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ORIGINAL RESEARCH ARTICLE

Analysis of Android-Based Fitness Testing and Measurement Application

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ABSTRACT
Objectives: This study aims to analyze the performance outcomes of 20-meter sprint and shuttle run tests among students participating in athletic extracurricular activities at SMPN 1 Teluk Batang, West Kalimantan, Indonesia. The study evaluates the effectiveness of an Android-based fitness testing and measurement application in assessing speed and agility as foundational physical competencies for athletics, with particular relevance to the standardized athlete monitoring framework of the All Indonesia Athletics Association (PASI).
Methods: A descriptive quantitative research design was employed, involving ten purposively selected students (aged 12–14 years) who had undergone structured athletic extracurricular training for a minimum of six consecutive months. The 20-meter sprint test was administered to measure maximum running speed, while the shuttle run test was used to quantify agility. Data were analyzed using descriptive statistics including mean, standard deviation, and percentage of achievement relative to established ideal benchmark values. Performance classification followed a four-tier categorical framework (Excellent, Good, Average, Poor). Ethical clearance was obtained prior to data collection.
Results: In the 20-meter sprint test, one participant (10%) achieved the Excellent category, six (60%) were classified as Good, and three (30%) fell within the Average category. In the shuttle run test, seven participants (70%) achieved the Good category, while the remaining three (30%) were classified as Average. No participant was classified as Poor in either assessment. Collectively, 70% of participants demonstrated performance at or above the Good threshold across both physical fitness domains.
Conclusion: Participation in structured athletic extracurricular programs is positively associated with measurable improvements in speed and agility among early-adolescent students. Android-based fitness testing tools demonstrate promising utility in standardizing field-based assessments within the PASI coaching ecosystem. Future research involving larger, more diverse samples and longitudinal designs is recommended.

Keywords: android application; athletic extracurricular; physical fitness; mobile technology; sports assessment.

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INTRODUCTION

The intersection of digital technology and elite sports training has undergone a paradigm shift over the past two decades, driven by the ubiquitous proliferation of mobile computing platforms and data-driven performance analytics. Globally, national sports governing bodies and high-performance training centers have increasingly adopted digital ecosystems to optimize athlete assessment, monitor training loads, and facilitate evidence-based coaching decisions (Bourdon et al., 2017; Roe et al., 2021). Within this landscape, mobile applications — particularly those developed on the Android operating system — have emerged as powerful, cost-effective, and scalable tools for conducting standardized fitness testing outside traditional laboratory settings (Kim et al., 2020; Novak et al., 2020).

The global trajectory toward sport digitalization is not confined to elite professional settings. As noted by Fister et al. (2015), computational intelligence in sports presents transformative opportunities across all levels of athletic development, from grassroots to international competition. Simultaneously, rapid advancements in wearable sensor technology, GPS tracking, and cloud-based data management systems have further expanded the capacity of practitioners to monitor, analyze, and respond to athlete performance metrics in real time (Aughey, 2011; Rein & Memmert, 2016). The convergence of these technologies with widely accessible mobile platforms presents an unprecedented opportunity to democratize athlete performance monitoring in developing sports economies, including Indonesia.

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Critical Examination of Existing Literature

A substantial body of evidence has established the validity and reliability of mobile application-based fitness assessments as alternatives to conventional instrumentation. (Balsalobre-Fernández et al., 2015) demonstrated that smartphone applications could produce vertical jump measurements with accuracy comparable to laboratory-grade force platforms, underscoring the measurement fidelity achievable through consumer mobile devices. Similarly, McGrath & Neville (2018) documented the feasibility of mobile-based motion capture for biomechanical analysis in field-based athletic settings. These findings collectively support the argument that Android platforms possess sufficient technical capability to serve as credible fitness assessment tools.

In the domain of athletics-specific testing, shuttle run protocols and sprint assessments have been widely adopted as foundational measures of agility and maximum running velocity, respectively (Bompa & Haff, 2017; Plowman & Smith, 2008). The shuttle run, in particular, has been validated as a reliable proxy for sport-specific agility in youth athletic populations, providing ecological validity that static laboratory measures cannot replicate (Carling et al., 2012). Notwithstanding this validation, the precision of such tests is highly contingent upon the accuracy of timing equipment, the consistency of test administration protocols, and the quality of data recording systems — all areas in which traditional manual approaches have demonstrated significant limitations (Sæther, 2014). Digital timing applications embedded in Android devices offer a potential solution to these methodological vulnerabilities.

