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Sensor-based assessment agreement and indirect effect of kinesthetic perception and BMI with planned change-of-direction performance in junior martial arts athletes

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Abstract

Background: Planned change-of-direction (COD) performance is important in martial arts, yet field-based assessment remains vulnerable to manual timing and scoring variability. Sensor-based systems may improve measurement standardisation, but their correspondence with conventional field methods and the cross-sectional relationships among kinesthetic perception, body mass index (BMI), sprint performance, and planned COD performance require careful evaluation.
Aims: This study evaluated sensor-based versus conventional measurements of planned COD performance and kinesthetic perception and estimated the cross-sectional indirect associations of kinesthetic perception and BMI with planned COD performance through 30-m sprint time.
Methods: A cross-sectional sample of 123 junior martial arts athletes aged 14-17 years completed the Smart Star Agility Test (SSAT), SmartPlus Autopad assessment, 30-m sprint test, Modified Martial Arts Dynamic Balance Test, and anthropometric measurements. Method association was described with Pearson correlation; the prespecified two-way mixed-effects, absolute-agreement, average-measures intraclass correlation coefficient (ICC) was retained as a descriptive agreement coefficient. Bland–Altman mean bias and approximate 95% limits of agreement (LoA) were calculated in a common sensor-minus-comparator direction. Cross-sectional indirect effects were estimated with PROCESS Model 4 using 5,000 bootstrap samples.
Results: SSAT and stopwatch measurements were strongly associated ($r = 0.996$, $p < 0.001$; average-measures ICC = 0.998). The SSAT-minus-stopwatch mean bias was -0.05 s, with approximate 95% LoA from -0.55 to 0.45 s. SmartPlus and manual kinesthetic scores were also strongly associated ($r = 0.964$, $p < 0.001$; average-measures ICC = 0.981); the SmartPlus-minus-manual mean bias was 0.12 points, with approximate LoA from -3.06 to 3.30 points. The bootstrap indirect association through 30-m sprint time was non-zero for kinesthetic perception (indirect effect = -0.0224; 95% BootCI [-0.0558, -0.0006]) and BMI (indirect effect = 0.0570; 95% BootCI [0.0121, 0.1191]).
Conclusion: The sensor-based measures showed very high correspondence and a small average bias relative to their field comparators under the present protocol. However, no a priori acceptable LoA were defined, and the comparator methods were not criterion standards; therefore, practical interchangeability is not established. The indirect-effect results describe cross-sectional statistical associations rather than causal mediation.

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INTRODUCTION

Change-of-direction (COD) performance is a central physical requirement in martial arts because athletes repeatedly accelerate, decelerate, reorient their bodies, and reposition themselves within limited space. Contemporary agility research distinguishes planned COD tasks from reactive agility: planned COD is executed along a predetermined movement path, whereas reactive agility additionally requires perception, anticipation, and decision-making in response to an external stimulus (Sheppard & Young, 2006; Sheppard et al., 2006; Nimphius et al., 2018; Čoh et al., 2018; Young et al., 2021). The present study therefore uses the term "planned COD performance" to refer to the Smart Star Agility Test (SSAT) outcome, rather than treating the task as a complete measure of reactive agility. Accurate field measurement of planned COD is important for athlete monitoring, but stopwatch timing and manual scoring can be affected by human reaction time and procedural variability. Electronic timing and sensor-assisted systems may reduce these sources of error and provide more standardised recording (Chen et al., 2021; Camomilla et al., 2018; Chambers et al., 2015; Cardinale & Varley, 2017).

Planned COD performance is related to multiple athlete characteristics rather than a single isolated capacity. Combat-sport performance requires rapid regulation of posture, body position, and movement in response to substantial acceleration, deceleration, and technical demands (Bridge et al., 2014; Chaabène et al., 2012; Franchini et al., 2011). Kinesthetic and proprioceptive information is therefore relevant to body-position awareness and movement control during these tasks (Jia et al., 2024). Anthropometric characteristics may also matter. Higher body mass relative to stature can increase the mass that must be accelerated and decelerated. At the same time, adolescent body-size indicators should be interpreted with caution because BMI does not distinguish between lean and fat mass and varies with growth and maturation (Brand et al., 2024; Pescari et al., 2024).

Linear sprint performance is another relevant component because planned COD tasks require repeated production and reduction of horizontal velocity. In this study, sprint performance was operationalised as 30-m sprint completion time; therefore, lower values indicate better performance. This direction is important when interpreting regression coefficients. The literature on COD performance consistently treats linear speed, strength/power, and task-specific deceleration/reacceleration capacity as related but non-identical determinants (Asadi et al., 2016; McBurnie et al., 2022; Nygaard Falch et al., 2019). Dynamic balance was also considered because postural stability contributes to movement control during rapid directional changes (Gribble et al., 2012; Grabara & Bieniec, 2024; Shen, 2024). Taken together, these variables provide a plausible framework for examining whether kinesthetic perception and BMI are statistically associated with planned COD performance, in part through their association with 30-m sprint time, while accounting for dynamic balance.

Sensor-based performance assessment has expanded rapidly because wearable and embedded sensors can automate event detection, timing, and movement-data acquisition (Camomilla et al., 2018; Cardinale & Varley, 2017; Chambers et al., 2015; Seçkin et al., 2023; Zhao et al., 2024). In sports settings, such technologies have been used to support objective and near-real-time performance evaluation across multiple movement-analysis contexts (Camomilla et al., 2018; Seçkin et al., 2023; Zhao et al., 2024). Nevertheless, a high correlation between a new system and a conventional method does not by itself establish agreement. Method-comparison studies should distinguish between association and absolute agreement and quantify both systematic bias and the dispersion of paired differences (Bland & Altman, 1986; Bland & Altman, 1999; Gerke, 2020; Kottner et al., 2011). This distinction is particularly important when a sensor-based method is proposed for routine field monitoring.

