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In-field temporal phase analysis of running: performance assessment of 36 IMU-based algorithms across different device positions and running speeds

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A B S T R A C T

Analysis of running temporal parameters is essential for evaluating runner's performance and preventing injury risk. Inertial measurement units (IMUs) are the most widely used and extensively studied technology for sports applications in the field. Various IMU-based methods for estimating stance and stride phases have been proposed based on different IMU positions, type of inertial signals analyzed, and different algorithms for signal processing and parameters extraction. However, a comprehensive guideline recommending the most suitable method for a specific experimental condition is still lacking. This study aimed to compare 36 algorithms for stance and stride estimation working on different device positions (foot, shank, lower back) across three running speeds. Ten participants performed running trials at 15, 20, and 25 km/h, for a total of 1034 stride while a photocell system served as reference system. Results indicated that foot-mounted IMUs provide the highest accuracy with the lowest median (Med) and interquartile range (IQR) error for both temporal parameters estimates (Med: 0 ms, IQR: 5 ms and 22 ms for stride and stance, respectively), followed by shank- and lower back-mounted ones. Stance estimation performance was significantly affected by running speed, highlighting the importance of taking into account speed when selecting an algorithm based on a given dataset. These findings provided practical recommendations to guide method selection for IMU-based temporal parameter estimation in running.

1. Introduction

Running is one of the most practiced recreational physical activities worldwide, offering notable benefits in terms of health and accessibility (Bredeweg et al., 2013). Consequentially, increasing attention has been devoted to biomechanical analysis of running, to optimize performance and prevent musculoskeletal injuries (Bel et al., 2021). In this context, running data are commonly segmented into strides, defined as the interval between two consecutive initial contacts (IC) of the same foot with the ground, whereas stance phase is the period between IC and toe-off (TO); this segmentation is essential to provide spatiotemporal parameters in relevant running phases (Rossanigo et al., 2021; Mendicino et al., 2025), whose accurate estimation provides interesting insights into athletic performance. For instance, temporal parameters play an important role in modulating impact forces and loading rates, which are critical for injury prevention. An increased stride rate (and decreased stride duration) has been observed to beneficially affect loading rates by decreasing vertical ground reaction forces, impact shock, and energy absorbed at lower limb joints (Schubert et al., 2014). Moreover, faster sprinters exhibit shorter ground contact times compared to slow sprinters (Weyand et al., 2010), while a reduction in stride frequency may improve running economy in long-distance running (Tartaruga et al., 2012). Therefore, stance and stride times represent useful metrics for coaches and technical staff for monitoring performance and providing targeted instructions to adjust technique during training or competitions and reduce injury risk (Hunter et al., 2004; Nijs et al., 2022; Schubert et al., 2014).

Traditionally, temporal parameters have been measured using laboratory-based gold standard systems, such as force plates, while photocell systems are widely adopted as practical and ecological in-field reference systems. While highly accurate, these systems involve restricted acquisition volume, high costs, and reduced ecological validity (Hong et al., 2012). Wearable technologies, especially inertial measurement units (IMUs), have therefore emerged as a practical solution, offering continuous and ecological monitoring of running mechanics (Camomilla et al., 2018). Numerous IMU-based methods have been proposed for gait event detection, differing in device positions, used signal, and computational strategy. Most adopt heuristic

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approaches, such as peak detection or thresholding, due to their simplicity and interpretability, while more recent methods include data-driven strategies, such as Machine Learning (ML) (Bach et al., 2022) and template-based techniques exploiting Dynamic Time Warping (DTW) (Rossanigo et al., 2025). In contrast to rules-based algorithms, these approaches leverage training data or reference templates to infer gait events.

Despite the wide availability of different solutions, their comparative performance remains poorly understood. Few studies (Bailey and Harle, 2015; Yang et al., 2022) have proposed novel algorithms without direct comparison against alternative methods, while in other cases comparative analyses were limited to specific device positions (e.g., on the lower back and shank (Kiernan et al., 2023) or foot (Mo and Chow, 2018; Rossanigo et al., 2025). Many algorithms rely on similar detection principles, differing mainly in secondary implementation choices (Benson et al., 2019; Donahue and Hahn, 2022). Moreover, only few studies have investigated the effect of running speed on a wide range of conditions (Falbriard et al., 2018; Kiernan et al., 2023; Rossanigo et al., 2025), underscoring the need for a comprehensive and systematic comparison of currently available methods.

Starting from a systematic review of the literature, we identified and compared 36 algorithms for IMU-based gait event detection during running. Their performance in estimating stance and stride phase durations during running and sprinting was evaluated across three speeds (15, 20, and 25 km/h) and multiple device positions (i.e., foot dorsum, fifth metatarsal head, heel, lateral and medial tibia, and lower back), using OptoJump as in-field reference system. The results aim to provide evidence-based guidance for selecting the most suitable algorithms under specific experimental condition and to support the development of new and more robust IMU-based methods (Cereatti et al., 2024).

2. Methods

2.1. Literature review

A literature search was conducted in PubMed and Scopus up to 21 May 2025, using combinations of the keywords: (1) *running*; (2) *temporal parameters* or *stance* or *stride*; (3) *IMU* or *inertial measurement unit* or *inertial sensor*; (4) *estimation* or *event detection* or *algorithm*. Only articles meeting the inclusion criteria (Table 1) were considered. The search yielded 78 articles. Duplicated and unrelated articles were excluded after a screening of titles and abstracts. When multiple articles described the same implementation strategy for gait event estimation, only the earliest publication was included, while for single papers describing multiple algorithms (Falbriard et al., 2018; Yang et al., 2022), only the recommended one was considered. This process resulted in a final set of 34 articles, including two studies describing two different detection methods (Benson et al., 2019; Donahue and Hahn, 2022). The selected 36 algorithms are summarized in Table 2 and classified based on:

1. IMU position (i.e., foot, shank, lower back);
2. Target signal (i.e., acceleration or angular velocity, raw or filtered);
3. Computational strategy: heuristic (including peak detection, thresholding, and zero-crossing) and data-driven methods (including ML and the template-based method).

Table 1
Inclusion criteria considered for systematic review.

Criteria	Definition
Measurement instruments	Wearable inertial sensors
Body positioning of IMUs	Feet, lower limb, and lower back
Motor tasks	Jogging, running
Areas of interest	Gait events detection and temporal parameters estimation
Publication type	Journal articles and papers in English
Participants under investigation	Healthy and able-bodied adults

2.2. Participants

Ten healthy amateur runners (9 males, 1 female; age 26 ± 4 years) participated in this study and provided informed consent before data collection. The experimental protocol was approved by the University of Bologna Ethical Committee (Prot. n. 0101251).