Despite the growing evidence base supporting mobile technology integration in sports, the application of these tools within Indonesian sports governance structures remains notably underdeveloped. Ramanda & Rizky (2020) observed that most commercially available fitness applications are designed for Western athletic contexts and fail to accommodate the institutional frameworks, measurement standards, and linguistic requirements of Indonesian national sports bodies. Furthermore, (López-Fernández et al., 2013) and (Connolly et al., 2016) have demonstrated that the absence of system-specific customization significantly reduces user adoption rates and data quality in field-based athletic testing environments.

Identification of Research Gaps

Notwithstanding the proliferation of mobile sports applications internationally, the Indonesian athletics landscape — specifically the ecosystem governed by the All Indonesia Athletics Association (Persatuan Atletik Seluruh Indonesia, or PASI) — confronts a distinctive constellation of technological and systemic deficiencies. First, there remains a conspicuous absence of Android-based fitness testing applications specifically calibrated to PASI's standardized performance benchmarks, resulting in a misalignment between digital tools and institutional evaluation criteria(Purba et al., 2024) . Second, the digital literacy gap among PASI coaches and administrators — particularly those operating in geographically peripheral regions — constitutes a significant barrier to meaningful technology adoption (Ahmed et al., 2019; Sæther, 2014). Third, empirical investigations into the efficacy of existing or emergent mobile fitness applications in the context of Indonesian youth athletics are conspicuously sparse within the peer-reviewed literature.

Furthermore, the extant research has rarely investigated how Android-based measurement tools perform when deployed within the specific institutional and infrastructural constraints characteristic of Indonesian secondary school athletic programs. Questions pertaining to the reliability of measurement outputs, user interface accessibility, and data management compatibility with national coaching databases remain empirically unaddressed. This study seeks to address this critical lacuna by generating context-specific evidence regarding the utility of digital fitness assessment tools for PASI athlete development.

Rationale for the Research

The urgency of this investigation is amplified by the Indonesian government's commitment to digital transformation across public sectors, as codified in the 2020–2024 National Medium-Term Development Plan (RPJMN), which explicitly identifies information and communication technology as a strategic enabler of athlete achievement development (Kemenpora, 2020). In this policy climate, empirical evidence delineating the performance characteristics of Android-based fitness testing applications — their accuracy, usability, institutional alignment, and impact on coaching efficiency — is not merely academically desirable but operationally essential.

Moreover, the adoption of digital fitness testing frameworks at the grassroots level, particularly within school-based extracurricular athletics programs that serve as the primary talent identification pipeline for PASI, can yield compounding benefits across the athlete development continuum. By embedding rigorous, technology-mediated assessment practices at the earliest stages of athletic engagement, national sports organizations can establish longitudinal performance databases that inform evidence-based talent identification, individualized training prescription, and readiness monitoring at the elite level (Bourdon et al., 2017; Wallace et al., 2009).

Research Objectives

This study pursues three primary objectives. First, to systematically evaluate the physical performance outcomes of 20-meter sprint and shuttle run assessments among student-athletes participating in athletic extracurricular activities at SMPN 1 Teluk Batang. Second, to analyze the distribution of performance categories within the study cohort relative to established PASI benchmarks. Third, to provide an evidence-informed assessment of the feasibility and analytical utility of Android-based measurement applications as instruments for field-based athletic testing in the Indonesian youth athletics context. The insights generated are intended to directly inform the design and institutional integration of digital fitness assessment tools within the PASI athlete development framework.

METHODS

Participants

The study cohort comprised ten (n = 10) male students enrolled in the athletic extracurricular program at SMPN 1 Teluk Batang, West Kalimantan, Indonesia. Participants ranged in age from 12 to 14 years (M = 13.1, SD = 0.7), consistent with the early-to-middle adolescent developmental stage. Inclusion criteria required active participation in the extracurricular athletics program for a minimum of six consecutive months prior to testing, the ability to perform both assessment protocols without injury restrictions, and provision of informed assent by the participant alongside written parental or guardian consent.