Evidence integrating method agreement with multivariable performance relationships remains limited in junior martial arts athletes. Existing studies commonly evaluate device validity or individual physical components separately, while less attention has been paid to how sensorimotor, anthropometric, balance, and sprint-related variables coexist within a single field-testing framework (Hülsdünker et al., 2023; McBurnie et al., 2022; Young et al., 2021). Moreover, cross-sectional indirect-effect models cannot establish temporal ordering and can yield biased representations of longitudinal mediation processes (Maxwell & Cole, 2007; Maxwell et al., 2011). The present study therefore treats indirect effects as regression-based statistical decompositions of concurrent associations rather than causal mechanisms, consistent with contemporary recommendations for mediation analysis (Hayes & Rockwood, 2017).

Accordingly, this study had two objectives. First, it evaluated the association and agreement between sensor-based and conventional assessments of planned COD performance and kinesthetic perception in junior martial arts athletes. Second, it examined whether 30-m sprint time statistically accounted for part of the cross-sectional associations between kinesthetic perception and BMI and planned COD performance, with dynamic balance considered as a covariate. We expected strong correspondence between paired assessment methods and non-zero bootstrap indirect effects through 30-m sprint time. The study was designed to provide field-based measurement evidence and hypothesis-generating information for subsequent longitudinal and intervention research.

METHOD

Research Design

A quantitative cross-sectional observational design was used. The study combined a method-comparison component, in which paired sensor-based and conventional measurements were obtained during the same testing trials, with cross-sectional regression-based indirect-effect analyses of performance variables. Because exposure, statistical intermediate, and outcome variables were measured within the same study period, the indirect-effect models were interpreted as associational rather than causal (Maxwell & Cole, 2007; Maxwell et al., 2011). The method-comparison component was reported with explicit distinction between correlation, reliability/agreement coefficients, and paired-difference analysis in accordance with established agreement-reporting principles (Kottner et al., 2011).

Participant

The accessible population comprised 180 junior martial arts athletes from eight disciplines in Pangkalpinang City, Indonesia: Pencak Silat (n = 44), Karate (n = 42), Taekwondo (n = 40), Boxing (n = 10), Wushu (n = 12), Wrestling (n = 10), Judo (n = 10), and Hapkido (n = 12). The original sampling plan targeted 123 athletes and applied proportionate stratified random sampling, with martial arts discipline as the stratum. Within each discipline, participants were randomly selected in Microsoft Excel until the predetermined proportional allocation was reached. The final sample comprised 30 Pencak Silat, 29 Karate, 27 Taekwondo, 7 Boxing, 8 Wushu, 7 Wrestling, 7 Judo, and 8 Hapkido athletes. There were 65 males (52.8%) and 58 females (47.2%); mean age was 15.5 ± 1.2 years, mean height 162.16 ± 7.67 cm, and mean body mass 54.02 ± 9.30 kg. The sample size decision was based on the sampling frame rather than on an analysis-specific precision or power calculation. This is a limitation because agreement studies are preferably planned around the desired precision of agreement estimates, and statistical analyses in sport science should report analysis-specific uncertainty rather than rely on generic sample-size rules (Gerke et al., 2022; Hopkins et al., 2009).

Eligible participants were active junior martial arts athletes with at least three years of regular training experience and medal-winning experience at regional multi-event championships. Athletes were excluded if they had experienced a musculoskeletal disorder or injury during the previous six months or had cognitive or motor limitations that could interfere with testing. Study aims, procedures, potential risks, and benefits were explained to participants and to their parents or legal guardians. Written parental or guardian informed consent was obtained before participation, and the procedures were explained to the athletes using age-appropriate language. Participation was voluntary. Ethical approval was granted by Universitas Negeri Jakarta (Approval No. 828/UN39.14/PT.01.05/VI/2026).

Instrument

Smart sensor-based performance assessment system , the smart sensor-based performance assessment system automated the acquisition of movement-related data during the planned COD and kinesthetic-perception tasks. The system integrated pressure-sensitive pads, piezoelectric contact sensors, a microcontroller-based data-acquisition unit, wireless transmission, and a smartphone processing interface. In the present apparatus, the contact sensors were used to identify foot-contact events and transmit task-event information to the processing interface; this use of embedded and wearable sensing is consistent with broader sports-performance sensor architectures described in the literature (Camomilla et al., 2018; Seçkin et al., 2023; Zhao et al., 2024). The application processed detected events into task-specific outputs, including completion time and kinesthetic-perception scores, and exported the values for statistical analysis. Before each testing session, each target pad was manually activated to verify sensor responsiveness, data transmission, and communication with the processing interface. This pre-session functional check was used to minimise device failures during field testing. The system workflow is shown in Figure 1.

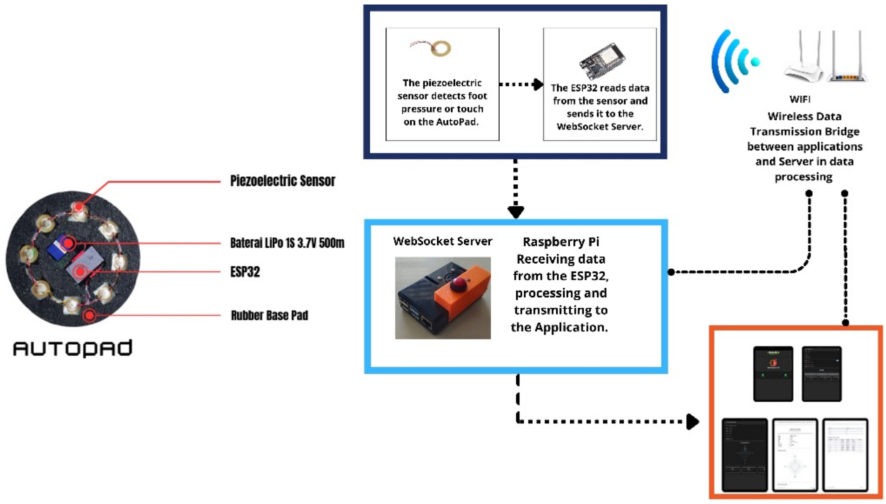

Figure 1. Workflow of the Smart Sensor-Based Performance Assessment System for Movement Data Acquisition and Performance Output Generation

