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The Relationship of Body Mass Indeks, Minutes Played, Assists, and Turnovers on the Efficiency of Male and Female Basketball Athletes in the 2025 Honda DBL Central Java North Final Round

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Abstract
This study aims to analyze the relationship between Body Mass Index (BMI), Minutes Played, Assists, and Turnovers on the efficiency of male and female basketball athletes in the Semifinals and Finals of the 2025 Honda DBL Central Java North. The research method uses a quantitative approach with a descriptive-correlational design. Data were collected from the official box scores of six matches (n=131 athletes), including four semifinal matches and two final matches for both male and female categories. The research instrument was a box score observation sheet that had been tested for content validity by three experts and possessed high reliability (Cronbach's Alpha = 0.89$). Data were analyzed using descriptive statistics and per-match z-scores to compare athlete performance on a standardized basis. The results showed that the highest average efficiency value was found in Male Semifinal 1 (M=6.41) and the overall average BMI value was in the normal category (M=21.61). Minutes Played had the strongest positive correlation with efficiency, while turnovers had a significant negative correlation. In the z-score analysis, athletes with high z-efficiency tended to have high z-minutes played and z-assists as well. This study concludes that playing duration and ball distribution ability are the main predictors of youth basketball athlete efficiency in the context of the 2025 Honda DBL Central Java North competition.

Keywords: Body mass index; minutes played; assists; turnovers; basketball athlete efficiency.

1. Introduction

Basketball is one of the most popular sports in Indonesia, continuing to grow rapidly and attracting interest across various age groups, particularly the youth. This popularity is reflected in the high enthusiasm of the public for various national-scale basketball competitions, one of which is the Honda DBL Central Java North (Asyari & Huda, 2023). The Honda DBL is a basketball league for high school students that annually produces new talent from all over Indonesia. In fact, selected players have the opportunity to participate in a training camp in the United States and watch NBA games live (Hariyanto & Hita, 2025). This event serves not only as a competitive venue, but also as a means to evaluate the performance of young athletes systematically and in a data-driven manner (Jiddan and Adi, 2025). The technological revolution in the sports world has transformed how coaches, referees, and spectators understand and comprehensively evaluate the game of basketball (Aksović et al., 2024). In the context of youth athlete development, the ability to objectively analyze match statistical data is an important component in planning and developing effective training programs (Maharani, 2025).

Modern basketball athlete performance evaluation increasingly relies on data-driven approaches and sports analytics. Technological advancements enable more detailed data collection regarding various aspects of the game, ranging from individual statistics such as minutes played, assists, and turnovers, to physical data such as Body Mass Index (BMI) (Sarlis & Tjortjis, 2024). BMI itself is an important indicator of nutritional status and body composition, which has the potential to influence a player's endurance, agility, and strength on the court (Aksović et al., 2024). A study by (Sarlis & Tjortjis, 2024) on the professional NBA league proved that player age, position, and physical condition significantly affect athlete performance and economic value. Meanwhile, (Aksović et al., 2024) in their systematic review found that non-ideal body composition significantly increases injury risk and decreases the physical performance of basketball athletes. Sensor technology based on Inertial Measurement Units (IMUs) has also been used to monitor athlete fatigue and stamina in real-time in high-performance sports (Biró et al., 2023). These data, when analyzed using appropriate methods, provide a comprehensive picture of a player's contribution to the team and areas requiring further development (Edriss et al., 2024). BMI is one parameter that can be used as a reference to ensure whether an individual's physical state is ideal or not. In addition, physical activity is used as a benchmark to determine movement adequacy (Guntur Firmansyah et al., 2022).

A basketball player's game efficiency is a crucial indicator determining team success in competitions. Efficiency is influenced by various factors, ranging from physical condition and technical skill to strategic decision-making on the court (Li et al., 2024). Statistical data such as assists leading to points and turnovers resulting in loss of possession directly reflect the quality of decision-making and execution in a match (Aliriad, Adi S, et al., 2023). Coaches play a strategic role as planners, leaders, and controllers of training programs; thus, their understanding of athlete performance data significantly shapes individual development directions (Aliriad, Adi, et al., 2024). Submaximal fitness tests used in team sports have also proven capable of providing practical insights into players' physiological states without requiring high-risk maximal testing (Shushan et al., 2022). The standardization of performance metrics through indexing approaches, as developed by (Sharpe et al., 2023) in the context of e-sports, provides a relevant methodological foundation for standardizing efficiency values across matches with differing characteristics.