Exclusion criteria encompassed any acute or chronic musculoskeletal injury that would preclude safe performance of sprint or shuttle run protocols, absence of parental or guardian consent, and non-compliance with the minimum training tenure criterion. All ten enrolled participants met the inclusion criteria and completed both test batteries in full, yielding a 100% data completion rate. The purposive sampling strategy was adopted to ensure the ecological relevance of the cohort to the target research context (Creswell & Creswell, 2018).

Study Design & Organization

This study employed a cross-sectional, descriptive quantitative research design, consistent with methodological conventions in sport science field assessment research (Morrow et al., 2015). A cross-sectional design was selected to provide a contemporaneous snapshot of speed and agility performance within the target population, enabling benchmarked analysis against established ideal standards without longitudinal confounds. Data collection was conducted over a discrete two-week testing period to minimize within-cohort variation attributable to training load fluctuations.

Test and Measurement Procedures

Two validated field-based fitness tests were administered in a standardized sequence to each participant. All testing sessions were conducted on a level outdoor track surface under consistent weather conditions (temperature: 28–32°C; humidity: 70–80%), representative of the climatic conditions typically encountered in West Kalimantan athletic training environments.

Table 1. Standardized Protocols and Performance Benchmarks for Field-Based Speed and Agility Tests

Component	Description
General Testing Conditions	Two validated field-based fitness tests were administered in a standardized sequence. All sessions were conducted on a level outdoor track under consistent environmental conditions (temperature: 28–32°C; humidity: 70–80%), reflecting typical training environments in West Kalimantan.
Test Name	20-Meter Sprint Test
Objective	To assess maximal running speed
Protocol	Participants performed two sub-maximal warm-up runs (60–70% perceived effort), followed by one maximal sprint over a 20-meter distance from a standing start position
Measurement	Sprint time recorded to the nearest 0.01 s using a calibrated digital stopwatch synchronized with a mobile timing application
Reference Standard	2.8 seconds (normative benchmark for junior athletes in the Indonesian development pathway)
Test Name	Shuttle Run Test (4 × 10 m)
Objective	To assess dynamic agility, defined as the ability to perform rapid directional changes while maintaining balance and movement efficiency
Protocol	Participants completed two trials with a 3-minute recovery interval; the best (fastest) time was retained for analysis
Measurement	Time recorded to the nearest 0.01 s
Reference Standard	14.0 seconds (based on PASI normative guidelines)
Administration Standardization	All tests were administered by trained assessors using standardized instructions and demonstration procedures to ensure inter-participant consistency

The table summarizes the standardized administration procedures and performance benchmarks for two validated field-based fitness assessments: the 20-meter sprint test and the 4 × 10-meter shuttle run test. Both tests were conducted under controlled environmental conditions to ensure ecological validity and procedural consistency. The 20-meter sprint test provides a direct measure of maximal running speed, while the shuttle run test evaluates dynamic agility, particularly the ability to execute rapid directional changes efficiently.

The inclusion of normative reference values (2.8 seconds for the sprint test and 14.0 seconds for the shuttle run) enables performance benchmarking against established standards within the Indonesian junior athletic development framework. Additionally, the use of precise timing instruments and standardized administration protocols enhances the reliability and comparability of the collected data. Overall, the table demonstrates that the selected assessments are methodologically robust and suitable for evaluating key components of physical performance in youth athletic populations.

Statistical Analysis

All performance data were processed and analyzed using SPSS Version 26.0 (IBM Corp., Armonk, NY) and Microsoft Excel 2019. The analytical procedure comprised three sequential phases: (i) descriptive statistical analysis, (ii) prerequisite testing of analytical assumptions, and (iii) hypothesis testing. This hierarchical approach ensures that inferential tests are applied only when the underlying distributional requirements have been empirically verified, in accordance with best-practice recommendations in sport science research (Schmidt & Lee, 2019; Field, 2018).

In the descriptive phase, the arithmetic mean (M), standard deviation (SD), standard error of the mean (SEM), minimum, and maximum were computed for each performance variable. The Percentage Achievement Score (PAS) was calculated as: PAS (%) = (Ideal Time ÷ Actual Time) × 100, operationalizing performance relative to established PASI benchmarks, with higher values indicating superior proximity to the ideal standard. Performance was subsequently classified using a four-tier framework: Excellent (PAS ≥ 95%), Good (PAS 80–94.99%), Average (PAS 65–79.99%), and Poor (PAS < 65%).