Validity and Reliability of the Study Instruments

Before the main data collection, three senior experts in sports science, coaching, and sports measurement reviewed the SmartPlus Autopad, SSAT, and Modified Martial Arts Dynamic Balance Test (MMDBT) for face and content relevance, procedural clarity, operational feasibility, and scoring consistency. Each expert had more than 20 years of academic and practical experience in martial arts-related measurement, and the instruments were revised following consensus recommendations. A one-week test–retest check was also conducted, and the original study record summarised score stability with Pearson correlations: SSAT $r = 0.92$, SmartPlus Autopad $r = 0.81$, and MMDBT $r = 0.77$. Because Pearson correlation quantifies association rather than absolute agreement, these coefficients are interpreted here only as preliminary stability indicators, not as definitive test–retest reliability estimates. Reliability research in sports measurement recommends an explicitly specified ICC, along with uncertainty and measurement-error indices such as the standard error of measurement (SEM) and, where relevant, the minimum detectable change (Atkinson & Nevill, 1998; Hopkins, 2000; Weir, 2005; Liljequist et al., 2019). This distinction is also consistent with contemporary device-validation practice (Zhang et al., 2023).

Kinesthetic Perception Measurement Task

The SmartPlus kinesthetic-perception task required directional foot movements from a predetermined central position toward four targets. Testing was conducted on a flat surface with an Android smartphone connected to the system. After a standardised warm-up, participants completed 3-4 familiarisation trials with eyes open, followed by 3-5 min of rest. For the recorded assessment, participants stood in the central position with their eyes closed; a 30-s trial began after they left the start position. One foot was moved alternately toward the front, right, left, and back targets while the participant maintained a forward-facing orientation. An auditory signal confirmed target contact. Sensor-based and conventional scoring were recorded simultaneously during the same trial. Each participant completed two trials; the higher-scoring trial was retained, and the sensor and conventional values were paired from that same selected trial. Two experienced assessors conducted the conventional procedure: one monitored the 30-s interval using a stopwatch and the other recorded successful and unsuccessful target contacts. Both methods used the same scoring rule: 5 points for a successful contact and 1 point for an unsuccessful contact. Figure 2 presents the movement sequence.

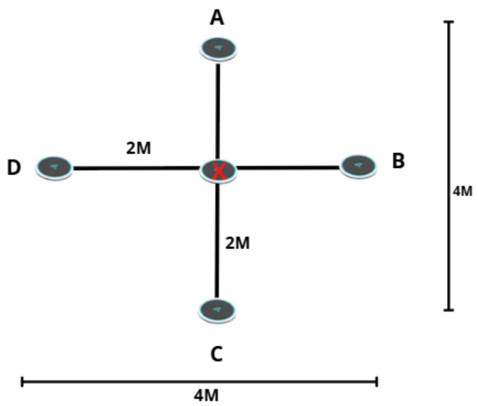

Figure 2. Movement Sequence in the SmartPlus Autopad Kinesthetic Perception Test: Center → A → Center → B → Center → D → Center → C → Center

Smart Star Agility Test (SSAT) Assessment

Planned COD performance was assessed with the Smart Star Agility Test (SSAT), a predetermined multidirectional protocol. Participants started from the central position and moved at maximal effort to eight targets arranged at 45° intervals, completing one clockwise rotation. Each target was positioned 2.5 m from the centre, forming a 5-m-diameter star configuration. The protocol was informed by established non-reactive agility and multidirectional field-test concepts, which emphasise the need to distinguish predetermined COD from reactive agility (Hadžović et al., 2023; Nimphius et al., 2018; Young et al., 2021). The sensor system recorded movement initiation, target contact, transition, and total completion times. Each athlete completed three trials with recovery between trials, and the fastest trial was retained as the final score; a lower time indicated better-planned COD performance. Stopwatch timing was recorded simultaneously by an experienced assessor during the same trials, and the stopwatch value corresponding to the selected fastest trial was paired with the sensor value for agreement analysis. Figure 3 shows the SSAT layout and movement directions.

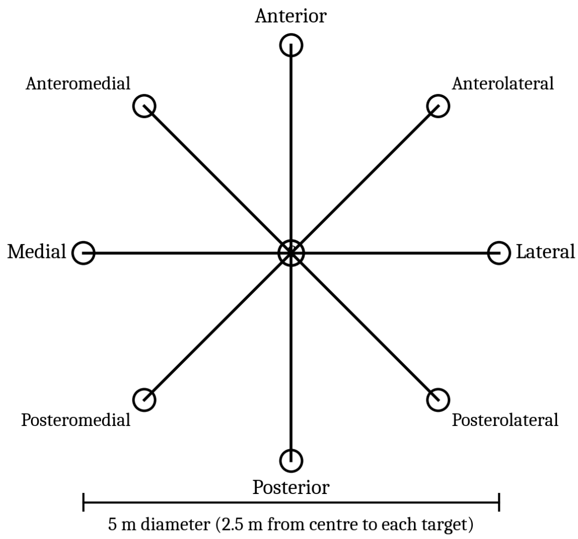

Figure 3. Smart Star Agility Test (SSAT) Configuration for Planned Multidirectional COD Assessment

BMI was calculated as body mass in kilograms divided by height in metres squared (kg/m^2). Body mass was measured with a calibrated digital scale and standing height with a stadiometer. BMI was analysed as a continuous variable. Because participants were 14–17 years old, raw BMI was not interpreted as a direct measure of adiposity or weight status and was treated cautiously in the discussion because BMI can misclassify body composition when used without direct adiposity measures, particularly in heterogeneous populations (Brand et al., 2024; Pescari et al., 2024).