2.3. Data acquisition

Seven IMUs (OPAL, APDM Wearable Technologies, Portland, USA; 3D accelerometer: range ± 200 g; 3D gyroscope: range ± 2000 dps; 3D magnetometer: range ± 8 Gauss; sampling rate: 800 Hz) were used. The IMUs were placed on the foot (dorsal surface of both right and left shoe, right 5th metatarsal head, and heel laterally on the shoe), the right shank (medial surface of the tibia and above lateral malleolus), and the lower back (at L5 level), and secured using transparent Fixomull adhesive tape (BSN Medical) (Fig. 1). Co-Plus LF elastic bandages (BSN Medical) were used for additional placing for shank devices, while an elastic belt was employed for the secure placement of the lower back device. OptoJump Next (MicroGATE Srl, Bolzano, Italy; 1000 Hz, 10 m) was used as the reference system, consisting of a straight 10-meter walkway with WittyGATE photocells (MicroGATE Srl, Bolzano, Italy; 1000 Hz) positioned at both ends to monitor the runners' speed and allowing for adjustments if necessary. Two GoPro HERO7 cameras (resolution: 1080p, frequency: 240 fps) were used to capture the running trials, providing a visual reference for the analysis.

After a self-guided warm-up, each participant performed running trials at 15, 20, and 25 km/h. Participants were instructed to maintain a constant speed while running along the walkway defined by the OptoJump system. A tolerance of ± 2 km/h around the target speeds was considered acceptable. The achieved running speeds were 15.4 ± 1.0, 20.1 ± 1.0, and 25.3 ± 1.2 km/h for the three target conditions, respectively.

2.4. Data analysis

Due to the lack of hardware synchronization between the IMU system and the OptoJump system, stride matching was performed manually using video recordings from the GoPro cameras. All 36 algorithms were implemented in MATLAB (The MathWorks Inc, 2023b, NATHSK, USA). Nineteen algorithms were reimplemented following the methodological details provided in the respective publications, including signal pre-processing steps such as filtering and segmentation strategies into running cycles. When no segmentation procedure was specified, running cycles from foot and shank data were segmented using a midswing-to-midswing approach, as commonly used in the literature (Falbriard et al., 2018; Rossanigo et al., 2025). Seventeen algorithms were applied with no changes using open-source codes: 15 algorithms from the repository provided by Kiernan et al. (2023) (available at: https://github.com/DovinKiernan/REID_IMU_Running_Event_ID), the algorithm proposed by Benson et al. (2019) (available for download from the paper), and the template-based algorithm proposed by Rossanigo et al. (2025) (https://github.com/H-MOVE-LAB/run_imu.git). Strohrmann et al. (2012) originally defined a threshold-based detection method using a 2 g acceleration threshold (g = 9.81 m/s^2). Since preliminary inspections indicated that this value could result in multiple threshold crossings around the same gait event under our experimental conditions, we evaluated two adapted configurations (3 g and 4 g) to assess the robustness of the threshold-based approach under our experimental conditions. Accordingly, all reported results for Strohrmann (3 g) and Strohrmann (4 g) refer to these adapted threshold settings. Details of all algorithms, including pre-processing and

Table 2
Details of algorithms selected from the literature review.

	Algorithms	IMU position	Target Variable IC	Target Variable TO	Computational Approach	Speed and conditions
Foot	Bailey and Harle, 2015	Foot (heel)	ω_{ML}	α_{VT}	Peak detection and thresholding (raw)*	8.3–12.2 km/h (treadmill)
	Benson et al., 2019	Foot (dorsum)	α_{R}	α_{VT}	Peak detection (IIR)	9.7, 11.9, and 13 km/h (treadmill); preferred speed, 25% faster than preferred, and 25% slower than preferred (indoor track)
	Blauberger et al., 2021	Foot (heel)	α_{R}	ω_{R}	Peak detection (IIR)*	Maximum 50 and 100-m sprints (track)
	Chew et al., 2018	Foot (dorsum)	α_{AP}	α_{AP}	Peak detection (raw)*	8–11 km/h (treadmill)
	Donahue and Hahn, 2022	Foot (dorsum)	α_{R}	α_{VT}	Peak detection (IIR)	8.6–19.4 km/h (track)
	Falbriard et al., 2018	Foot (dorsum)	α_{R}	α_{R}	Peak detection (IIR)*	8 km/h up to maximum speed (treadmill)
	Falbriard et al., 2020	Foot (dorsum)	ω_{ML}	ω_{ML}	Peak detection (IIR)*	8, 12, and 16 km/h (treadmill)
	Giandolini et al., 2014	Foot (heel + 5th metatarsal head)	α_{VT}	–	Peak detection (NS)*	Preferred running speed (12.3 ± 2.8 km/h) and 14 (females) and 16 km/h (males); 10, 12, and maximum aerobic speed (10.9 ± 1.4 km/h) (treadmill)
	Maiwald et al., 2015	Foot (heel)	α_{VT}	–	Peak detection (NS)	Preferred aerobic pace (10.4 ± 1.1 m/s) (treadmill)
	Mitschke et al., 2018	Foot (heel)	α_{VT}	α, ω	Peak detection and thresholding (IIR)*	Self-selected (13 ± 1.4 km/h) (treadmill)
	Reenalda et al., 2019	Foot (dorsum)	α_{R}	ω_{R}	Peak detection (raw)*	15.8 ± 1.4 m/s at the beginning and 16.2 ± 1.1 m/s at the end (track)
	Rossanigo et al., 2025	Foot (dorsum)	α_{R}	ω_{ML}	DTW*	8, 10 (track), 14 (treadmill), and 19–30 km/h (track)
	Strohrmann et al., 2012	Foot (dorsum)	α_{R}	α_{R}	Peak detection and thresholding (raw)*	9–17.8 km/h
	Van Werkhoven et al., 2019	Foot (dorsum)	α_{R}	–	Peak detection (raw)*	Self-selected speed (treadmill)
Shank	Aminian et al., 2002	Shank	ω_{ML}	ω_{ML}	Peak detection (NS)	Self-selected (treadmill)
	Aubol and Milner, 2020	Tibia (medial)	α_{R}	–	Peak detection (IIR)	10.8 ± 0.5 km/h (overground)
	Bach et al., 2022	Tibia (medial)	$\alpha_{AP, ML, VT}$	$\alpha_{AP, ML, VT}$	RS and thresholding (raw)	7.9 ± 0.5 m/s (treadmill)
	Fadillioglu et al., 2020	Shank	ω_{ML}	ω_{ML}	Thresholding and peak detection (IIR)	Moderate and fast running (overground)
	Greene et al., 2010	Shank	ω_{ML}	ω_{ML}	Peak detection (IIR)	1.73–5.6 km/h (treadmill)
	Mercer et al., 2003	Tibia (medial)	α_{VT}	α_{VT}	Peak detection (raw)	11.2–13.7 km/h (treadmill)
	Mizrahi et al. (2000)	Tibial tuberosity	α_{VT}	–	Peak detection (raw)	12.6 ± 0.7 km/h (treadmill)
	Mo and Chow, 2018 **	Foot (dorsum) + tibia (medial)	α_{R}	α_{VT}	Peak detection (raw)*	11.2 ± 0.4 km/h and 14.8 ± 4.3 km/h (10-m walkway)
	Norris et al., 2016	Tibia (medial)	α_{ML}	–	Thresholding (IIR)	Self-selected (overground)
	Purcell et al., 2005	Tibia (medial)	α_{AP}	$\alpha_{AP, ML}$	Peak detection (raw)	Self-selected jog, run and sprint
	Schmidt et al., 2016	Tibia (lateral)	α_{VT}	α_{VT}	Peak detection (raw)*	Maximal sprints (track)
	Sinclair et al., 2013	Tibia (medial)	α_{VT}	α_{VT}	Thresholding (NS)	14.4 ± 0.7 km/h (overground)
	Whelan et al., 2015	Tibia (medial)	α_{AP}	–	Peak detection (IIR)	<50% of maximum effort (overground)
	Yang et al., 2022	Tibia (lateral)	α_{R}	ω_{ML}	Peak detection (IIR)*	75%, 85%, and 95% of maximum speed
Lower back	Auvinet et al., 2002	Lower back	$\alpha_{AP, VT}$	α_{VT}	Peak detection & Zero-crossing (NS)	18.6 ± 0.2 km/h (track)
	Benson et al., 2019	Lower back	α_{AP}	α_{AP}	Peak detection (IIR)	9.7, 11.9, and 13 km/h (treadmill); preferred speed, 25% faster than preferred, and 25% slower than preferred (indoor track)
	Bergamini et al., 2012	Lower back	$\omega^{''}_{R}$	$\omega^{''}_{R}$	Peak detection (WB)	Average speed range: 20.5–38.9 km/h (indoor/outdoor track)
	Donahue and Hahn, 2022	Lower back	α_{AP}	α_{AP}	Peak detection (IIR)	8.6–19.4 km/h (track)
	Lee et al., 2010	Lower back	α_{AP}	α_{AP}	Peak detection (raw)	10–12, 13–15, and 16–19 km/h (treadmill)
	Patoz et al., 2022	Lower back	α_{VT}	α_{VT}	Thresholding (TFS)	9,11, and 13 km/h (treadmill)
	Reenalda et al., 2021	Lower back	α_{VT}	–	Peak detection (SPF)	11, 13, and 15 km/h (treadmill)
	Wixted et al., 2010	Lower back	α_{AP}	α_{VT}	Peak detection & Zero-crossing (FIR)	Average 1500 race velocity: 21.3–22.2 km/h (outdoor track)