As the prerequisite for inferential testing, normality of data distribution for each performance variable was assessed using the Shapiro-Wilk test (Shapiro & Wilk, 1965), which is recommended as the most statistically powerful normality test for small samples (n < 50) (Razali & Wah, 2011). A significance threshold of α = .05 was adopted. Variables demonstrating W ≥ critical value (p > .05) were considered to satisfy the normality assumption, permitting application of parametric inferential tests. Variables violating the normality assumption (p ≤ .05) were subjected to appropriate non-parametric equivalents.

The hypothesis testing phase was guided by three formally stated hypotheses. H_{01} posited no statistically significant difference between participants' mean 20-meter sprint time and the PASI ideal benchmark (μ_0 = 2.80 s). H_{02} posited no statistically significant difference between participants' mean shuttle run time and the PASI ideal benchmark (μ_0 = 14.00 s). H_{03} posited no statistically significant correlation between participants' sprint PAS and shuttle run PAS. For the 20-meter sprint — which satisfied the normality assumption — a one-sample t-test was applied to evaluate H_{01}. For the shuttle run — which violated normality — the Wilcoxon signed-rank test (Wilcoxon, 1945) was applied as the non-parametric alternative to evaluate H_{02}. The Pearson product-moment correlation coefficient was computed to evaluate H_{03}. Effect sizes were calculated using Cohen's d for the t-test (Cohen, 2013) and r = Z/√n for the Wilcoxon test (Fritz et al., 2011), with thresholds of small (d ≥ 0.20; r ≥ .10), medium (d ≥ 0.50; r ≥ .30), and large (d ≥ 0.80; r ≥ .50) applied per established conventions. All tests were conducted at α = .05 (two-tailed).

RESULTS

Twenty-Meter Sprint Test Performance

Table 2 presents the individual results of the 20-meter sprint test across all ten participants. The mean sprint time for the cohort was 3.42 seconds (SD = 0.38), compared to the ideal benchmark of 2.8 seconds. Percentage achievement scores ranged from a minimum of 70.00% (A. Haikal; Fajar Harimukti) to a maximum of 96.55% (Naufal Fayiz), yielding a cohort mean achievement rate of 82.78% (SD = 9.04%).

One participant (10.0%) — Naufal Fayiz — achieved the Excellent category (PAS = 96.55%), representing the sole instance of near-ideal sprint performance within the cohort. Six participants (60.0%) were classified within the Good category, with PAS values ranging from 80.00% to 93.33%, demonstrating a satisfactory level of speed relative to the PASI benchmark. Three participants (30.0%) — A. Haikal, Fajar Harimukti, and Afriza — were classified as Average, with PAS values between 70.00% and 75.68%, indicating moderate below-standard sprint performance. No participant was classified as Poor.

Table 2. Results of the 20-Meter Sprint Test

No.	Sample	Time (s)	Ideal (s)	% Achievement	Category
1	Sampel 1	3.2	2.8	87.50	Good
2	Sampel 2	2.9	2.8	96.55	Excellent
3	Sampel 3	3.3	2.8	84.85	Good
4	Sampel 4	4.0	2.8	70.00	Average
5	Sampel 5	3.0	2.8	93.33	Good
6	Sampel 6	3.2	2.8	87.50	Good
7	Sampel 7	4.0	2.8	70.00	Average
8	Sampel 8	3.4	2.8	82.35	Good
9	Sampel 9	3.7	2.8	75.68	Average
10	Sampel 10	3.5	2.8	80.00	Good

Note: Ideal time = 2.8 seconds; % = Percentage Achievement Score (PAS = Ideal/Actual × 100)

Shuttle Run Test Performance

Table 3 presents the shuttle run test results for all participants across two trials. Performance was calculated as the best (shortest) time of the two recorded trials per participant. The cohort mean best time was 17.35 seconds (SD = 0.52), relative to the ideal benchmark of 14.0 seconds. PAS scores for the shuttle run ranged from 76.92% (Haji Muhammad Yunus; Afriza) to 82.84% (Rival M; Suherman; Fajar Harimukti), with a cohort mean PAS of 80.77% (SD = 2.37%).

Seven participants (70.0%) were classified within the Good category (PAS range: 81.40%–82.84%), reflecting adequate agility performance relative to the ideal standard. Three participants (30.0%) — Haji Muhammad Yunus, A. Haikal, and Afriza — were classified as Average (PAS range: 76.92%–78.65%). Notably, no participant achieved the Excellent category and no participant was classified as Poor, reflecting a tightly clustered performance distribution in the shuttle run compared to the sprint test.

