Journal of Coaching and Sports Science
Volume 5, Issue 4, 31-43.
e_ISSN: 2963-1483
https://www.journal.foundae.com/index.php/jcss/index
DOI: 10.58524/jcss.v5i4.1492

Criterion agreement and 48-hour test–retest reliability of a microcontroller-based cadence counter during in-place running

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Article Info

Article history:
Received: August 20, 2026
Revised: September 10, 2026
Accepted: November 15, 2026

Keywords:
In-place running;
Microcontroller;
Measurement agreement;
Running cadence;
Test-retest reliability.

Abstract

Background: Running cadence should be assessed with systems that demonstrate acceptable agreement with a reference method and adequate repeatability under the intended testing conditions.
Aim: To quantify criterion agreement with high-speed video and 48-hour test–retest repeatability of a microcontroller-based contact-mat cadence counter during controlled in-place running.
Methods: Thirty track and field athletes completed a 60-s in-place running trial on a microcontroller-based contact mat while synchronized 240-frames/s video was recorded. Independently reviewed and adjudicated video counts served as the criterion; contact-mat testing was repeated after 48 h. Agreement was assessed using ICC(A,1), absolute-error indices, and Bland–Altman statistics. Repeatability was quantified using ICC(A,1), SEM, MDC95, and session limits of agreement.
Results: Criterion ICC(A,1) was 0.995 (bootstrap 95% CI 0.990–0.997); MAE was 1.10 spm, RMSE was 1.40 spm, and MAPE was 0.63%. Mean device–video bias was −0.10 spm, with 95% limits of agreement from −2.89 to +2.69 spm. Test–retest ICC(A,1) was 0.990 (bootstrap 95% CI 0.979–0.995), with SEM of 1.44 spm and MDC95 of 3.98 spm.
Conclusions: The contact-mat counter yielded closely aligned aggregate cadence values and favorable short-interval repeatability in a fixed 60-s in-place task. These estimates are protocol-specific and do not establish interchangeability with overground running systems or performance in competition settings.

To cite this article: Akhmad, I., Suharjo., Nurkadri., Hariadi., Amansyah., Lubis, A. P. (2026). Criterion agreement and 48-hour test–retest reliability of a microcontroller-based cadence counter during in-place running. *Journal of Coaching and Sports Science, 5*(4), 31-43. https://doi.org/10.58524/jcss.v5i4.1492
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INTRODUCTION

Running cadence, expressed as total steps per minute (spm), is an interpretable spatiotemporal measure of running. One step denotes a single foot-contact event, whereas one stride comprises two successive steps. Cadence has no universal optimum: it varies with speed, running style, task constraints, fatigue, and individual coordination strategies, and deliberate step-rate changes can alter multiple biomechanical outcomes. Accordingly, cadence is best treated as a context-dependent monitoring variable rather than a single prescriptive target (Anderson et al., 2022; Chase et al., 2023; Nijs et al., 2023; Goss et al., 2026).

Portable sensing has moved gait and running analysis beyond specialized laboratories, but validity cannot be assumed across devices. Systematic evidence shows that sensor location, acquisition settings, signal processing, event-detection logic, and the choice of criterion reference can materially alter validity and reliability estimates (Zeng et al., 2022; Mason et al., 2023; Xiang et al., 2024; Prisco et al., 2025). Device-specific studies further show that apparently similar outputs can behave differently across running speeds, environments, and anatomical placements, including vertical oscillation, spatiotemporal parameters, and joint kinematics (Smith et al., 2022; Uno et al., 2023; Sibson et al., 2024; Wolski et al., 2024; Mason et al., 2024). These findings make direct validation essential before a new cadence counter is used for coaching or research decisions.

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For coaches, a central challenge is to measure cadence efficiently and repeatably without labor-intensive video analysis or a complex wearable setup. Adoption may also depend on ease of use, sensor placement, feedback quality, and perceived utility (Lacey et al., 2022). Low-cost sensing architectures may expand access to objective gait assessment, provided that their operating characteristics are transparent and empirically established (Manupibul et al., 2023). Studies of smart patches, portable inertial sensors, and commercial running devices support the feasibility of portable step-rate monitoring while emphasizing the need for system-specific evidence of agreement and reliability (Verdel et al., 2024; Mason et al., 2025; Cabrera-Linares et al., 2025).