IC – initial contact; TO – toe-off; α – acceleration; ω – angular velocity; AP – antero-posterior; ML – medio-lateral; VT – vertical; IIR – infinite impulse response filter; FIR – finite impulse response filter; WB – wavelet-based approach; SPF – software proprietary filtering; TFS – truncated Fourier series; RS – reservoir computing; NS – non-specified filters (cut-off frequency is reported, but the specific type of filter is not explicitly mentioned).
* Algorithms implemented following a pre-segmentation of the running trials into cycles, each defined as the interval between two consecutive mid-swing instants

following a running cycle segmentation approach established in the literature (Falbriard et al., 2018; Rossanigo et al., 2025).
** Among the shank-based methods, the algorithm by Mo and Chow (2018) was also included, despite utilizing one IMU on the dorsum of the foot, for IC estimation using Strohrmann (2012) method, and another on the medial tibia.

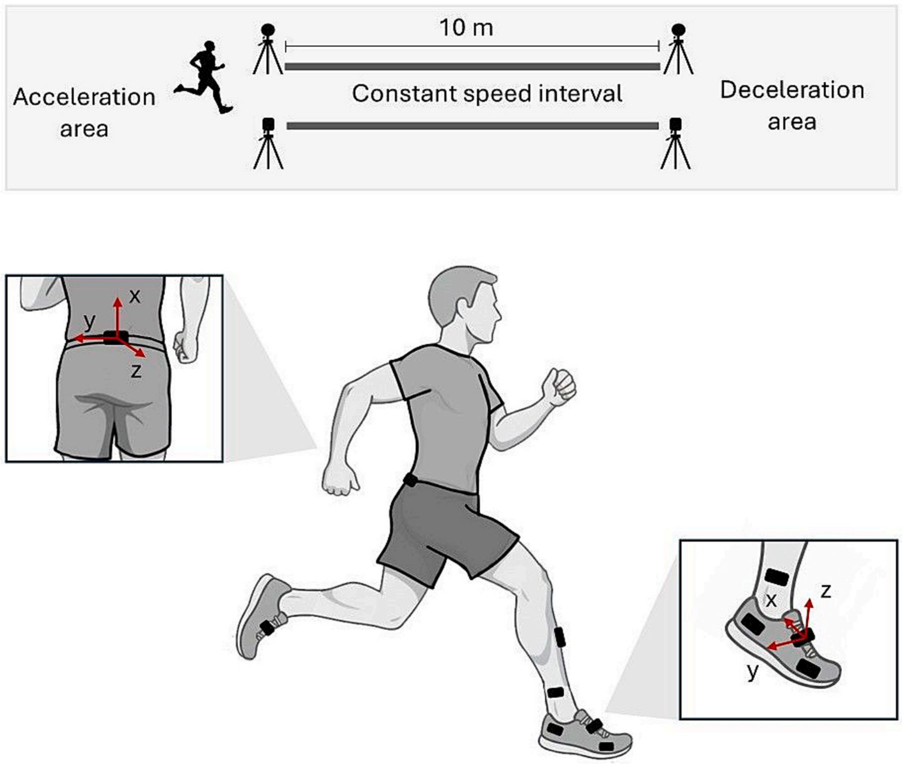

Fig. 1. Experimental setup and IMU placement. *Top*: 10-m Optojump walkway; *Bottom*: IMUs body position and relative axis orientations. Right and left dorsal foot: x-axis aligned antero-posteriorly (AP) pointing posteriorly, y-axis medio-laterally (ML) pointing to the subject's right, and the z-axis vertically (VT) pointing upward; right heel, fifth metatarsal head, and lateral tibia: x-axis aligned VT upward, y-axis AP pointing posteriorly, and z-axis ML pointing to the subject's right; right medial tibia: x-axis VT pointing upward, y-axis aligned AP pointing anteriorly, and z-axis ML pointing to the subject's left; lower back: x-axis aligned VT upward, y-axis ML pointing to the subject's left, and z-axis AP pointing posteriorly.

segmentation procedures, are reported in Table 2. IC and TO events were identified from IMU data for each stride cycle and stride and stance time durations were computed for each algorithm. All strides were analyzed for the IMUs placed on the dorsum of both feet and on the lower back, which allowed bilateral stride analysis. Conversely, only right-foot strides were analyzed for the IMUs placed on the right heel, fifth metatarsal head, and shank, due to unilateral IMU placement.

All algorithms reimplemented in this study and the dataset used for evaluation are available in our publicly accessible repository (https://github.com/MyriamLubrano/Running_IMU).