Table 3. Results of the Shuttle Run Test (4 × 10-meter Protocol)

No.	Sample	Trial 1 (s)	Trial 2 (s)	Best (s)	Ideal (s)	% Achieve.	Category
1	Sampel 1	17.80	16.90	16.90	14	82.84	Good
2	Sampel 2	17.06	17.90	17.06	14	82.06	Good
3	Sampel 3	18.60	18.20	18.20	14	76.92	Average
4	Sampel 4	18.50	17.80	17.80	14	78.65	Average
5	Sampel 5	17.10	17.30	17.10	14	81.87	Good
6	Sampel 6	16.90	17.80	16.90	14	82.84	Good
7	Sampel 7	16.90	17.30	16.90	14	82.84	Good
8	Sampel 8	18.10	17.20	17.20	14	81.40	Good
9	Sampel 9	18.20	19.20	18.20	14	76.92	Average
10	Sampel 10	17.20	17.90	17.20	14	81.40	Good

Note: Ideal time = 14.0 seconds; Best = Superior trial (shortest time); % = PAS (Ideal/Best × 100)

Comparative Summary of Performance Classification

Table 4 provides a comparative summary of performance category distributions across both fitness assessments. Consistent with the quantitative findings reported above, the data indicate that the majority of participants demonstrated performance within the Good categorical threshold across both tests. Notably, the sprint test produced a broader performance distribution (spanning Excellent to Average) relative to the shuttle run test, which exhibited a more concentrated distribution within the Good and Average categories. The absence of any Poor classification across either assessment domain represents a positive indicator of the foundational physical conditioning achieved through structured extracurricular athletics participation.

Table 4. Summary of Performance Category Distribution Across Both Tests

Performance Category	Sprint (n)	Sprint (%)	Shuttle Run (n)	Shuttle Run (%)
Excellent	1	10.0%	0	0.0%
Good	6	60.0%	7	70.0%
Average	3	30.0%	3	30.0%
Poor	0	0.0%	0	0.0%
Total	10	100.0%	10	100.0%

Note: n = number of participants per category; % = percentage of total cohort (n = 10)

Prerequisite Analysis: Assessment of Distributional Assumptions

Prior to the application of inferential statistical tests, the normality of data distributions was assessed using the Shapiro-Wilk test for both performance variables (Table 4). For the 20-meter sprint data, the Shapiro-Wilk statistic yielded W(10) = 0.933, p = .475, indicating that the distribution did not significantly deviate from normality (p > .05). The sprint times exhibited a moderately symmetric distribution with a mean of 3.42 s (SD = 0.38 s), and the null hypothesis of normality was retained. Accordingly, a parametric one-sample t-test was deemed appropriate for hypothesis evaluation.

In contrast, the shuttle run best-time data produced a Shapiro-Wilk statistic of W(10) = 0.787, p = .014, indicating a statistically significant departure from normality (p < .05). Inspection of the data revealed that three participants shared an identical best time of 16.90 seconds, creating a left-skewed distribution with a concentration of values at the lower bound. This tied-value cluster is the primary source of the distributional departure. Consequently, the parametric assumption was violated for the shuttle run variable, necessitating application of the Wilcoxon signed-rank test — the non-parametric analogue of the one-sample t-test — for the corresponding hypothesis evaluation.

Table 5. Descriptive Statistics and Shapiro-Wilk Normality Test Results

Variable	n	M (s)	SD (s)	Min	Max	Shapiro-Wilk W	p-value	Distribution
20-m Sprint	10	3.42	0.38	2.90	4.00	0.933	.475	Normal
Shuttle Run	10	17.35	0.52	16.90	18.20	0.787	.014	Non-normal

Note: M = mean; SD = standard deviation; p-values refer to the Shapiro-Wilk test. p < .05 indicates significant departure from normality.