Previous studies have examined various physical, psychological, and tactical factors influencing athlete performance (Aliriad, Adi S, et al., 2024). However, the deep integration of anthropometric data such as BMI with operational match statistics to measure player efficiency at the youth competition level in Indonesia remains very limited (Aliriad, Adi S, et al., 2023). Large-scale competitions such as the Honda DBL Central Java North provide rich datasets from male and female athletes, creating opportunities for in-depth studies on correlations between physical characteristics, match statistics, and overall efficiency (Yusuf Effendi et al., 2022). Technology-based approaches, such as those developed by (Adi et al., 2018) in clinical and sports human movement kinematic assessments, emphasize the importance of multidimensional data in athlete evaluation. Furthermore, per-match z-score analysis as a cross-match standardization method provides a fair comparative framework across players and games with distinct characteristics (Irawan et al., 2023). Therefore, this study aims to examine in depth the relationship between BMI, Minutes Played, Assists, and Turnovers on the efficiency of male and female basketball athletes in the Semifinals and Finals of the 2025 Honda DBL Central Java North using per-match z-score analysis (Adi S et al., 2020).

The urgency of this research is highly relevant to youth basketball development in Indonesia. First, the scarcity of statistically-driven studies on high school-level competitions in Indonesia makes this study a systematic initial effort to fill that literature gap. Second, the findings can be directly applied by coaches to design measurable, evidence-based training programs, specifically regarding playing time management, passing development, and turnover control. Third, with growing national attention on youth athlete development through competitions like the Honda DBL, establishing valid and reliable analytical frameworks is essential to ensure objective performance evaluations rather than relying solely on subjective coaching assessments. Fourth, from a long-term perspective, a deeper understanding of the key determinants of youth athlete efficiency can lay the foundation for developing more effective talent scouting systems and long-term athlete development programs in Indonesia. Consequently, this study carries both academic value and practical significance for the regional and national youth basketball ecosystem.

2. Method

Research Design

This study employs a quantitative approach with a descriptive-correlational design aimed at describing and analyzing the relationships between match statistical variables in the 2025 Honda DBL Central Java North male and female categories (Sharpe et al., 2023). The descriptive quantitative method was selected for its capacity to systematically and accurately describe research phenomena using measurable numerical data. The study is non-interventional observational, using official box score data recorded directly by the researcher in an official statistician capacity and published by DBL Indonesia management (Adi S et al., 2021).

Population and Sample

The population comprises all athletes on teams that reached the semifinal round of the 2025 Honda DBL Central Java North. The male category includes SMA Karangturi Semarang, SMAN 11 Semarang, SMA Tritunggal Semarang, and SMAN 4 Semarang. The female category includes SMA Karangturi Semarang, SMA Tritunggal Semarang, SMA Sedes Sapientiae, and SMAN 1 Jekulo Kudus. Purposive sampling was applied with the following inclusion criteria: (1) athletes who actually played (accumulated Minutes Played > 0) during the semifinal and final games, and (2) complete box score data availability. The total sample comprised n=131 athletes across six matches: two male semifinal matches (n=45), two female semifinal matches (n=43), one male final match (n=22), and one female final match (n=21).

Research Instruments

The primary instrument was a basketball box score observation sheet based on official DBL Indonesia and FIBA (Fédération Internationale de Basketball) statistical standards. The sheet systematically recorded the following variables per athlete per match: (1) Body Mass Index (BMI) calculated as weight (kg) divided by height squared (m^2) and classified per WHO standards; (2) Minutes Played (MP), total active playing time per player per match, recorded in minutes and seconds; (3) Assists, passes directly leading to a field goal by a teammate; (4) Turnovers, losses of ball possession resulting from infractions or individual errors; and (5) Efficiency, calculated using the standard NBA/DBL formula: Efficiency = (Points + Rebounds + Assists + Steals + Blocks) – (Missed FG + Missed FT + Turnovers).