2.5. Statistical analysis

Algorithms performance was evaluated by computing stance and stride times errors with respect to the reference values provided by the OptoJump system. Normality of the error distributions was tested using Shapiro-Wilk tests. The effect of running speed on stride and stance time estimation errors was evaluated using linear mixed-effects (LME) models to account for repeated observations within participants. Although trials were performed at three predefined target speeds, statistical analysis was based on the actual running speed measured for each trial, treated as a continuous variable in the linear mixed-effects models. Statistical significance was set at $p < 0.05$. A subset of algorithms for stride and stance time estimation were identified separately based on predefined error thresholds. Specifically, only algorithms whose error distributions fell within tolerance windows ($\pm$20 ms for stride time, $\pm$100 ms for stance time) were visually represented in the main figures and discussed in the corresponding sections. These thresholds were not intended as performance acceptance criteria and were not used to exclude any algorithm from the analysis. All 36 algorithms were included in the statistical analyses. The selected subset was used exclusively to reduce visual complexity and to facilitate interpretation of the results across methods, ensuring the identification of algorithms with both low estimation bias and high repeatability across strides.

The median error (Med) was calculated as a measure of estimation accuracy, while precision was assessed through interquartile range (IQR), defined as the difference between the 75th and 25th percentiles of the error distribution. The robustness of each algorithm was also evaluated by quantifying the number of missed events, occurring where an algorithm failed to detect gait events. This aspect could be particularly relevant, as missed detections can compromise the reliability of a fully automatic estimation. To ensure comparability across algorithms that were applied to different subsets of data (e.g., some analyzing only the right foot, others both sides), missed events were expressed as a percentage of the total number of analyzed strides.

The minimal detectable change (MDC) was computed to quantify the smallest change that can be detected beyond measurement error (Weir, 2005; de Vet et al., 2011).

3. Results

Starting from the 36 algorithms identified in the literature, 20 methods were retained for stride estimation (13 for the foot, 4 for the shank, and 3 for the pelvis) and 15 for stance estimation (8 for the foot, 3 for the shank, and 4 for the pelvis), according to the criteria described in Section 2. Tables 3-5 report complete results for all selected methods.

A total of 1034 strides were collected across all subjects using the OptoJump, including 524 right-foot and 510 left-foot steps.

3.1. Foot

Most of the selected foot-based algorithms (Fig. 2) showed a speed-invariant stride time estimation, while stance estimation showed sensitivity to running speed.

Stride time estimation – Absolute Med_{stride} was between 0 and 2 ms, while absolute IQR_{stride} was between 3 and 5 ms. Only the algorithm proposed by Mitschke (2018) exhibited performance that was significantly affected by running speed ($p < 0.05$). Missed stride detections were observed only for Falbriard (2020) and Van Werkhoven (2019).

Stance time estimation – Absolute Med_{stance} was between 15 and 58 ms, while absolute IQR_{stance} was between 17 and 25 ms. All algorithms were significantly affected by running speed, except for Strohrmann (3 g) and Strohrmann (4 g), with most of them showing a tendency to underestimate stance duration, and errors generally decreasing as running speed increased. Missed stance detection were observed only for Blauberger (2021) and Falbriard (2018).

3.2. Shank

Stride time estimation was speed-invariant for selected shank-based algorithms (Fig. 3), while stance estimation was more affected by speed.

Stride time estimation – Absolute Med_{stride} was between 0 and 1 ms, while absolute IQR_{stride} was between 4 and 8 ms. None of these algorithms exhibited a statistically significant effect of running speed on estimation performance ($p > 0.05$).

Stance time estimation – The algorithms provided absolute Med_{stance} between 4 and 28 ms and absolute IQR_{stance} between 24 and 33 ms. Schmidt (2016) and Yang (2022) were not significantly affected by running speed, while for both Mo and Chow (2018) and Purcell (2005), the estimation error decreased at higher speed. Schmidt (2016) was the only one to not exhibit missed event detections for both temporal parameters.

3.3. Lower back

Most selected lower back-based methods (Fig. 4) were affected by running speed, particularly for stance time estimation.

Table 3
Stride and stance errors obtained from all the algorithms with foot-mounted IMUs.

	Stride time					Stance time				
Algorithms	**Errors** **Med (IQR) [ms]**	**Errors per speed (15, 20, 25 km/h)** **Med (IQR) [ms]**	**Missed strides** **[%]**	**MDC values** **[ms]**	**p-value**	**Errors** **Med (IQR) [ms]**	**Errors per speed (15, 20, 25 km/h)** **Med (IQR) [ms]**	**Missed stances** **[%]**	**MDC values** **[ms]**	**p-value**
Bailey and Harle, 2015	−3 (34)		7	111	0.063	63 (39)		6	40	0.053
Benson et al., 2019	0 (28)		4	79	0.508	6 (246)		3	62	0.221
Blauberger et al., 2021	0 (3)		0	72	0.568	30 (17)	33 (23) 27 (12) 31 (15)	1	35	<0.001 *
Chew et al., 2018	1 (5)		0	73	0.525	−15 (21)	−20 (20) −15 (15) −7 (18)	0	29	<0.001 *
Donahue and Hahn, 2022	2 (5)		0	70	0.488	−17 (23)	−24 (20) −14 (23) −9 (21)	0	25	<0.001 *
Falbriard et al., 2018	1 (5)		0	71	0.160	−19 (18)	−25 (20) −16 (19) −13 (15)	1	26	<0.001 *
Falbriard et al., 2020	1 (5)		1	75	0.799	−27 (25)	−42 (25) −25 (21) −20 (14)	0	20	<0.001 *
Giandolini et al., 2014	0 (3)		0	74	0.062	NA		NA	NA	NA
Maiwald et al., 2015	0 (4)		0	72	0.365	NA		NA	NA	NA
Mitschke et al., 2018	0 (4)	0 (4) 0 (5) 0 (6)	0	72	0.035 *	−69 (39)	−67 (78) −73 (21) −65 (49)	0	61	<0.001 *
Reenalda et al., 2019	1 (5)		0	72	0.360	−38 (24)	−50 (22) −38 (17) −26 (18)	0	27	<0.001 *
Rossanigo et al., 2025	**0 (5)**		**0**	**55**	**0.459**	**0 (22)**	**−11 (18)** **0 (13)** **13 (15)**	**0**	**48**	**<0.001 ***
Strohrmann et al., 2012 (3 g)	1 (5)		0	71	0.891	−58 (24)		0	33	0.109
Strohrmann et al., 2012 (4 g)	1 (5)		0	71	0.750	−47 (19)		0	23	0.103
Van Werkhoven et al., 2019	1 (5)		1	70	0.490	NA		NA	NA	NA

Median error (Med), Interquartile range (IQR) values, missed events (%), MDC, and p-values for the 15 foot-based algorithms. Med and IQR values are also reported separately for each target speed (15, 20, and 25 km/h) when a significant effect of running speed was observed ($p < 0.05$). * indicates a statistically significant effect of running speed ($p < 0.05$). NA indicates non-applicable values, as the algorithm estimates only one of the two temporal parameters. The suggested method is highlighted in bold.

Table 4
Stride and stance errors obtained from all the algorithms with shank-mounted IMUs.