Agreement and repeatability require complementary statistics. Correlation quantifies association but does not establish interchangeability, whereas agreement-oriented validation combines relative coefficients with absolute error and difference-based analyses. Recent validation studies commonly report ICC-type coefficients together with MAE/RMSE or percentage error and Bland–Altman estimates, because a high association can coexist with systematic or practically important disagreement (Mora-Gonzalez et al., 2022; Cudejko et al., 2022; Kelly et al., 2022; Jung et al., 2023; Nassajpour et al., 2025). This multidimensional reporting strategy is particularly important for a cadence device intended to support repeated athlete monitoring.

Three methodological considerations motivate the present investigation. First, published running-sensor validations have predominantly examined wearable or inertial systems, whereas fixed contact-mat counters have received comparatively limited attention. Second, performance depends on testing conditions and event-detection methods: algorithms validated under controlled conditions may not perform similarly during unconstrained running, and treadmill, overground, and other environments are not necessarily interchangeable (Donahue & Hahn, 2022, 2023; Baker et al., 2024; DeJong Lempke et al., 2025; Meingast et al., 2025). Third, advances in machine learning and sensor fusion do not reduce the need to establish criterion agreement for simpler contact-based devices (Wu et al., 2026; Yuan et al., 2026; Hu et al., 2026). This study aimed to quantify (1) agreement between a microcontroller-based contact-mat cadence counter and an independently adjudicated 240-frames/s video reference; and (2) 48-hour test–retest repeatability during standardized in-place running. Agreement, association, and within-athlete measurement error were considered separately to support context-specific interpretation of device performance.

METHOD

Study Design

This methodological study evaluated criterion agreement and short-interval repeatability at the participant level. Thirty athletes performed a 60-s in-place running trial while contact-mat counts and high-speed video were acquired concurrently. The contact-mat assessment was repeated after 48 h. Criterion comparisons used one device count and one adjudicated video count per athlete; each participant contributed a single independent observation to the primary analysis.

Material

The system comprised a rubberized contact mat with pressure-sensitive sensing elements, an ESP32-class microcontroller, Bluetooth communication, and an Android display application (Figures 1 and 2). Sensor states were sampled at 100 Hz, and a 60-ms software debounce interval was applied to suppress duplicate transitions. Accepted contact events were timestamped and transmitted to the application, which displayed elapsed time, step count, and cadence. This configuration defined the measurement system evaluated in the study.



Figure 1. Microcontroller-Based Contact-Mat Cadence Counter (Hardware Configuration)

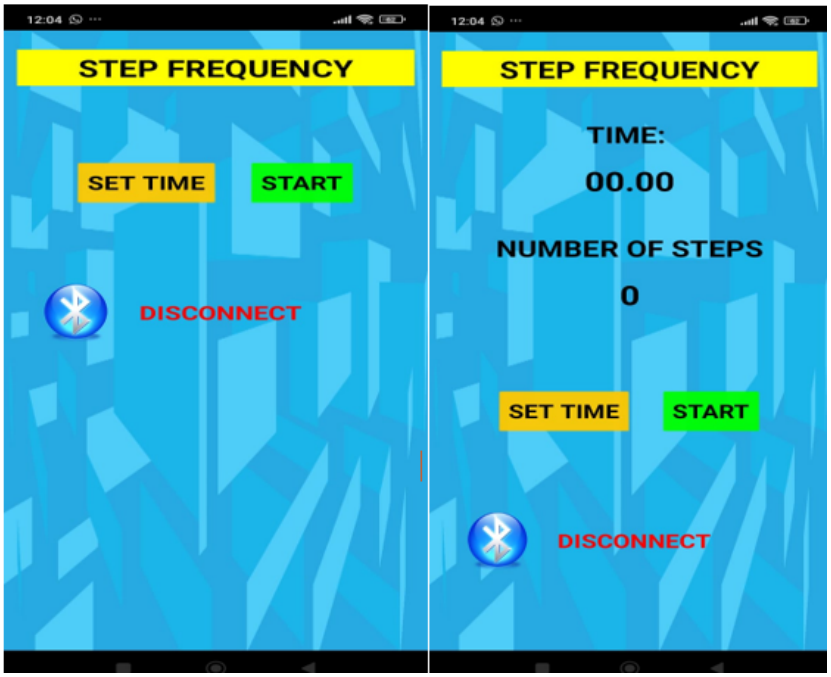


Figure 2. Android Application Interface for Step Counting and Cadence Monitoring

Mat positioning and electrical continuity were checked before each trial. During the criterion assessment, the device timer and 240-frames/s video were synchronized using a visible start marker. Participants remained on the mat for a fixed 60-s interval, with each accepted foot contact counted as one step. The synchronized acquisition boundaries allowed direct comparison of device and reference counts. At this duration, a difference of one counted contact corresponded to a cadence difference of 1 spm.