Linear sprint performance was assessed with a 30-m sprint from a standing start. Each athlete performed three maximal trials, and the fastest completion time was retained for analysis. The analysed variable was completion time in seconds, not velocity; therefore, a lower value represented better sprint performance. The term 30-m sprint time is used throughout the statistical results to avoid direction-of-scale ambiguity. Linear sprint performance and planned COD are related but distinct physical qualities, so sprint time was treated as a separate performance variable rather than as a synonym for agility (Sheppard et al., 2006; Čoh et al., 2018; McBurnie et al., 2022).

Modified Martial Arts Dynamic Balance Test (MMDBT)

Dynamic balance was assessed with the Modified Martial Arts Dynamic Balance Test (MMDBT), a field protocol adapted in the present study to reflect forward and backward repositioning used in martial arts. Participants began with both hands on the waist and moved the left and right legs alternately toward designated targets. At each target, they maintained a single-leg toe-standing position for 3 s while keeping the supporting foot within the target area. The same sequence followed ten forward steps in reverse. The assessor monitored landing accuracy, stabilisation, and compliance with the required technique, using an audio cue to standardise the 3-s stabilisation interval. A successful landing/stabilisation task received 5 points, and an unsuccessful task received 1 point; the total score ranged up to 100, with higher values indicating better dynamic balance. The inclusion of dynamic balance as a covariate was conceptually supported by evidence linking postural control and balance performance with sport-specific movement and agility (Gribble et al., 2012; Grabara & Bieniec, 2024; Shen, 2024).

Data Analysis

All analyses were performed in IBM SPSS Statistics version 26. All 123 participants had complete values for the variables summarised in Table 1. Descriptive statistics are reported as mean ± standard deviation and range. Marginal normality tests were not used as gatekeepers for the inferential analyses because they do not establish the assumptions of correlation, agreement, or regression models; statistical interpretation instead emphasised effect estimates, uncertainty, and design limitations (Hopkins et al., 2009). For method comparison, Pearson correlation was used to describe linear association between paired methods. The prespecified two-way mixed-effects, absolute-agreement, average-measures ICC generated in SPSS was retained as a descriptive agreement coefficient. Because it is an average-measures coefficient, it is not interpreted as a single-measure interchangeability statistic; the interpretation of ICC depends on the model, type, and unit of analysis (Atkinson & Nevill, 1998; Hopkins, 2000; Weir, 2005; Liljequist et al., 2019). Bland–Altman agreement was summarised using a common sensor-minus-comparator direction. Mean bias was calculated from the paired method means. To ensure internal numerical consistency, the SD of the paired differences was recovered from the reported marginal SDs and Pearson correlation using the standard variance identity Var(X-Y) = Var(X) + Var(Y) - 2Cov(X, Y); approximate 95% LoA were then calculated as bias ± 1.96 SD of the paired differences. Because the manuscript reports rounded summary inputs, the LoA are explicitly presented as approximate. In the absence of prospectively defined acceptable differences, the LoAs are interpreted descriptively rather than as evidence of practical equivalence or unrestricted interchangeability (Bland & Altman, 1986; Bland & Altman, 1999; Gerke, 2020; Kottner et al., 2011). No formal claim regarding proportional bias is made from the summary-based agreement display. Cross-sectional indirect associations were estimated with PROCESS Model 4 using 5,000 bootstrap samples. In Model 1, the kinesthetic-perception score was the focal predictor, the 30-m sprint time the statistical intermediate variable, the planned COD completion time the outcome, and BMI and dynamic balance were covariates. In Model 2, BMI was the focal predictor, with kinesthetic perception and dynamic balance as covariates; the 30-m sprint time and planned COD time retained their roles. The total effect (c), direct effect (c′), and indirect effect (a × b) were reported as unstandardized coefficients with 95% confidence intervals. Bootstrap inference for indirect effects was used because the sampling distribution of a product term is commonly non-normal (Preacher & Hayes, 2008; Hayes & Rockwood, 2017). An indirect effect was considered statistically different from zero when its 95% bootstrap confidence interval excluded zero. All tests were two-sided with $\alpha = .05$. Given the cross-sectional design, these estimates are described as indirect statistical associations rather than causal mediation, because cross-sectional estimates cannot establish temporal ordering and may misrepresent longitudinal mediation processes (Maxwell & Cole, 2007; Maxwell et al., 2011).

RESULTS AND DISCUSSION

Results

Table 1 summarises the study variables. The 123 athletes had a mean age of 15.5 ± 1.2 years, height of 162.16 ± 7.67 cm, and body mass of 54.02 ± 9.30 kg. Mean SmartPlus and manual kinesthetic scores were 28.19 ± 5.87 and 28.07 ± 6.11, respectively. Mean BMI was 20.43 ± 2.58 kg/m^2 and mean 30-m sprint time was 5.11 ± 0.48 s. Planned COD completion time averaged 20.68 ± 2.85 s with the SSAT sensor and 20.73 ± 2.84 s with stopwatch timing. Mean MMDBT score was 71.70 ± 13.72. These descriptive statistics establish the scale and dispersion of the measurements used in the subsequent agreement and indirect-effect analyses.