	Stride time					Stance time				
Algorithms	**Errors** **Med (IQR) [ms]**	**Errors per speed (15, 20, 25 km/h)** **Med (IQR) [ms]**	**Missed strides** **[%]**	**MDC values** **[ms]**	**p-value**	**Errors** **Med (IQR) [ms]**	**Errors per speed (15, 20, 25 km/h)** **Med (IQR) [ms]**	**Missed stances** **[%]**	**MDC values** **[ms]**	**p-value**
Aminian et al., 2002	1 (47)		22	93	0.295	−3 (109)		20	90	0.773
Aubol and Milner, 2020	0 (4)		16	76	0.323	NA		NA	NA	NA
	6 (35)		45	124	0.103	172 (216)	52 (226) 111 (186) 218 (86)	49	31	<0.001 *
Fadillioglu et al., 2020	0 (14)		0	70	0.995	28 (39)	45 (67) 29 (34) 19 (22)	0	33	<0.001 *
Greene et al., 2010	1 (11)		1	75	0.611	52 (29)	58 (34) 55 (23) 37 (28)	1	33	<0.001 *
Mercer et al., 2003	−1 (8)		2	71	0.546	203 (121)	212 (173) 192 (150) 203 (54)	2	77	0.021 *
Mizrahi et al. (2000)	1 (7)		0	74	0.592	NA		NA	NA	NA
Mo and Chow, 2018	NA		NA	NA	NA	−14 (29)	−20 (33) −16 (27) −4 (23)	6	36	<0.001 *
Norris et al., 2016	1 (41)		56	145	0.623	NA		NA	NA	NA
Purcell et al., 2005	1 (8)		0	76	0.517	−11 (24)	−15 (36) −14 (29) −8 (11)	0	34	0.005 *
Schmidt et al., 2016	**−1 (8)**		**0**	**79**	**0.671**	**4 (29)**		**0**	**25**	**0.080**
Sinclair et al., 2013	−1 (24)		18	101	0.246	119 (184)		15	60	0.313
Whelan et al., 2015	0 (17)		1	73	0.958	NA		NA	NA	NA
Yang et al., 2022	−3 (41)	−2 (35) −1 (41) −11 (55)	1	73	<0.001 *	28 (33)		32	52	0.706

Median error (Med), Interquartile range (IQR) values, missed events (%), MDC, and p-values for the 14 shank-based algorithms. Med and IQR values are also reported separately for each target speed (15, 20, and 25 km/h) when a significant effect of running speed was observed ($p < 0.05$). * indicates a statistically significant effect of running speed ($p < 0.05$). NA indicates non-applicable values, as the algorithm estimates only one of the two temporal parameters. The suggested method is highlighted in bold.

Stride time estimation – Absolute Med_{stride} was between 0 and 1 ms, while absolute IQR_{stride} was between 6 and 9 ms. Benson (2019) and Wixted (2010) showed no significant effect of speed, whereas Donahue and Hahn (2022) and Lee (2010) exhibited increasing estimation errors at higher speeds.

Stance time estimation – Absolute Med_{stance} was between 16 and 23 ms, while absolute IQR_{stance} was between 23 and 32 ms. All algorithms showed a decrease in estimation errors with increasing speed, although the speed effect was not statistically significant for Donahue and Hahn (2022) (p = 0.125). Missed events were observed for all methods for both temporal parameters.

4. Discussion

This study conducted a comprehensive assessment of 36 state-of-the-art IMU-based methods for temporal parameters estimation during running, comparing their performance across multiple IMU positions on foot, shank, and lower back, and three running speeds (15, 20, and 25 km/h). While previous studies have evaluated subsets of these methods, or focused on either specific speeds (Bailey and Harle, 2015) or device placements (Mo and Chow, 2018), this work jointly considers both factors, offering a broad comparison of IMU-based methods for running analysis across multiple sensor locations and running speeds.

As expected, for all device positions, stride estimation consistently showed higher accuracy and precision (average absolute Med_{stride} and IQR_{stride}: 1 ms and 14 ms) compared to stance time estimation (average absolute Med_{stance} and IQR_{stance}: 43 ms and 56 ms), since it only relies on IC detection, whereas stance estimation additionally requires TO identification, which is established in the literature to be more challenging (Kiernan et al., 2023; Rossanigo et al., 2025).

Most of the analyzed algorithms (22 out of 36) exhibited a significant dependance on speed changes ($p < 0.05$), in accordance with previous findings of recent works (Kiernan et al., 2023; Rossanigo et al., 2025). Overall, only 6 algorithms exhibited speed-dependent stride time estimation, while 20 algorithms provided speed-dependent stance time estimation. Across different IMU positions, stance time estimation errors generally decreased with increasing speed, except for Blauberger (2021) and Rossanigo (2025).

As previously reported in Donahue and Hahn (2022) for event detection, foot positioning enabled to reach the highest performances, followed by shank-mounted algorithms, and, lastly, by lower back-mounted IMUs. For the sake of clarity, selected algorithms relying on shank and lower back-mounted devices provided lower repeatability in both stride and stance estimation (IQR_{stride}: 7 ms; IQR_{stance}: 28 and 26 ms, respectively) than foot-mounted IMUs (IQR_{stride}: 5 ms; IQR_{stance}: 21 ms). However, shank-based methods enabled overall comparable accuracy to algorithms using foot-mounted IMUs and a greater robustness to speed variations, since the only algorithm demonstrating speed-independent performance for the estimation of both parameters across device placements was Schmidt (2016). Foot-based methods also demonstrated the highest detection robustness, with missed events occurring on average in only 0.15% of stride and 0.25% of stance times.

Table 5
Stride and stance errors obtained from all the algorithms with lower back-mounted IMUs.

	Stride time					Stance time				
Algorithms	Errors Med (IQR) [ms]	Errors per speed (15, 20, 25 km/h) Med (IQR) [ms]	Missed strides [%]	MDC values [ms]	p-value	Errors Med (IQR) [ms]	Errors per speed (15, 20, 25 km/h) Med (IQR) [ms]	Missed stances [%]	MDC values [ms]	p-value
Auvinet et al., 2002	−3 (15)	−1 (11) −3 (15) −6 (22)	4	77	0.003 *	78 (27)	79 (28) 74 (26) 69 (25)	7	37	<0.001 *
Benson et al., 2019	**−1 (9)**		**2**	**65**	**0.655**	**−9 (26)**	−15 (81) −7 (24) −8 (18)	**2**	**23**	**<0.001 ***
Bergamini et al., 2012	−5 (38)	−10 (204) −4 (24) −3 (17)	12	69	<0.001 *	−77 (125)	109 (100) −69 (107) −14 (136)	23	61	<0.001 *
Donahue and Hahn, 2022	0 (6)	0 (5) 0 (6) 0 (44)	3	83	<0.001 *	−16 (32)		6	35	0.125
Lee et al., 2010	0 (7)	1 (5) 0 (6) −1 (13)	12	100	0.002 *	−19 (26)	−25 (22) −18 (21) 1 (36)	14	28	<0.001 *
Patoz et al., 2022	0 (17)		2	77	0.234	–23 (32)	−38 (35) −18 (25) −12 (26)	2	17	<0.001 *
Reenalda et al., 2021	−3 (19)		2	71	0.062	NA		NA	NA	NA
Wixted et al., 2010	0 (7)		13	95	0.268	−16 (23)	−24 (15) −10 (18) −2 (28)	11	31	<0.001 *

Median error (Med), Interquartile range (IQR) values, missed events (%), MDC, and p-values for the 8 lower back-based algorithms. Med and IQR values are also reported separately for each target speed (15, 20, and 25 km/h) when a significant effect of running speed was observed ($p < 0.05$). * indicates a statistically significant effect of running speed ($p < 0.05$). NA indicates non-applicable values, as the algorithm estimates only one of the two temporal parameters. The suggested method is highlighted in bold.