Participants

Thirty competitive track and field athletes aged 18 to 25 were recruited purposively through university athletic clubs and regional training centers. Eligibility required at least two years of

structured athletics training, regular running-event participation, no musculoskeletal injury within the preceding six months, and written informed consent. Exclusion criteria included conditions that could compromise running performance or participant safety. A sample size of 30 participants was recruited, consistent with established methodological guidelines for initial agreement and reliability studies of novel hardware prototypes, ensuring sufficient degrees of freedom for Bland-Altman and ICC estimations. Ethics approval was granted by the Ethics Committee of the Sports Science Study Program, Universitas Negeri Medan (Approval No. 045/UN33/KEPK.IK/II/2025, dated February 10, 2025).

Instrumentation

Microcontroller-Based Running Cadence Counter

Foot-contact events were identified from transitions in the mat sensor state and logged locally before transmission to the Android interface. Accepted events were timestamped, checked against the acquisition interval, and summed to obtain the total step count. Identical detection thresholds and debounce settings were used across sessions. Displayed counts were cross-checked against stored event records. The outcome was aggregate cadence expressed in spm; event-level sensitivity, specificity, and spatial gait characteristics were not assessed.

Reference Method

The criterion reference was obtained from a 240-frames/s camera positioned laterally to provide an unobstructed view of both feet and the contact surface. A visible synchronization marker established the same 60-s interval for the video and device recordings. A step was defined as initial visible foot–mat contact following an unloading or flight phase. Two trained analysts, blinded to the device counts, independently reviewed the recordings frame by frame. Disagreements were resolved through joint adjudication to obtain one consensus count per participant. Inter-analyst agreement was evaluated using a two-way mixed-effects, single-measure, absolute-agreement ICC(A,1).

Research Procedures

After informed consent and participant assessment, athletes completed a standardized 10-min dynamic warm-up. The contact mat was positioned on a level surface, and its event log was checked before acquisition. At the first visit, high-speed video was synchronized with the device using a visible marker. Participants wore their usual running shoes and completed a familiarization bout followed by one 60-s continuous in-place running trial at a comfortable self-selected cadence. A two-minute seated recovery separated familiarization and measurement. The contact-mat protocol, footwear requirements, and apparatus positioning were retained 48 h later; video served as the criterion only during the first visit. The time-of-day difference between visits did not exceed two hours.

For criterion analysis, one 60-s device count and one adjudicated video count were retained for each participant at Session 1. At Session 2, the 60-s contact-mat protocol was repeated without an additional video criterion recording. Cadence was calculated as the number of accepted contacts divided by observation time in seconds and multiplied by 60. Because the observation interval was 60 s, each count corresponded numerically to 1 spm. Trial records were retained at the participant level, and technical measurements were not treated as independent participants.

Data Analysis

Analyses were conducted in Python using NumPy and SciPy, with the participant as the unit of inference. Criterion agreement and 48-hour repeatability were quantified using a two-way mixed-effects, single-measure, absolute-agreement intraclass correlation coefficient [ICC(A,1)]. Percentile 95% confidence intervals (CIs) were estimated from 5,000 participant-level bootstrap resamples. Pearson's correlation coefficient was reported as an association statistic rather than evidence of agreement. Absolute criterion errors were described using mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE), with consensus video cadence as the MAPE denominator. Bland–Altman mean bias and 95% limits of agreement (LoA) were calculated as the mean device–reference difference ± 1.96 times its standard deviation. Approximate 95% CIs were calculated for the mean bias and both LoA. Proportional bias was examined by regressing

paired differences on their corresponding paired means, while the Shapiro–Wilk test described the distribution of the differences. Video-analyst agreement was assessed separately using ICC(A,1).

For test–retest analysis, the paired difference was defined as Session 2 minus Session 1. Absolute repeatability was quantified using the within-athlete standard error of measurement (SEM = SD of session differences / $\sqrt{2}$), minimal detectable change at the 95% confidence level (MDC95 = 1.96 × $\sqrt{2}$ × SEM), and within-athlete coefficient of variation (CV = 100 × SEM / pooled session mean). Test–retest LoA were calculated from the distribution of session differences. Given the sample size, uncertainty intervals were interpreted cautiously. Due to the context-dependent nature of running cadence, acceptable measurement thresholds vary across coaching applications; accordingly, high agreement coefficients were not considered evidence of equivalence or unrestricted interchangeability.

Scope and Limitations of the Methodology

The target of inference was restricted to competitive athletes aged 18–25 years performing a 60-s station-based in-place running task with the specified contact-mat and video configuration. The design did not evaluate treadmill running, overground locomotion, varying surface conditions, prolonged fatigue, or other populations. The sample of 30 participants provided an initial estimate of agreement and repeatability but was not intended to establish a universally acceptable measurement-error threshold. Criterion agreement and between-session repeatability were analyzed as separate measurement properties.