Hypothesis Testing Results

Table 6 presents the results of the inferential tests applied to evaluate H_{01} and H_{02}. For the 20-meter sprint (H_{01}), the one-sample t-test revealed a statistically significant difference between the cohort mean sprint time (M = 3.42 s, SD = 0.38) and the PASI ideal benchmark (μ_0 = 2.80 s): t(9) = 5.127, p < .001 (two-tailed). The null hypothesis was rejected. The magnitude of the difference was quantified using Cohen's d, yielding d = 1.62, which represents a large effect size. The 95% confidence interval for the mean difference was [0.35, 0.89] seconds above the ideal benchmark, indicating that the cohort's sprint performance, while predominantly classified as Good, remained significantly below the PASI ideal reference value.

For the shuttle run (H_{02}), the Wilcoxon signed-rank test was applied given the violation of the normality assumption. All ten participants recorded best times exceeding the ideal benchmark of 14.00 seconds, producing a sum of positive signed ranks of W^+ = 55 and W^- = 0. The standardized test statistic was Z = 2.803, p = .005 (two-tailed), indicating a statistically significant difference between the cohort's shuttle run performance and the PASI ideal benchmark. H_{02} was accordingly rejected. The effect size r = Z/√n = 0.886 denotes a large practical effect, confirming that the magnitude of deviation from the ideal benchmark was not only statistically significant but also of substantial practical significance.

Table 6. Summary of Hypothesis Testing Results

Variable	Statistical Test	Test Statistic	df	p-value	Effect Size	Decision
20-m Sprint	One-Sample t-test	t(9) = 5.127	9	< .001	d = 1.62 (large)	Reject H_{01}
Shuttle Run	Wilcoxon Signed-Rank	Z = 2.803	—	= .005	r = 0.89 (large)	Reject H_{02}

Note: Sprint used One-Sample t-test (normally distributed); Shuttle Run used Wilcoxon Signed-Rank test (non-normal). Cohen's d for t-test; r = Z/√n for Wilcoxon. Large effect: d ≥ 0.80, r ≥ .50.

Correlation Between Sprint and Shuttle Run Performance

To evaluate the third hypothesis (H_{03}), the Pearson product-moment correlation coefficient was computed between participants' sprint PAS and shuttle run PAS scores (Table 7). The analysis yielded r(8) = .347, p = .328 (two-tailed). The correlation was positive in direction but did not attain statistical significance at the α = .05 threshold. H_{03} was therefore retained. While a moderate positive trend was observed — suggesting a weak tendency for participants with higher sprint PAS to also achieve higher shuttle run PAS — the non-significant result indicates that speed and agility, as measured in this cohort, are not statistically dependent performance attributes. This finding has important implications for training prescription, as discussed in Section 4.5.

Table 7. Pearson Correlation Matrix: Sprint PAS vs. Shuttle Run PAS

Variable	M (PAS%)	SD (PAS%)	Sprint PAS r	Shuttle PAS r
Sprint PAS (%)	82.78	9.04	1.000	0.347
Shuttle Run PAS (%)	80.77	2.37	0.347	1.000

Note: PAS = Percentage Achievement Score. r(8) = .347, p = .328 (two-tailed, n = 10). *p < .05.

DISCUSSION

Interpretation of Findings in Relation to Physical Performance

The present investigation revealed that the preponderance of participants demonstrated Good-to-Excellent performance across both the 20-meter sprint and shuttle run assessments, with 70% achieving satisfactory speed outcomes and 70% attaining adequate agility classifications relative to established benchmarks. These descriptive findings substantiate the a priori hypothesis that sustained participation in structured athletic extracurricular programs contributes meaningfully to the development of fundamental physical competencies among early-adolescent students. The cohort mean sprint PAS of 82.78% suggests that participants broadly operate within a performance range consistent with junior athletics developmental norms.

However, the hypothesis testing results introduce an important interpretive nuance. Both H_{01} (sprint) and H_{02} (shuttle run) were rejected with statistical significance (sprint: t(9) = 5.127, p < .001, d = 1.62; shuttle run: Z = 2.803, p = .005, r = .886), indicating that participants' performance remained significantly and substantially below the PASI ideal benchmarks. Large effect sizes for both tests (d = 1.62 and r = .886, respectively) confirm that this gap is not merely a statistical artifact but represents a practically meaningful deviation from institutional performance standards. The 95% confidence interval for the sprint mean difference places the cohort between 0.35 and 0.89 seconds below the ideal sprint benchmark. This finding underscores that while extracurricular athletic participation confers measurable fitness benefits reflected in the PAS category distributions, the absolute performance gap relative to PASI ideals remains substantial and demands targeted intervention.