Table 1. Descriptive Statistics

Statistic	SmartPlus Autopad	Manual score	BMI	30-m sprint time (s)	SSAT time (s)	Stopwatch time (s)	MMDBT
N	123	123	123	123	123	123	123
Min	10	10	15.62	3.79	14.74	14.79	42.00
Max	40	41	29.00	6.45	31.58	31.63	96.00
M ± SD	28.19 ± 5.87	28.07 ± 6.11	20.43 ± 2.58	5.11 ± 0.48	20.68 ± 2.85	20.73 ± 2.84	71.70 ± 13.72

Note: Values are mean ± standard deviation unless otherwise indicated. BMI = body mass index; SSAT = Smart Star Agility Test; MMDBT = Modified Martial Arts Dynamic Balance Test. Lower 30-m sprint and planned COD completion times indicate better performance.

Association and Agreement Between Sensor-Based and Conventional Assessments

Table 2 presents the paired-method results using a consistent sensor-minus-comparator direction for the difference estimates. SSAT time was strongly correlated with stopwatch time ($r = 0.996$, $p < .001$), and the prespecified two-way mixed-effects absolute-agreement average-measures ICC was 0.998. SmartPlus and manual kinesthetic scores were also strongly correlated ($r = 0.964$, $p < .001$), with an average-measures ICC of 0.981. The average-measures ICCs corroborate the strong paired correspondence but are not interpreted as single-measure interchangeability coefficients. Absolute agreement is therefore interpreted primarily in terms of mean bias and the approximate 95% LoA.

Table 2. Association and Agreement Summary for Sensor-Based and Conventional Assessments

Assessment pair	Pearson r (p)	Average-measures ICC	Mean bias	Approx. 95% LoA
SSAT - stopwatch	0.996 (p < .001)	0.998	-0.05 s	[-0.55, 0.45] s
SmartPlus – manual kinesthetic	0.964 (p < .001)	0.981	0.12 points	[-3.06, 3.30] points

Note: r = Pearson correlation. ICC = prespecified two-way mixed-effects, absolute-agreement, average-measures intraclass correlation coefficient. Bias direction is sensor-based method minus comparator. Approximate LoA were recalculated from the reported paired means, standard deviations, and Pearson r using the standard variance identity for paired differences described in the Data analysis section. Because the summary inputs are rounded, the LoAs are presented as approximate values. No a priori acceptable LoA were specified; therefore, practical interchangeability is not established.

Figure 4 visualises the internally consistent Bland–Altman summary estimates from Table 2. For planned COD, the SSAT-minus-stopwatch mean bias was -0.05 s and the approximate 95% LoA were -0.55 to 0.45 s. For kinesthetic perception, the SmartPlus-minus-manual mean bias was 0.12 points, and the approximate 95% LoA were -3.06 to 3.30 points. The small average biases indicate little systematic mean displacement between paired methods, whereas the LoA quantify the substantially wider range within which individual paired differences may occur. Because acceptable differences were not defined prospectively and the comparators were not criterion standards, the agreement results support protocol-specific correspondence rather than formal equivalence.

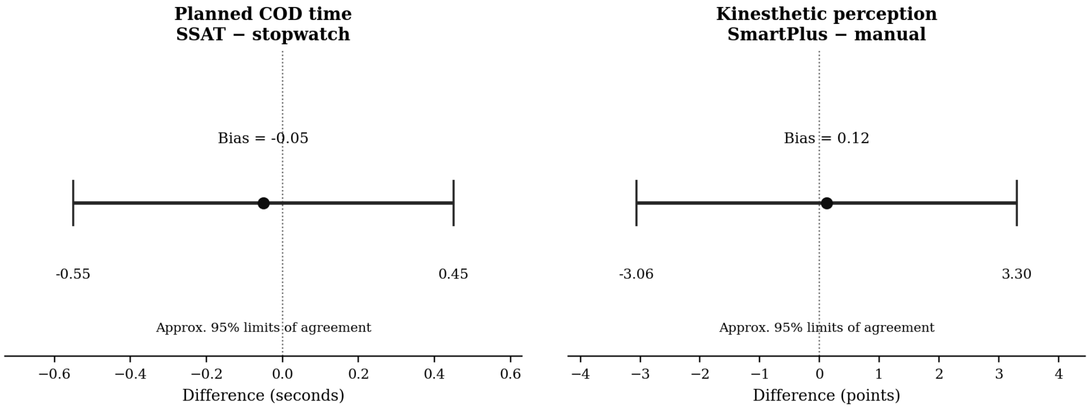

Figure 4. Bland–Altman Agreement Summary for Paired Sensor-Based and Conventional Assessments

Note: Central markers show mean bias and horizontal lines show the approximate 95% limits of agreement. Difference direction is sensor-based method minus comparator. The display is based on the internally consistent summary estimates reported in Table 2.

The agreement summary emphasises the distinction between average bias and individual-level disagreement: near-zero mean bias does not imply that the two methods are interchangeable for every athlete. Accordingly, subsequent interpretation treats the sensor systems as showing close field-based correspondence under the tested protocol, while criterion validation and prospectively defined acceptable differences remain necessary.

Cross-Sectional Indirect-Effect Analysis Through 30-m Sprint Time

The first model examined the cross-sectional association between kinesthetic perception and planned COD performance, and its statistical decomposition using 30-m sprint time, while controlling for BMI and dynamic balance. Kinesthetic perception was associated with shorter 30-m sprint time (B = -0.0142, SE = 0.0071, p =0.0471), and longer 30-m sprint time was associated with longer planned COD time (B = 1.5726, SE = 0.4989, p = 0.0021). The total association between kinesthetic perception and planned COD time was negative (B = -0.1224, p = 0.0028), and the direct association remained negative after 30-m sprint time was included (B = -0.1000, p = 0.0122). The bootstrap indirect effect was -0.0224 (95% BootCI [-0.0558, -0.0006]), indicating a non-zero cross-sectional indirect statistical association (Table 3; Figure 5).