RESULTS AND DISCUSSION

Results

Participant Characteristics

All 30 participants completed both sessions without missing cadence values. Participants were 13 women and 17 men, age 21.4 ± 2.5 years, height 171.0 ± 10.3 cm, body mass 63.8 ± 9.8 kg, and athletic experience 5.8 ± 1.9 years. Running-event groups comprised 12 sprint, 10 middle-distance, and 8 distance athletes. Video consensus cadence ranged from 141 to 201 spm (mean 177.2 ± 14.1 spm).

Criterion Agreement with the Video Reference

Device and video counts were obtained from the same 60-s interval for each participant. Criterion agreement was ICC(A,1) = 0.995 (bootstrap 95% CI 0.990–0.997), with Pearson's r = 0.995. Absolute error was MAE = 1.10 spm, RMSE = 1.40 spm, and MAPE = 0.63%. The mean device–video difference was −0.10 spm. The resolution of a 60-s contact-count measure was consistent with the observed integer-valued discrepancies (Table 1).

Table 1. Criterion Agreement of the Cadence Counter Against Adjudicated Video

Variable	Value	Statistical role
ICC(A,1), absolute agreement	0.995 (0.990–0.997)	Bootstrap 95% CI
Mean absolute error (MAE)	1.10 spm	Absolute error
Root mean square error (RMSE)	1.40 spm	Absolute error
Mean absolute percentage error	0.63%	Relative error
Pearson r (secondary)	0.995	Association only
Video analyst ICC(A,1)	0.999 (0.997–1.000)	Video count agreement

Criterion agreement was high within the evaluated protocol, with small absolute differences between mat and reference measurements (Table 1). The two independent video analysts produced different initial counts for seven of the 30 participants; adjudicated counts were used as the criterion. The ICC confidence interval describes uncertainty in the coefficient and should not be interpreted as a prespecified tolerance for device error.

Test–Retest Reliability

The 48-hour test–retest ICC(A,1) was 0.990 (bootstrap 95% CI 0.979–0.995), and Pearson's r was 0.990. The average Session 2 − Session 1 difference was +0.07 spm (95% CI −0.69 to +0.83 spm). Relative reliability and absolute measurement error are reported separately because they address different aspects of repeated-measure performance. The standard deviation of session

differences was 2.03 spm, corresponding to a within-athlete SEM of 1.44 spm, MDC95 of 3.98 spm, and CV of 0.81%. Test–retest 95% LoA ranged from −3.92 to +4.05 spm. These indices describe variability under the tested conditions; they are not, by themselves, universally applicable thresholds for meaningful changes in running cadence.

Table 2. Repeatability and Absolute Measurement Error over 48 Hours

Variable	Value	Statistical role
Test–retest ICC(A,1)	0.990 (0.979–0.995)	Bootstrap 95% CI
Mean difference (S2 − S1)	+0.07 spm	Session bias
Pearson r (secondary)	0.990	Association only
Retest interval	48 h	Prespecified design interval
Within-athlete SEM	1.44 spm	Absolute repeatability
MDC95	3.98 spm	Estimated 95% detectable change
Within-athlete CV	0.81%	Scale-adjusted error
Test–retest 95% LoA	-3.92 to +4.05 spm	Individual session differences

The high retest ICC indicates that between-athlete ranking was largely preserved over 48 h, whereas SEM, MDC95, and LoA describe the uncertainty of individual repeated measurements. Interpretation of longitudinal changes should consider both measurement error and a prospectively specified threshold of practical importance.

Difference-Based Agreement Analysis

The mean mat-minus-video difference was −0.10 spm (95% CI −0.63 to +0.43), with a standard deviation of 1.42 spm. The lower 95% LoA was −2.89 spm (approximate 95% CI −3.81 to −1.97), and the upper 95% LoA was +2.69 spm (approximate 95% CI +1.77 to +3.61). Proportional bias was evaluated by regressing the paired differences on the corresponding paired means; the Shapiro–Wilk test was used to characterize the difference distribution.