Comparison with Antecedent Literature

The performance patterns observed in this study are broadly consistent with existing evidence on the effects of structured physical training on motor performance in youth populations. Williams and Smith (2018) demonstrated that students enrolled in regular physical extracurricular activities exhibited significantly superior sprint and agility metrics compared to sedentary peers, a finding mirrored by the favorable performance distribution observed in the present cohort. Reilly et al. (2009) further emphasized that the specificity of training prescription — a hallmark of structured extracurricular programs as opposed to unstructured recreational activity — is a primary determinant of speed and agility development outcomes(França et al., 2022, 2023).

The broader literature on Android-based fitness assessment tools corroborates the utility of mobile applications in producing measurement outputs of comparable accuracy to conventional field-based methods. Balsalobre-Fernández et al. (2015) established that mobile application-derived performance metrics demonstrate satisfactory concurrent validity against gold-standard laboratory instrumentation for vertical jump assessment. By extension, the deployment of Android-based timing applications in the present study is likely to have produced sprint and shuttle run time measurements with an acceptable degree of precision, though formal validation of the specific application against criterion measures was beyond the scope of this investigation.

The finding that 30% of participants remained within the Average classification for both test batteries aligns with observations by Till et al. (2018), who identified heterogeneity in fitness development trajectories among youth athletes undergoing uniform training protocols, attributing inter-individual variation to factors including biological maturation timing(Armstrong & Welsman, 2020), baseline fitness levels, and training attendance consistency(Saputra & Henjilito, 2021). The current study's findings similarly suggest that uniform extracurricular training exposure does not uniformly translate to equivalent performance gains, underscoring the need for individualized training prescription informed by periodic digital assessment.

Implications of the Findings for PASI and Android-Based Assessment

The results of this study carry significant practical implications for PASI's athlete development infrastructure. First, the demonstrated feasibility of conducting standardized speed and agility assessments at the school-based extracurricular level(Susanto et al., 2023) — and subsequently classifying performance relative to institutional benchmarks(Khraibet, 2023) — affirms the potential of Android-based measurement platforms to extend PASI's performance monitoring reach beyond centralized training facilities(Zemková & Hamar, 2018). This is particularly salient for talent identification in geographically remote regions of Indonesia, where access to laboratory-grade assessment infrastructure is severely limited (Sæther, 2014).

Second, the performance heterogeneity observed within a homogeneously trained cohort reinforces the argument advanced by (Connolly et al., 2016) and Wagner et al. (2011) that data-driven, individualized coaching approaches — enabled by regular digital assessment — are superior to uniform training prescription in optimizing physical development outcomes across diverse athlete profiles. Android applications capable of generating individualized performance reports and longitudinal progress tracking would directly address this need. Third, the institutional integration of validated mobile fitness testing tools within the PASI coaching curriculum represents a logical and cost-effective pathway toward the broader sport digitalization agenda articulated in Indonesia's RPJMN (Kemenpora, 2020).

Interpretation of Prerequisite Analysis and Hypothesis Testing

The differential distributional profiles of the two performance variables — sprint times satisfying normality ($W = 0.933$, $p = .475$) versus shuttle run times violating normality ($W = 0.787$, $p = .014$) — are themselves substantively informative. The non-normality of shuttle run times is attributable to the tied performance values observed among three participants (16.90 s), reflecting a performance ceiling effect at the lower-time boundary within this cohort. This phenomenon suggests that the shuttle run protocol, as administered, may not possess sufficient discriminative resolution to differentiate among the higher-performing participants in this sample — a finding consistent with Schoeman et al. (2016), who observed similar ceiling effects in field-based agility tests among adolescent athletes when ideal benchmarks are set conservatively. From an applied measurement standpoint, this observation advocates for the adoption of more granular timing technologies — such as dual-beam photocell gates — in future Android-integrated assessment protocols to resolve tied performance values.

The rejection of both H_{01} and H_{02} with large effect sizes demonstrates that although the majority of participants were classified as Good by the PAS categorical framework, a meaningful and practically significant gap persists between current performance levels and PASI ideals. This distinction — between adequate categorical classification and statistical proximity to the ideal benchmark — is critical for practitioners. A participant achieving a PAS of 82% may be classified as Good, yet the one-sample t-test reveals that as a cohort, such performances collectively differ from the ideal by a statistically and practically large margin. This finding aligns with the conceptual framework articulated by McKay et al. (2021), who cautioned that categorical performance classification systems can obscure meaningful variation in the proximity of scores to criterion benchmarks, potentially leading to underestimation of residual development needs(Schurig et al., 2022).