In contrast, shank- and lower back-based algorithms showed higher missed events rates, although remaining below 10% across all device positions. Lower back-based methods exhibited larger estimation errors than foot- or shank-mounted IMUs, reflecting the greater distance from the interaction of the foot with the ground, as already observed for gait (Pacini Panebianco et al., 2018). However, this configuration offers the practical advantage of enabling event detection for both limbs using a single IMU.

Notably, although stride time could be accurately estimated with IMUs placed at all foot locations, most selected foot-based algorithms for stance time estimation relied on the dorsum placement. The only exception was Blauberger (2021), developed for a heel-mounted IMU. Overall, the dorsum placement showed better performance than the heel and fifth metatarsal head placements. In contrast, between the two different positions tested on the shank (lateral distal and medial proximal), neither consistently outperformed the other.

Most of the selected algorithms used the peak detection approach, except for the template-based method proposed by Rossanigo (2025) and the threshold-based ones by Strohrmann (2012), Patoz (2022), and Wixted (2010). Unlike heuristic approaches, which often require tuning across different subjects and speeds, the open-source template-based method proposed by Rossanigo (2025) did not require any parameters tuning or prior knowledge. Notably, the selected heuristic methods that were the least affected by speed changes (i.e., Strohrmann et al., 2012 (4 g), Schmidt et al., 2016, and Donahue and Hahn, 2022) relied exclusively on acceleration components for estimating both temporal events.

To translate these findings into practical recommendations, we next highlight the recommended method among the evaluated algorithms for each IMU position, representing the best compromise between temporal parameters estimation and based on accuracy, repeatability, and sensitivity to speed changes. Among foot-based algorithms, the method by Rossanigo (2025) emerged as the most reliable overall (Med_{stride} and IQR_{stride}: 0 ms and 5 ms; Med_{stance} and IQR_{stance}: 0 ms and 22 ms), providing high accuracy and repeatability for both temporal parameters. For shank-mounted IMUs, the method proposed by Schmidt (2016) provided the lowest estimation errors, even with moderately increased variability (Med_{stride} and IQR_{stride}: −1 ms and 8 ms; Med_{stance} and IQR_{stance}: 4 ms and 29 ms). Furthermore, its performance was not significantly affected by running speed for either stride or stance times. Finally, for lower back-mounted IMUs, although algorithms such as Lee (2010) exhibited median stride time errors closer to zero, Benson (2019) is recommended because its stride time estimates were not significantly affected by running speed (Med_{stride} and IQR_{stride}: −1 ms and 9 ms; Med_{stance} and IQR_{stance}: −9 ms and 26 ms), also achieving the lowest median stance time errors among the evaluated methods. These findings highlight that algorithm selection should not be based on a single overall ranking. Rather, it should be guided by the specific application, considering the biomechanical variable of interest, the experimental conditions, practical constraints such as sensor placement, and the feasibility of implementing any required algorithm-specific parameter adjustments.

For practical interpretation, MDC values were compared to threshold values reported in previous literature, assumed to represent the smallest worthwhile changes (SWC) for typical running-related outcomes. Regarding injury risk, for example, Helton et al. (2025) reported that runners exhibiting longer contact times (>0.42 s) experienced a higher incidence of overuse musculoskeletal injuries than those with shorter contact times (<0.28 s). Although contact time is strongly influenced by running speed and locomotor strategy, the approximately 140 ms difference observed between groups highlights the magnitude of stance time variations that may be associated with meaningful biomechanical differences. MDC values were consistently below this threshold across all the selected algorithms estimating stance, indicating that these algorithms can discriminate individuals at higher injury risk. Conversely, MDC values exceeded SWC associated with performance-related differences between elite and recreational runners. For stance time, where