Table 3. Bland–Altman Statistics for Device–Video Criterion Agreement

Parameter	Estimate	95% CI
Mean bias	-0.10 spm	-0.63 to +0.43 spm
Lower 95% limit of agreement	-2.89 spm	-3.81 to -1.97 spm
Upper 95% limit of agreement	+2.69 spm	+1.77 to +3.61 spm
SD of paired differences	1.42 spm	—
Shapiro–Wilk of differences	W = 0.959; p = 0.294	—
Proportional-bias slope	+0.0037 (p = 0.849)	Difference / paired mean

Figure 3 plots the device–video differences against the paired mean cadence for all 30 athletes. Two pairs of observations share identical coordinates and are distinguished by the numeral 2 within their plotted markers. The horizontal lines represent the observed mean bias and the 95% LoA. The regression-based assessment of proportional bias is summarized separately in Table 3.

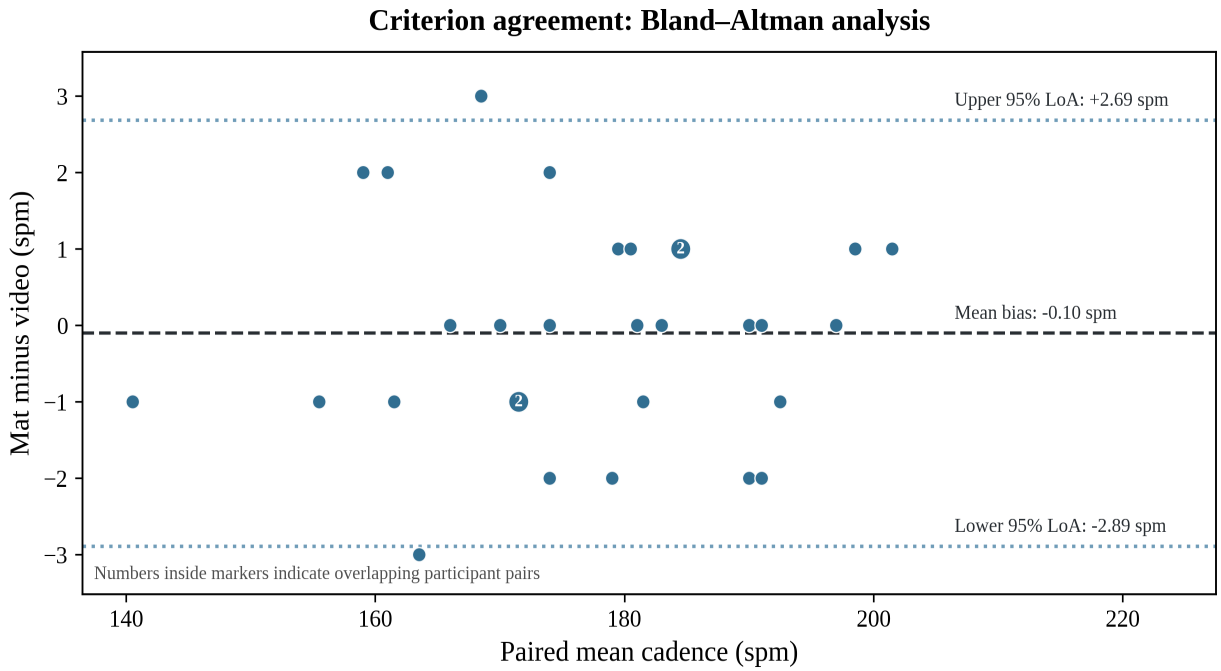


Figure 3. Bland–Altman agreement of the contact mat against video (n = 30; numbers inside markers indicate overlapping pairs)

The confidence interval for mean bias (−0.63 to +0.43 spm) was narrower than those surrounding the LoA. Mean bias summarizes the average systematic offset, whereas the LoA characterize the range within which differences for individual observations are expected to fall, subject to the assumptions of the Bland–Altman approach.

A mean difference close to zero does not exclude errors that may be unacceptable for a particular coaching application. The practical adequacy of the observed LoA therefore depends on an acceptable-error threshold specified independently of the present results. These agreement estimates pertain to a fixed 60-s in-place running task and cannot be generalized to overground running, different speeds, or variable surfaces without further validation.

Figure 4 shows the frequency distribution of the 30 integer-valued mat-minus-video differences. At a 60-s observation duration, each contact-count discrepancy corresponds to 1 spm. The dashed vertical line denotes the estimated mean bias.