Table 3. Indirect-Effect Analysis of Kinesthetic Perception on Planned COD Performance Through 30-m Sprint Time

Path	B	SE	*T*	*p*	95% CI
Total effect: KP → planned COD (c)	-0.1224	0.0401	-3.0560	0.0028	[-0.2018, -0.0431]
KP → 30-m sprint (a)	-0.0142	0.0071	-2.0067	0.0471	[-0.0283, -0.0002]
30-m sprint → planned COD (b)	1.5726	0.4989	3.1519	0.0021	[0.5846, 2.5606]
Direct effect: KP → planned COD (c′)	-0.1000	0.0393	-2.5461	0.0122	[-0.1778, -0.0222]
Indirect effect (a × b)	-0.0224	0.0142	–	–	[-0.0558, -0.0006]

Note: B = unstandardized coefficient; SE = standard error; CI = confidence interval; BootCI = bootstrap confidence interval. Model 1 adjusted for BMI and dynamic balance. The indirect effect used 5,000 bootstrap samples. Because the design is cross-sectional, a × b is interpreted as an indirect statistical association rather than causal mediation.

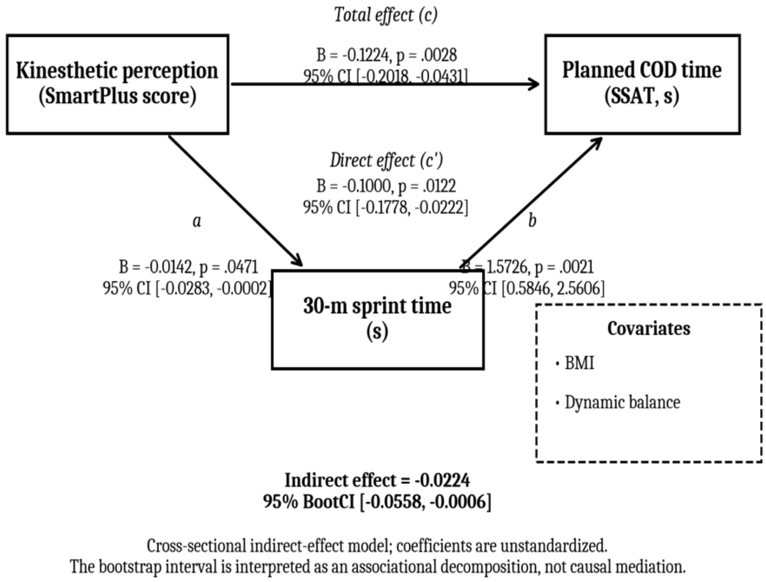

Figure 5. Cross-Sectional Indirect-Effect Model Linking Kinesthetic Perception with Planned COD Completion Time through 30-m Sprint Time. Coefficients Are Unstandardized; BMI and Dynamic Balance Were Covariates

The direction of the coefficients reflects the measurement scales. Higher kinesthetic-perception scores indicate better performance, whereas lower 30-m sprint and planned COD times indicate better performance. Accordingly, the negative a path indicates that higher kinesthetic-perception scores were associated with faster sprint times, and the negative total/direct effects indicate association with faster planned COD performance. The bootstrap indirect effect should be read as a statistical decomposition of concurrent associations rather than evidence that kinesthetic perception temporally causes changes in sprint or COD performance.

The second model examined BMI as the focal predictor while controlling for kinesthetic perception and dynamic balance (Table 4; Figure 6). Higher BMI was associated with longer 30-m sprint time ($B = 0.0362$, $SE = 0.0162$, $p = 0.0269$), and 30-m sprint time remained positively associated with planned COD time ($B = 1.5726$, $SE = 0.4989$, $p = 0.0021$). The total association between BMI and planned COD time was positive ($B = 0.3039$, $p = 0.0011$), and the direct association remained significant after 30-m sprint time was included ($B = 0.2470$, $p = 0.0069$). The bootstrap indirect effect was 0.0570 (95% BootCI [0.0121, 0.1191]). Thus, higher BMI was statistically associated with slower planned COD performance both directly and through the concurrent association with 30-m sprint time; the model does not establish temporal mediation.

Table 4. Indirect-Effect Analysis of BMI on Planned COD Performance Through 30-m Sprint Time

Path	B	SE	*t*	*p*	95% CI
Total effect: BMI → planned COD (c)	0.3039	0.0912	3.3319	0.0011	[0.1233, 0.4845]
BMI → 30-m sprint (a)	0.0362	0.0162	2.2408	0.0269	[0.0042, 0.0682]
30-m sprint → planned COD (b)	1.5726	0.4989	3.1519	0.0021	[0.5846, 2.5606]

Path	B	SE	*t*	*p*	95% CI
Direct effect: BMI → planned COD (c′)	0.2470	0.0898	2.7499	0.0069	[0.0691, 0.4248]
Indirect effect (a × b)	0.0570	0.0278	–	–	[0.0121, 0.1191]

Note: B = unstandardized coefficient; SE = standard error; CI = confidence interval; BootCI = bootstrap confidence interval. Model 2 adjusted for kinesthetic perception and dynamic balance. The indirect effect used 5,000 bootstrap samples and is interpreted as a cross-sectional statistical association.

Taken together, the two models show internally coherent coefficient patterns: better kinesthetic-perception scores were associated with shorter sprint and planned COD times, whereas higher BMI was associated with longer sprint and planned COD times. In both models, the direct association remained statistically significant after 30-m sprint time was included, indicating that the indirect component represented only part of the observed cross-sectional association.

