accuracy for estimating overall distance (indoor + outdoor) 97.7-99.9%	Fair (+)	
	MMA7260Q Freescale Semiconductor (3-axial ACC [used only 2-axis])	Sonenblum et al. (2012)	VR and MD	CA for estimating wheelchair moving duration and distance calculated from acceleration (g's), wheel revolutions and speed (m/s)(sampling frequency 60Hz)	Wheelchair propulsion and 5 daily activities in semi-natural settings	2 devices on the plane of the wheel	Accuracy for estimating the wheelchair moving time: Test 1. 91%	Poor (+)	Very low
							Test 2. 96%	Poor (+)	
							Test 3. 94%	Poor (+)	
							Accuracy for estimating the time spent stationary 93%	Poor (+)	
							Accuracy for estimating the distance measured 96% (SD = 2%) (Distance results not reported separately)	Poor (?)	
	Wheeleri (3-axial gyroscope, central processing unit and mobile application)	Karinharju et al. (2021)	MD	Accuracy of the cycling computer estimating wheelchair moving distance	Discontinuous linear wheelchair propulsion with different speeds, continuous wheelchair propulsion with turning, wheelchair propulsion with maneuvering, confined space maneuvering in semi-natural settings	1 device in spokes of the right wheel	Accuracy estimating wheelchair movement distance: Total distance MAPE = 5.6% (mean bias [±95% LoA] = 48.0 [40.9 to 55.1] m) Linear discontinuous propulsion MAPE = 1.3% (mean bias [±95% LoA] = 0.1 [0.0 to 0.1] m) Continuous forward propulsion MAPE = 5.3% (mean bias [±95% LoA] = 4.3 [3.3 to 5.3] m) Propulsion with maneuvering MAPE = 9.6% (mean bias [±95% LoA] = 1.2 [0.9 to 1.6] m) Maneuvering within confined spaces MAPE = 28.4% (mean bias [±95% LoA] = 1.2 [0.9 to 1.6] m)	Poor (?)	Very Low