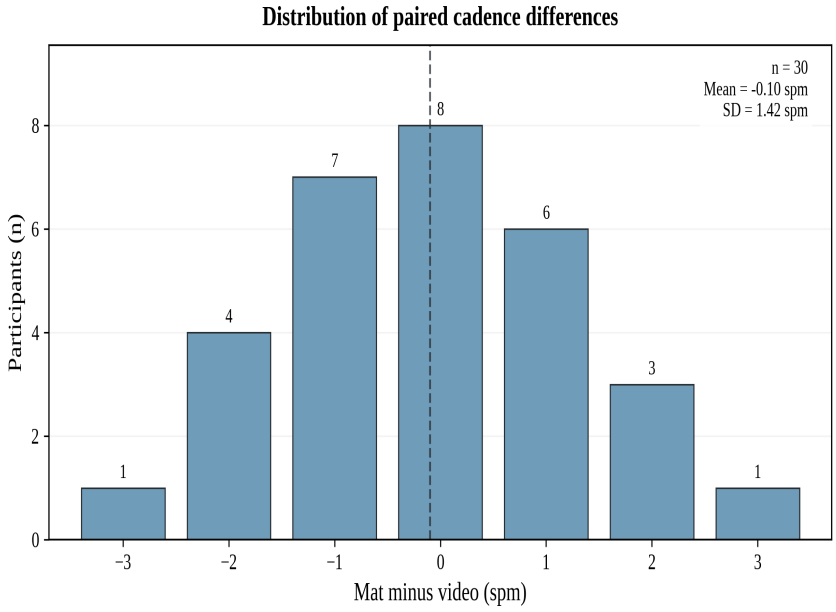


Figure 4. Frequency distribution of device-minus-video differences during a 60-s counting task (n = 30)

The most frequent difference was 0 spm (8/30 observations), followed by −1 spm (7/30) and +1 spm (6/30). Differences ranged from −3 to +3 spm, consistent with integer contact counts obtained over a common 60-s interval.

Figure 5 presents three single-measure absolute-agreement ICC estimates (criterion, test–retest, and video analysts) alongside two Pearson correlation coefficients. The shared horizontal scale facilitates visual comparison, but the coefficients represent different statistical properties and should not be interpreted interchangeably.

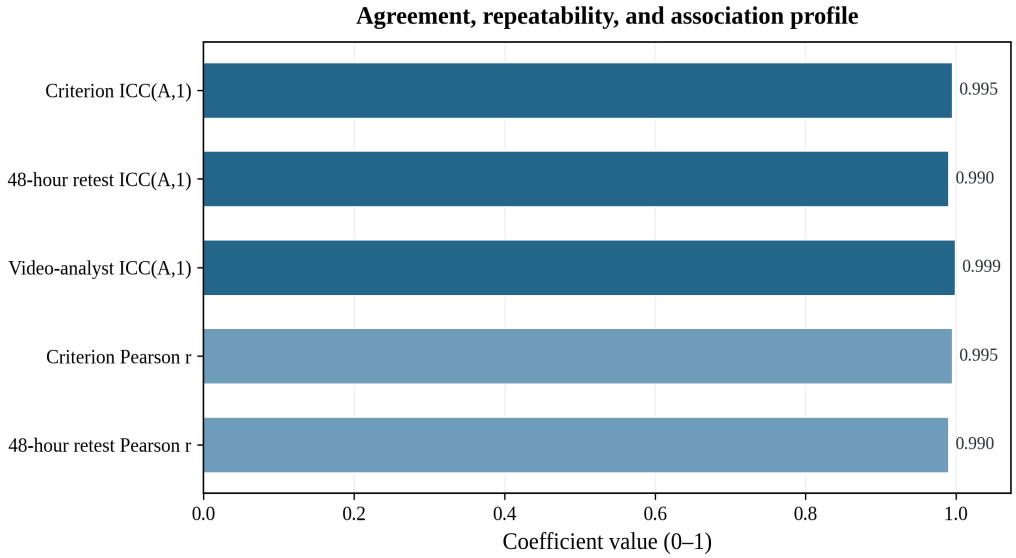


Figure 5. Absolute-agreement ICC point estimates and Pearson correlations from three distinct comparisons

The ICC estimates address absolute agreement under their respective measurement designs; the Pearson coefficients describe linear association. Video-analyst agreement pertains to the reliability of the criterion-counting procedure and does not directly measure contact-mat performance.

Discussion

The present study demonstrated close criterion agreement between the microcontroller-based contact-mat cadence counter and adjudicated high-speed video during a standardized 60-s in-place running protocol. The high ICC(A,1) of 0.995, MAE of 1.10 spm, and 95% limits of agreement (LoA) ranging from −2.89 to +2.69 spm collectively indicate small measurement discrepancies under controlled conditions. These findings are consistent with previous studies emphasizing that sensor validity depends on device architecture, testing conditions, and reference measurement procedures (Verdel et al., 2024; Mason et al., 2024; Cabrera-Linares et al., 2025). Nevertheless, favorable agreement within a stationary task does not establish equivalent performance during treadmill or overground running, where movement characteristics and sensor interactions may differ substantially.