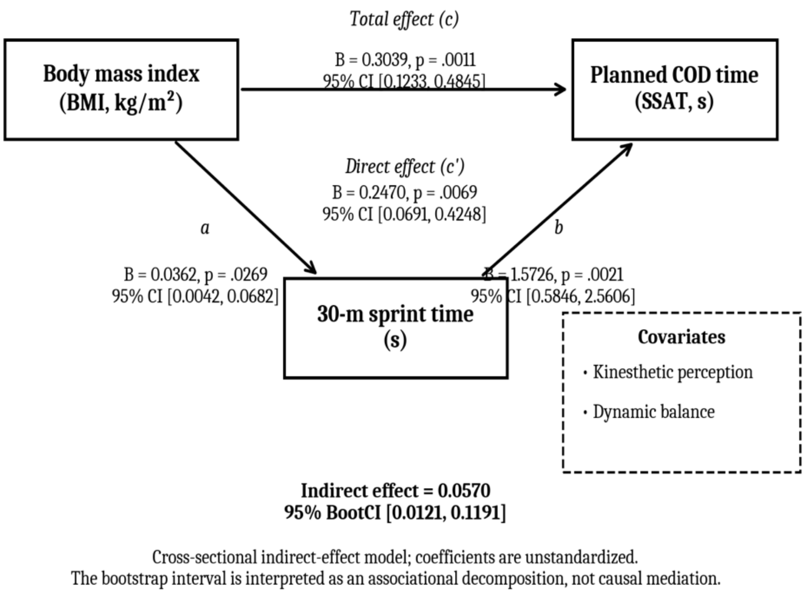

Figure 6. Cross-Sectional Indirect-Effect Model Linking BMI with Planned COD Completion Time through 30-m Sprint Time. Coefficients Are Unstandardized; Kinesthetic Perception and Dynamic Balance Were Covariates

Discussion

The primary measurement finding was a very high degree of correspondence between the sensor-based and conventional field assessments. SSAT and stopwatch times were strongly associated and differed by an average of -0.05 s. In contrast, SmartPlus and manual kinesthetic scores differed by an average of 0.12 points in the common sensor-minus-comparator direction. The corresponding approximate 95% LoA were -0.55 to 0.45 s for planned COD time and -3.06 to 3.30 points for kinesthetic perception. These results are consistent with broader evidence that wearable, embedded, and electronic measurement systems can support more standardised event detection and timing in field sport assessment (Camomilla et al., 2018; Cardinale & Varley, 2017; Chambers et al., 2015; Chen et al., 2021; Hülsdünker et al., 2023). Importantly, the present results support correspondence under the specific test protocol rather than criterion validity or unrestricted interchangeability.

That distinction is methodologically important. Pearson correlation evaluates the strength of a linear relationship, not the magnitude of disagreement between methods. Likewise, the reported ICC is an average-measures coefficient and is therefore not equivalent to a single-measure coefficient for a single method on a single athlete (Atkinson & Nevill, 1998; Hopkins, 2000; Weir, 2005; Liljequist et al., 2019). Bland–Altman analysis adds information on mean paired bias and the dispersion of individual differences (Bland & Altman, 1986; Bland & Altman, 1999). In the present report, LoA were recalculated from the paired summary statistics to maintain numerical consistency; because those inputs are rounded, the limits are reported as approximate. More importantly, acceptable LoA were not prospectively defined. Reporting guidance emphasises that practical interchangeability requires observed differences to be judged against tolerances that are defined in advance for the intended application (Gerke, 2020; Kottner et al., 2011). Consequently, the sensor system can be described as showing close field-based correspondence with the comparator methods, while stronger validation against criterion timing systems and prespecified tolerance limits remains necessary.

The cross-sectional indirect-effect analyses provide a second, complementary finding. Higher kinesthetic-perception scores were associated with shorter sprint and planned COD times, whereas higher BMI was associated with longer sprint and planned COD times. In both models, the bootstrap interval for the indirect effect through 30-m sprint time excluded zero. This pattern is compatible with evidence that linear speed, power-related qualities, and anthropometric characteristics co-vary with COD performance while remaining distinct constructs (Asadi et al., 2016; McBurnie et al., 2022; Nygaard Falch et al., 2019; Brand et al., 2024). However, because all variables were observed cross-sectionally, the models cannot establish that kinesthetic perception or BMI temporally influences sprint performance, or that sprint performance subsequently changes COD performance (Maxwell & Cole, 2007; Maxwell et al., 2011).

For kinesthetic perception, the coefficient directions were theoretically coherent. Combat sports place substantial demands on body-position control, rapid postural adjustment, and movement regulation (Bridge et al., 2014; Chaabène et al., 2012; Franchini et al., 2011). Proprioceptive and related sensorimotor functions are also relevant to combat-sport movement control (Jia et al., 2024). The present data extend this context by showing that higher kinesthetic-perception scores were concurrently associated with both faster 30-m sprint time and faster planned COD time. The direct association remained statistically significant after sprint time was included, suggesting that sprint performance did not fully account for the observed concurrent relationship.

For BMI, the positive coefficients indicate that athletes with higher BMI tended to record slower 30-m sprint and planned COD times. This direction is consistent with evidence that body size and body composition characteristics are associated with speed- and agility-related performance in adolescents (Brand et al., 2024). Nevertheless, raw BMI is an imperfect anthropometric exposure because it does not distinguish between lean and fat mass and may not closely reflect directly measured adiposity (Pescari et al., 2024). The observed BMI coefficients should therefore be treated as descriptive associations rather than evidence that greater adiposity caused poorer performance.