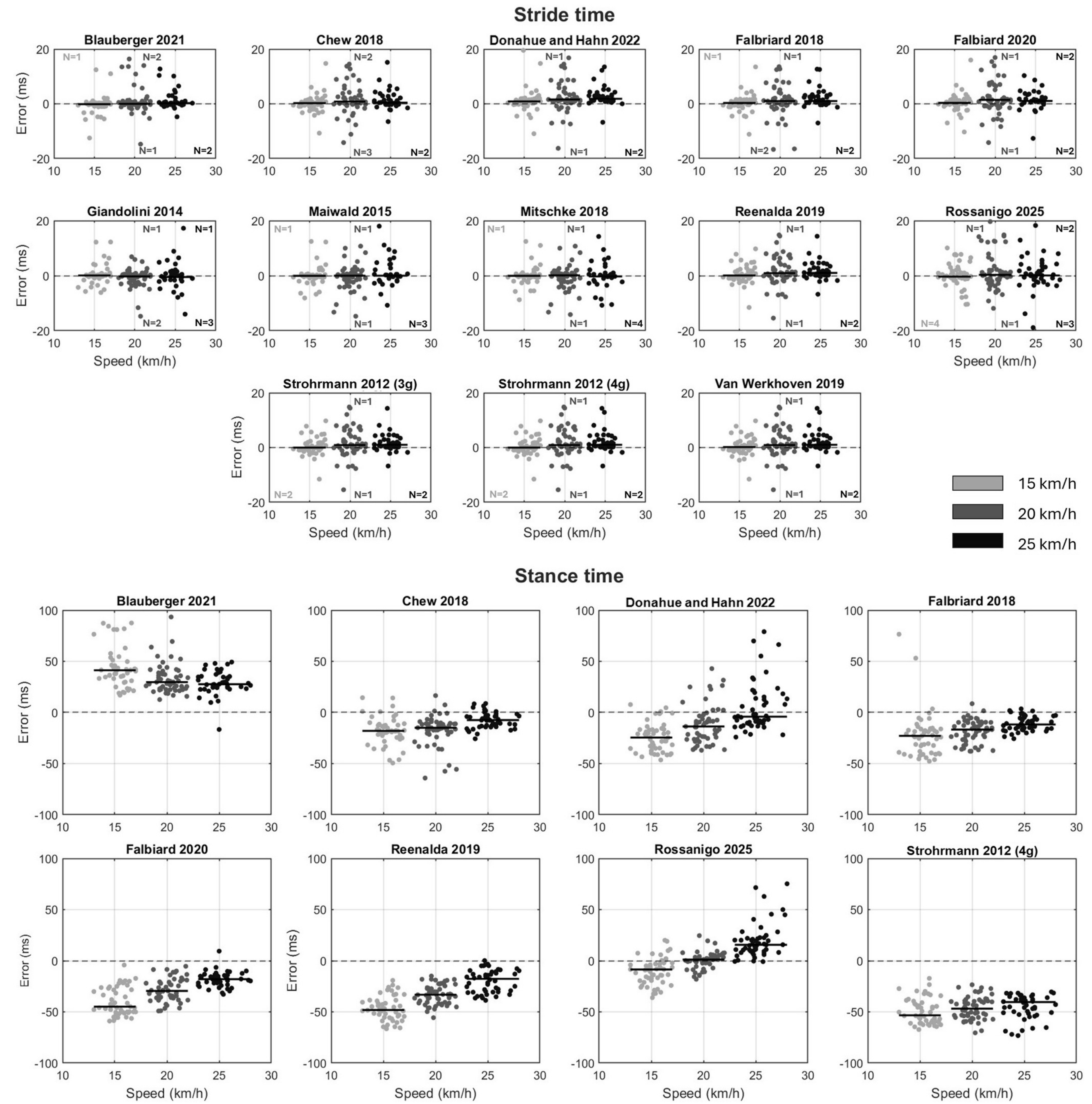

Fig. 2. Selected foot-based algorithms errors. Estimation errors of the selected foot-based algorithms. Mean estimation error for each subject and trial plotted against the actual trial speed for stride (*top*) and stance (*bottom*) times. Marker shades identify the target running speed clusters (15, 20, and 25 km/h). The horizontal solid line represents the median of the plotted data points for each speed cluster, while the dashed line indicates zero error. N denotes the number of observations lying outside the displayed y-axis range.

SWC ranged from 20 to 24 ms (Bergamini et al., 2012; Brahms et al., 2022), MDC values were below this threshold only for a limited subset of foot- and lowerback-based algorithms (Donahue and Hahn, 2022; Falbriard et al., 2018; Strohrmann et al., 2012 (4 g); Lee et al., 2010; Patoz et al., 2022) and never across all running speeds. For stride duration, MDC values exceeded the SWC of 14 ms (Brahms et al., 2022) for all methods, indicating that even selected algorithms were not sensitive enough to detect more subtle performance-related variations.

The findings of the study must be interpreted considering some limitations. Firstly, minor implementation-level adjustments were required for some heuristic approaches (Blauberger et al., 2021; Lee et al., 2010; Mo and Chow, 2018). These adjustments ensured correct peak identification across the investigated running speeds and did not modify the original methodological definitions of the algorithms. In contrast, the method proposed by Strohrmann (2012) was evaluated using two alternative threshold configurations (3 g and 4 g), representing an explicit adaptation of the original decision criterion. Although these choices were necessary to ensure consistent implementation on our dataset, they may limit direct comparability with results obtained under different implementation settings or datasets.

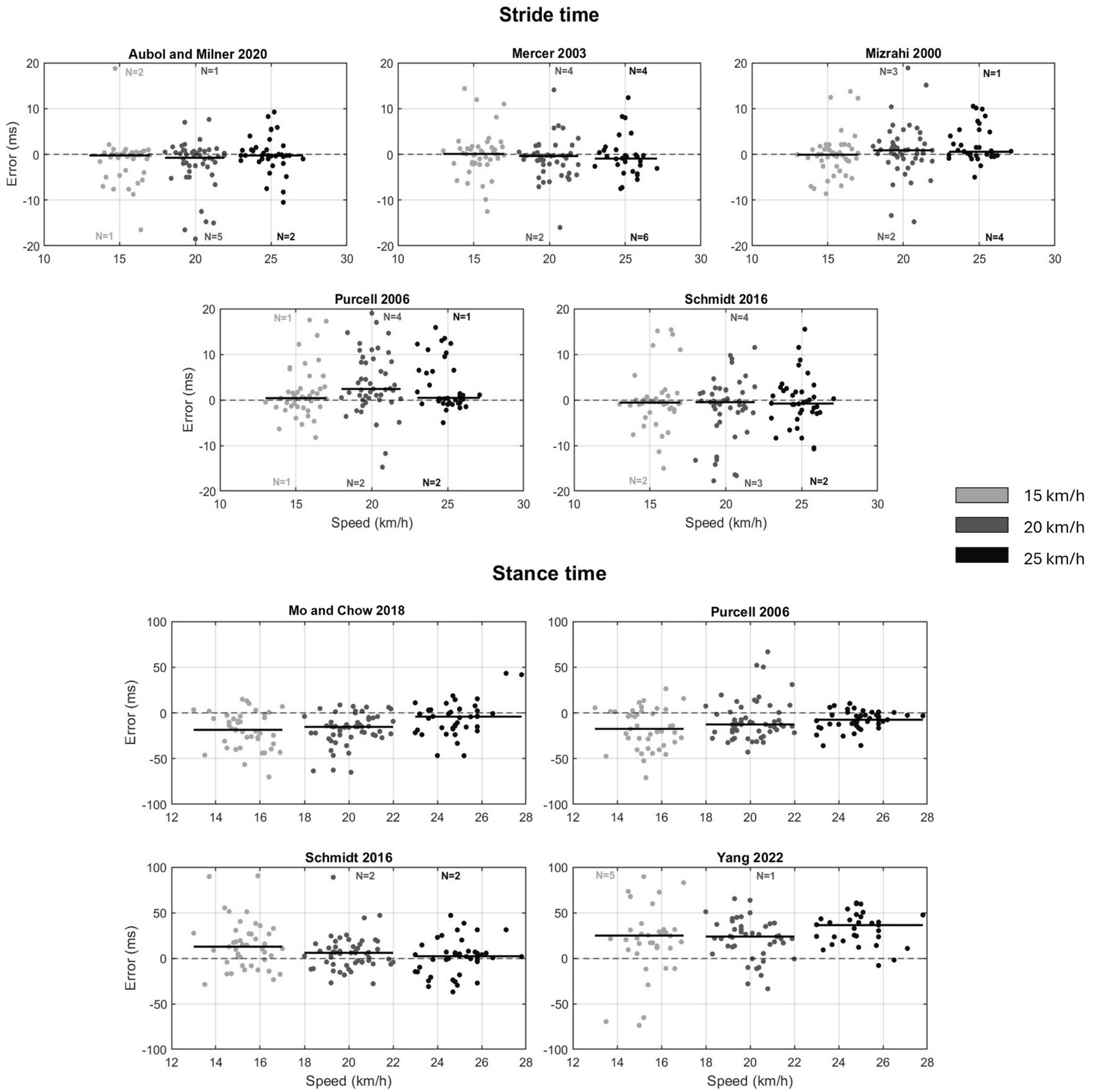

Fig. 3. Selected shank-based algorithms errors. Estimation errors of the selected shank-based algorithms. Mean estimation error for each subject and trial plotted against the actual trial speed for stride (*top*) and stance (*bottom*) times. Marker shades identify the target running speed clusters (15, 20, and 25 km/h). The horizontal solid line represents the median of the plotted data points for each speed cluster, while the dashed line indicates zero error. N denotes the number of observations lying outside the displayed y-axis range.