Although Pearson's correlation was similarly high (r = 0.995), correlation alone cannot establish measurement interchangeability. Strong associations may reflect substantial between-athlete variability despite meaningful individual measurement discrepancies. Accordingly, the combined interpretation of ICC, absolute-error indices, and Bland–Altman statistics provides a more comprehensive assessment of device performance than correlation alone (Wolski et al., 2024; Meingast et al., 2025; Nassajpour et al., 2025). The near-zero mean bias (−0.10 spm) suggests minimal systematic disagreement, whereas the LoA characterize the expected dispersion of individual differences. Their practical acceptability should therefore be evaluated against a prespecified measurement tolerance rather than inferred solely from favorable statistical estimates.

The practical relevance of these findings depends on the magnitude of cadence changes targeted during training. Previous investigations indicate that deliberate step-rate modifications can influence running biomechanics, although their effects vary according to individual characteristics

and intervention objectives (Anderson et al., 2022; Nijs et al., 2023; Goss et al., 2026). Consequently, the contact-mat system may provide useful feedback for relatively substantial cadence adjustments during controlled drills, while smaller changes require more cautious interpretation. Importantly, measurement agreement should not be equated with sensitivity to meaningful performance improvements, particularly when expected adaptations approach the magnitude of measurement uncertainty.

The 48-hour test–retest assessment further demonstrated high relative repeatability (ICC(A,1) = 0.990), with SEM and MDC95 values of 1.44 and 3.98 spm, respectively. These complementary indices distinguish consistency in athlete ranking from absolute within-athlete measurement error. Although the mean between-session difference was only +0.07 spm, this small average shift does not exclude meaningful individual fluctuations. An observed change exceeding approximately 4 spm would provide stronger evidence of change beyond measurement error under comparable testing conditions, but would not necessarily indicate practical improvement. Such distinctions are essential because reliability estimates may vary with environmental conditions, device configuration, and analytical procedures (Berzosa et al., 2024; Jones et al., 2025).

The standardized 60-s observation interval represents an important methodological feature because each additional or missed foot contact corresponds to a cadence difference of 1 spm. This relationship provides transparent numerical resolution and limits the amplification of counting discrepancies associated with shorter observation windows. However, longer trials may introduce variation related to fatigue, movement consistency, or attentional demands. Similarly, reference-video accuracy depends on synchronization, contact-event definitions, and reproducible assessment procedures. The high inter-analyst ICC(A,1) of 0.999 (bootstrap 95% CI 0.997–1.000) supports the consistency of video-based counting, although agreement between analysts cannot eliminate systematic reference-measurement errors.

The contact-mat system occupies a distinct technological position compared with wearable gait-analysis devices. Whereas ear-worn sensors, inertial measurement units, and data-driven approaches can capture running characteristics during locomotion, they may introduce challenges involving attachment, calibration, and cross-device comparability (Jung et al., 2023; Donahue & Hahn, 2023; Baker et al., 2024; Mason et al., 2025). The stationary contact-mat configuration may simplify standardized cadence assessment but restricts measurement to a predefined sensing surface. Furthermore, aggregate cadence agreement does not establish accurate detection of individual foot strikes or validate additional spatiotemporal parameters. Its potential application should therefore remain focused on controlled cadence monitoring rather than comprehensive running-biomechanics assessment.

Technical reproducibility constitutes another important consideration. Changes in sensing components, firmware, event-detection thresholds, or calibration procedures may influence measurement outcomes, even when the underlying device architecture remains similar. Detailed documentation of hardware specifications, acquisition characteristics, signal-processing rules, and software versions is therefore necessary to support independent replication and subsequent validation (Manupibul et al., 2023; Prisco et al., 2025). The relatively small sample, short retest interval, and single-task design further constrain generalizability. Future investigations should evaluate measurement stability across longer testing periods, different movement intensities, and more heterogeneous athlete populations.

Overall, the findings indicate favorable criterion agreement and short-term repeatability for aggregate cadence measurement under a fixed 60-s in-place running protocol. The integration of agreement coefficients, absolute-error indices, and measurement-uncertainty estimates provides a useful basis for evaluating the system's potential application in standardized training assessments. However, broader validation remains necessary before extending these findings to continuous running, different environments, or individualized performance decisions.

Implications

Under conditions matching the evaluated protocol, a fixed-station counter may support standardized cadence assessment during technique drills. Cadence should not be treated as a universal target; acceptable changes depend on the athlete, task, intervention objective, and measurement error.