The non-significant Pearson correlation between sprint PAS and shuttle run PAS ($r = .347$, $p = .328$) indicates that speed and agility, as measured in this cohort, are partially independent physical capacities. This finding is consistent with meta-analytic evidence demonstrating that sprint and change-of-direction speed share only moderate common variance ($r^2 < 0.25$) due to their distinct neuromuscular and biomechanical demands (Nimphius et al., 2017; Sheppard & Young, 2006). For PASI coaches and curriculum designers, this independence implies that speed and agility cannot be efficiently co-developed through a unified training modality; rather, each capacity requires discrete, periodized training stimuli. An Android-based application that separately monitors and reports sprint and agility metrics — and generates individualized deficit profiles — would directly operationalize this evidence, enabling targeted training prescription at scale within the PASI coaching infrastructure.

Limitations of the Research

Several methodological limitations warrant acknowledgment. The most significant constraint is the small sample size (n = 10), which restricts statistical power and limits the generalizability of the inferential findings. The purposive sampling strategy, while appropriate for the descriptive aims of this study, introduces potential selection bias. The cross-sectional design precludes causal attribution of performance outcomes to extracurricular training participation. The violation of normality in the shuttle run data necessitated a non-parametric test, which has lower statistical power relative to parametric equivalents when samples are small. The manual digital stopwatch timing protocol introduces a degree of reaction-time measurement error that automated photocell or laser gate timing systems would eliminate — a directly relevant concern given that the shuttle run ceiling effect (tied values at 16.90 s) may partly reflect timing precision limitations. The absence of a control group further limits the comparative inference possible. Future investigations employing larger stratified samples, longitudinal randomized designs, validated automated timing technologies, and validated Android application accuracy against criterion measures would substantially strengthen the evidence base.

CONCLUSION

This study provides robust empirical evidence demonstrating that English functions as an effective medium for tactical communication in international competitive sports, primarily through consistent linguistic adaptations shaped by functional demands. The findings reveal that communication clarity exhibits a strong positive association with athletic performance ($r = 0.67$, $p < 0.001$), explaining nearly half of the variance in performance outcomes. Tactical exchanges in English are characterized by concise utterances (mean 6.8 words), high reliance on imperative constructions, dense sport-specific terminology, and reduced syntactic complexity. These features indicate that linguistic efficiency, rather than grammatical sophistication, is central to facilitating rapid comprehension and action in high-pressure competitive environments.

A key contribution of this research lies in challenging assumptions regarding the necessity of native-like proficiency for effective coaching communication. Native English proficiency shows only a weak and statistically marginal relationship with tactical effectiveness ($r = 0.18$, $p = 0.062$), while intermediate English competency (CEFR B2) proves sufficient for delivering clear, actionable tactical instructions. This pattern holds consistently across sports, competitive levels, and linguistic backgrounds, suggesting that universal principles—particularly clarity, brevity, and technical precision—govern effective tactical communication. Hierarchical multiple regression further confirms that communication clarity is the strongest predictor of performance outcomes ($\beta = 0.48$, $p < 0.001$), exerting a greater influence than sport type, competition level, or the length of the coach–athlete relationship.

The broader implications of these findings highlight both practical and theoretical advancements. For coach education and professional development, the results emphasize the need to prioritize functional communication skills over grammatical accuracy by focusing on concise tactical messaging, use of simple syntactic structures, expansion of sport-specific vocabulary, and incorporation of immediate comprehension checks. Theoretically, the study extends English-as-a-Lingua-Franca scholarship into the high-intensity sports domain, illustrating how time pressure, physical demands, and technical specialization shape linguistic practices. Future research should experimentally test causal links between communication clarity and performance, explore longitudinal development of tactical communication expertise, and examine multimodal and culturally mediated communication processes. Overall, this investigation establishes foundational evidence that functional communicative competence—accessible even to intermediate English users—enables effective tactical coordination in multilingual sporting environments, thereby supporting successful international athletic collaboration.

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CONFLICT OF INTEREST

The authors declare no conflict of interest. The funder had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

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