Overall, the study supports a multidimensional monitoring perspective in which planned COD, sprint time, kinesthetic perception, and dynamic balance are considered together rather than interpreted as interchangeable constructs. Sensor-based assessment may help standardise data acquisition, whereas multivariable analysis can help identify performance characteristics that co-vary within the athlete profile (Camomilla et al., 2018; Seçkin et al., 2023; Zhao et al., 2024). The practical value lies primarily in structured monitoring and hypothesis generation. The present cross-sectional evidence is insufficient to prescribe individualised training or to infer that changing one measured characteristic will necessarily improve another.

Implications

The findings have practical relevance for field-based athlete monitoring. Coaches may consider combining planned COD, 30-m sprint, kinesthetic-perception, and dynamic-balance assessments to obtain a broader performance profile, particularly during adolescence when physical capacities are developing rapidly (Tingelstad et al., 2023). Evidence from COD-training research also indicates that performance adaptations are task- and training-specific, reinforcing the value of monitoring multiple qualities rather than assuming that one test represents a complete agility profile (Asadi et al., 2016; Nygaard Falch et al., 2019). The sensor system may reduce dependence on manual timing and scoring during repeated monitoring sessions. Still, its use should remain protocol-specific until test–retest measurement error, single-measure agreement, and agreement against stronger criterion systems are established. The current data do not test whether training targeted at sprint, kinesthetic perception, balance, or body composition will improve planned COD performance.

Research contribution

This study contributes by integrating a field-based sensor-conventional-method comparison with a cross-sectional indirect-effect analysis in a heterogeneous sample of junior martial arts athletes. The measurement component quantifies both relative correspondence and absolute paired differences. In contrast, the regression component indicates that 30-m sprint time statistically accounts for part of the concurrent association between kinesthetic perception and BMI and planned COD performance. The combined framework offers a more cautious and reproducible basis for multidimensional athlete monitoring than an interpretation based solely on correlations or isolated performance scores.

Limitations

Several limitations constrain interpretation. First, the cross-sectional design precludes claims of temporal or causal mediation. Second, the conventional comparator methods were not criterion standards; therefore, correspondence should not be interpreted as criterion validity. Third, the available ICC statistic was the prespecified average-measures absolute-agreement coefficient; a single-measure absolute-agreement ICC with its 95% confidence interval would be more directly relevant to replacement of one method by another in an individual athlete. Fourth, the Bland–Altman LoA reported here were recalculated from rounded paired summary statistics and are therefore approximate; participant-level proportional bias and heteroscedasticity diagnostics are not reported. Fifth, a priori acceptable agreement limits were not defined, so practical interchangeability cannot be established. Sixth, the preliminary one-week test–retest check was summarised with Pearson correlations rather than ICC-based reliability and measurement-error indices. Seventh, the original sampling plan was not based on analysis-specific agreement precision or indirect-effect power. Eighth, raw BMI is developmentally limited in athletes aged 14-17 years, and age, sex, biological maturation, training experience, and martial arts discipline were not included as covariates; residual confounding is therefore possible. Finally, inclusion of eight disciplines introduces sport-specific heterogeneity. These limitations favour cautious, protocol-specific interpretation and independent replication.

Suggestions

Future work should prioritise prospective validation and longitudinal designs. Sensor-based timing should be compared with electronic timing gates or another defensible criterion, with prespecified acceptable differences, and single-measure absolute agreement ICCs, Bland–Altman confidence intervals, SEM, MDC, and test–retest reliability reported (Atkinson & Nevill, 1998; Weir, 2005; Kottner et al., 2011). Agreement studies should be planned using precision-based sample-size methods (Gerke et al., 2022). Longitudinal models should establish temporal ordering among kinesthetic perception, 30-m sprint performance, and planned COD performance, rather than inferring causal mediation from concurrent data (Maxwell & Cole, 2007; Maxwell et al., 2011). In adolescent samples, direct body-composition measures and biological maturation should be considered alongside age, sex, discipline, and training experience. Replication within individual martial arts disciplines would further clarify the generalisability of the present field-testing framework.

CONCLUSION

Under the present field-testing protocol, the sensor-based SSAT and SmartPlus assessments showed very high correspondence and small mean bias relative to their conventional field comparators. The approximate 95% LoA quantify materially wider individual paired differences than the mean biases alone, and the absence of prospectively acceptable differences and criterion comparators prevents a claim of definitive interchangeability. Cross-sectional indirect-effect models also showed that 30-m sprint time accounted for part of the concurrent associations between kinesthetic perception and BMI and planned COD performance. These findings support cautious use of the sensor system for structured athlete monitoring and justify prospective criterion validation and longitudinal research, rather than causal or training-effect conclusions.

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AUTHOR CONTRIBUTION STATEMENT

All authors meet the criteria for authorship in accordance with established ethical guidelines. D.K.A.F. contributed to the conceptualisation, study design, methodology, data collection, formal and statistical analysis, manuscript preparation, and funding acquisition. J.L. contributed to the conceptualisation, study design, methodology, manuscript preparation, writing—review and editing, and funding acquisition. R.P. contributed to the conceptualisation, study design, methodology, and manuscript preparation. W.D. contributed to the conceptualisation, study design, and methodology. All authors have critically reviewed and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

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AI DISCLOSURE STATEMENT

During manuscript preparation, the authors used artificial intelligence tools only for language refinement and readability. AI tools were not used to generate, alter, or analyse the study data or to determine the statistical results. The authors reviewed and verified the final manuscript and take full responsibility for its accuracy, integrity, and scientific content.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

ETHICAL APPROVAL

Participation was voluntary, and all participants provided informed consent. Ethical approval was granted by Universitas Negeri Jakarta (Approval No. 828/UN39.14/PT.01.05/VI/2026), and the study was conducted in accordance with the principles of the Declaration of Helsinki.

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