For repeated-measure applications, absolute error, Bland–Altman LoA, and test–retest uncertainty should be considered alongside relative reliability. Measurements obtained with different devices or under different running conditions should not be assumed interchangeable without direct comparison.

Research Contribution

The present work examines a comparatively simple measurement configuration: a stationary contact-sensing mat assessed against independently reviewed video and retested after 48 h. This task-specific approach complements an evidence base that has concentrated primarily on wearable systems. The methodological contribution lies in reporting complementary relative and absolute indices: ICCs with uncertainty intervals, independent video-analyst agreement, absolute criterion errors, proportional-bias analysis, SEM, MDC95, and test–retest LoA. Together, these indices provide a more complete assessment of measurement properties than correlation alone.

Limitations

Several limitations constrain interpretation. The sample was purposively recruited and comprised only 30 athletes, and the 60-s in-place running task does not reproduce the mechanical demands of natural overground running. The restricted age range, running-event profile, sensing surface, and observation duration limit generalizability. Device performance may also change with footwear, cadence, firmware, or prolonged use. The LoA estimates remain subject to sampling uncertainty at this sample size. Only one measured trial was obtained per session, preventing separation of within-session technical variability from between-day variation. The video reference relied on manual identification of contacts and therefore remained susceptible to occlusion and observer judgment. Event-level sensitivity and specificity, foot-specific timing, and a prospectively defined acceptable-error threshold were not evaluated. Consequently, the present estimates do not establish suitability for competition-level or other unrestricted applications.

Suggestions

Future studies should recruit a larger and more diverse sample, justify sample size using the desired precision of the LoA, and prespecify acceptable-error thresholds. Multiple trials at each visit would permit estimation of within-session variability, while systematic testing across cadence ranges would characterize the stability of agreement. Complete engineering documentation should include component specifications, circuit diagrams, calibration procedures, acquisition-clock validation, firmware versions, and event-detection settings. External validation should proceed from fixed-duration in-place assessments to controlled treadmill running and subsequently to overground and field conditions. Additional analyses should examine heteroscedasticity across broader cadence ranges, missed and spurious contact events, between-operator reproducibility, and repeated-session variability. Preservation of raw contact timestamps and synchronized video would facilitate independent reanalysis.

CONCLUSION

During the standardized 60-s in-place running task, the microcontroller-based contact-mat system demonstrated excellent criterion agreement with adjudicated high-speed video counts (ICC(A,1) = 0.995; MAE = 1.10 spm) and narrow 95% limits of agreement (−2.89 to +2.69 spm), alongside robust 48-hour test–retest reliability (ICC(A,1) = 0.990) and a minimal detectable change (MDC95) of 3.98 spm. This MDC95 threshold provides a highly practical metric for practitioners, indicating that longitudinal cadence adaptations exceeding ∼4 spm can be confidently attributed to true biomechanical changes rather than technical measurement error. These findings confirm that a low-cost, ESP32-driven hardware architecture can achieve the accuracy and temporal resolution necessary for reliable cadence monitoring, avoiding the computational overhead and calibration challenges typical of wearable sensors. While these measurement properties are strictly specific to the examined stationary protocol and do not inherently guarantee interchangeability with unconstrained overground running, the system offers a highly accessible, objective assessment tool for resource-constrained environments, establishing a rigorous foundation for its future integration

into structured technique drills, localized rehabilitation assessments, and real-time gait retraining programs.

ACKNOWLEDGMENT

The authors acknowledge the institutional support of LPPM Universitas Negeri Medan.

AUTHOR CONTRIBUTION STATEMENT

IA: Conceptualization, methodology, investigation, data curation, formal analysis, and writing the original draft. SH: Methodology, investigation, validation, review, and editing. NK: Methodology, software, validation, investigation, data curation. HR: Formal analysis, visualization, writing review, and editing. AM: Supervision, resources, writing review, and editing. HPL: Conceptualization, supervision, funding acquisition, project administration, writing review, and editing. All authors reviewed and approved the final manuscript and accept responsibility for its content.

AI DISCLOSURE STATEMENT

The authors used ChatGPT and Grammarly solely to assist with language editing and manuscript organization. These tools were not used to generate, modify, or analyze the research data. All scientific content, statistical results, citations, and references were independently verified by the authors, who take full responsibility for the final manuscript.

CONFLICT OF INTEREST

The authors declare no financial, professional, or personal conflicts of interest that could have influenced the conduct or reporting of this study.

ETHICAL APPROVAL

This study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of the Sports Science Study Program, Universitas Negeri Medan (Approval No. 045/UN33/KEPK.IK/II/2025, dated February 10, 2025). Written informed consent was obtained from all individual participants prior to their inclusion in the study.

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