The data-driven ML method (Bach et al., 2022) was not retrained on the present dataset, and the template-based method (Rossanigo et al., 2025) relied on publicly available templates that did not match the specific speed and sampling frequency of our dataset. Both methods could potentially achieve better accuracy if appropriately retrained or using newly generated, dataset-specific templates. Furthermore, the reported findings pertain to specific running conditions (straight running on track at constant speeds between 15 and 25 km/h), and the relatively small sample size, although in line with previous validation studies of IMU-based algorithms (Mendicino et al., 2025), may limit their generalizability. Therefore, caution should be paid when extending these results to different conditions.

Moreover, the lack of synchronization between IMUs and the reference system prevented the computation of event-specific errors (i.e., IC and TO). Although applied sports contexts typically rely on phase durations, accurate event detection is still crucial to identify sources of error, such as undetected IC biases that may not emerge from duration-based metrics alone. Finally, the use of the OptoJump as reference system must be acknowledged. Although it systematically overestimates stance duration by approximately 5 ms in running (Healy et al., 2015) due to the 3 mm elevation of its LED sensors above the ground, previous literature has reported a good to excellent agreement between

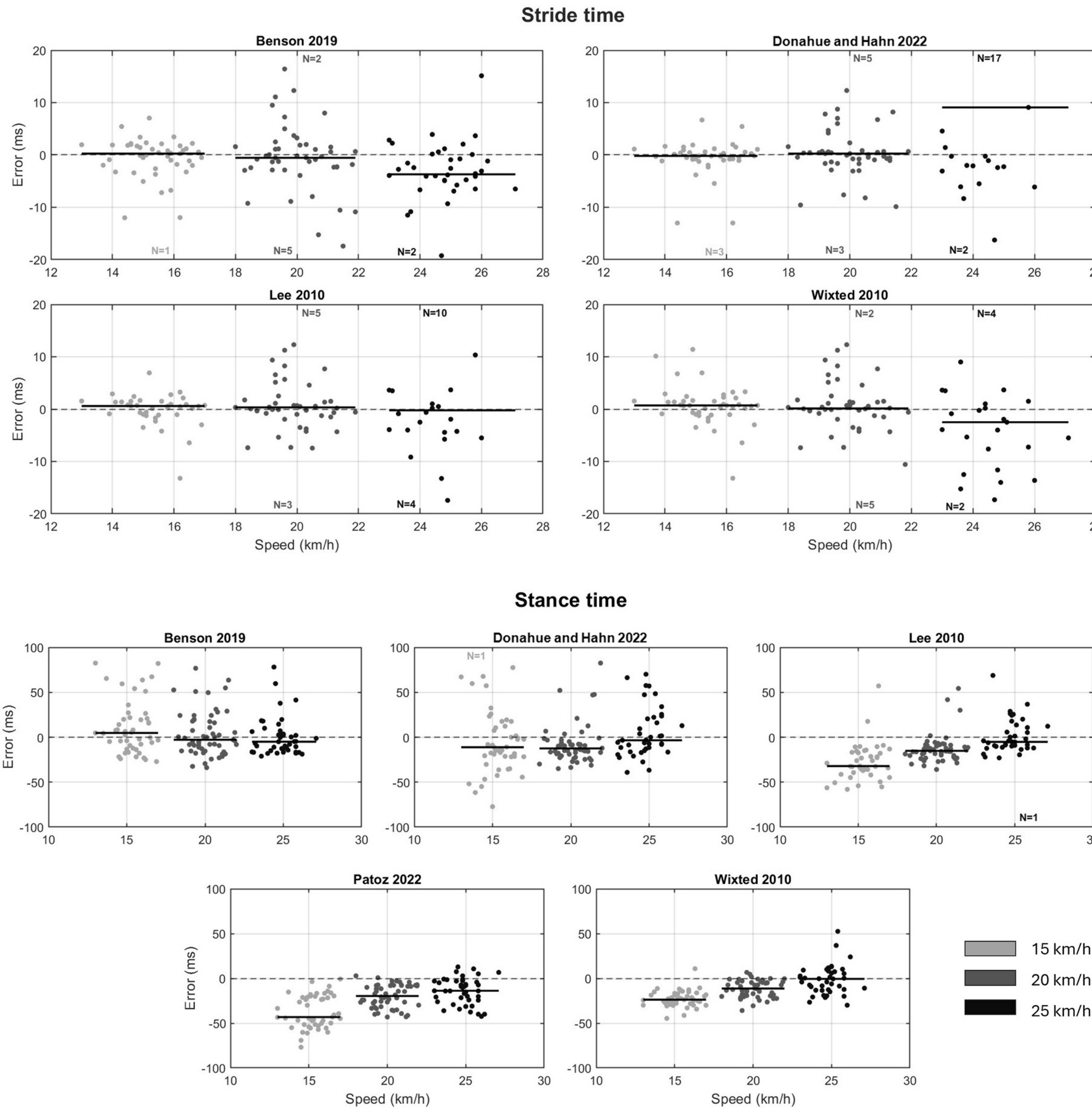

Fig. 4. Selected lower back-based algorithms errors. Estimation errors of the selected lower back-based algorithms. Mean estimation error for each subject and trial plotted against the actual trial speed for stride (*top*) and stance (*bottom*) times. Marker shades identify the target running speed clusters (15, 20, and 25 km/h). The horizontal solid line represents the median of the plotted data points for each speed cluster, while the dashed line indicates zero error. N denotes the number of observations lying outside the displayed y-axis range.

OptoJump and force plates for stance and stride time measurement during running (Healy et al., 2015), indicating that comparative analyses are not compromised. Moreover, it is largely adopted by coaches and practitioners for field-based assessments.

In conclusion, foot- and shank-mounted IMUs are recommended for accurate and robust estimation of both stride and stance estimation across different running speeds. Although heuristic approaches remain the most widely investigated solutions in the literature, their performance may depend on implementation-specific choices and parameter tuning, potentially limiting their transferability across datasets and running conditions. From a practical perspective, methods requiring minimal user intervention may be more easily deployed in real-world applications and across independent datasets. This comparative performance analysis provides valuable guidance for practitioners in selecting the most suitable method based on specific experimental conditions and temporal parameters of interest, as the choice of method should be driven by a trade-off between performance and practical feasibility. The results highlight the strengths and limitations of each analyzed method, enabling more informed and context-specific decisions.

CRediT authorship contribution statement

Myriam Lubrano: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rachele Rossanigo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Andrea Cereatti:** Writing – review & editing, Visualization, Supervision, Project administration, Conceptualization. **Cristiano Cuppini:** Writing – review & editing, Visualization, Supervision, Project administration. **Silvia Fantozzi:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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