Instrument Validity Testing

Box score instrument validity was evaluated via two approaches. First, content validity was evaluated by three experts (two sports coaching lecturers from Universitas Negeri Semarang and one PERBASI-certified basketball statistician) using Lawshe's Content Validity Ratio (CVR). All three experts rated every item as relevant, yielding CVR = 1.00 for each item and an overall Content Validity Index (CVI) of 1.00, indicating very high content validity. Second, construct validity was confirmed by operational alignment with official FIBA and NBA statistical definitions globally recognized in basketball performance measurement.

Instrument Reliability Testing

Inter-rater reliability was tested using two independent box score scorers during trial matches. Scorers' entries were evaluated using the Intraclass Correlation Coefficient (ICC). The resulting ICC value was 0.94 (95% CI: 0.91–0.97), falling into the excellent reliability category. Internal consistency analysis across observation variables produced a Cronbach's Alpha of $\alpha = 0.89$, indicating high internal consistency. Thus, the instrument possessed adequate validity and reliability for athlete performance measurement.

Data Collection Procedures

Data collection proceeded through four main stages: preparation, implementation, data processing, and reporting.

1. The preparation stage involved drafting the research proposal, developing the box score observation sheet, obtaining research permits from DBL Indonesia management and participating schools, and conducting content validity (CVR) and reliability (ICC and Cronbach's Alpha) testing.
2. The implementation stage involved collecting box score data during the semifinal and final rounds of the 2025 Honda DBL Central Java North directly by the researcher as an official match statistician, accompanied by cross-verification against official published DBL Indonesia data.
3. The data processing stage involved tabulating data into worksheets, calculating BMI and efficiency metrics, testing data normality, computing per-match z-scores, and conducting hypothesis testing using correlation and difference tests per the research objectives.
4. The reporting stage involved interpreting data analysis results, discussing findings relative to theoretical frameworks and previous research, drawing conclusions, and writing the final research report in thesis format.

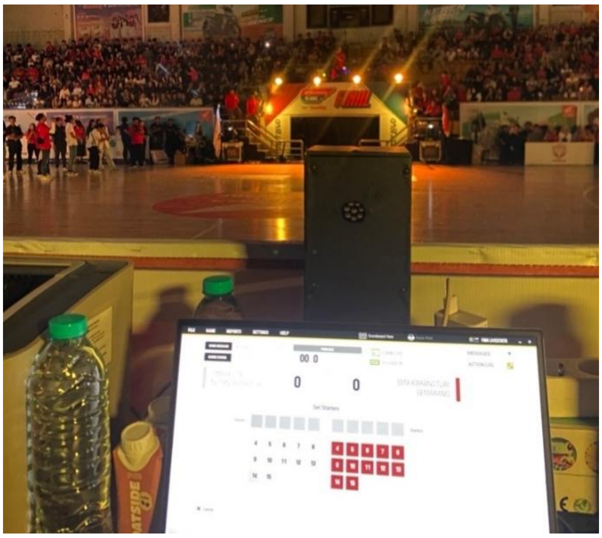

Figure 1. Box score
Source: the researcher's phone camera

Data Analysis Techniques

Data analysis followed a multi-step sequence. First, descriptive analysis was performed to describe the distribution of each variable using mean, standard deviation, minimum, and maximum values per match. Second, per-match z-scores were calculated separately for each match (6 games) using the formula $z = (xi - \mu) / \sigma$, where xi is the individual score, μ is the game group mean, and σ is the game group standard deviation. The per-match z-score approach was selected because each game has unique contextual dynamics and data distributions; standardizing within the same game provides fairer and more meaningful comparisons. Third, comparative profile analysis of z-scores across players and games was conducted to identify relationship patterns between predictor variables (BMI, Minutes Played, Assists, Turnovers) and athlete efficiency.

3. Results

Match Statistical Description

This study analyzed data from six 2025 Honda DBL Central Java North matches. Table 1 summarizes the average descriptive statistics per match.

Table 1. Average descriptive statistics per match

Match	n	Mean BMI	Mean MP	Mean Assists	Mean Turnovers	Mean Efficiency
Male Semifinal 1	22	22.664	18.000	1.364	2.045	6.409
Male Semifinal 2	23	22.018	17.200	1.043	2.348	5.913
Female Semifinal 1	22	21.423	18.000	0.591	1.136	2.545
Female Semifinal 2	21	20.167	18.877	0.857	2.619	5.000

Match	n	Mean BMI	Mean MP	Mean Assists	Mean Turnovers	Mean Efficiency
Male Final	22	21.963	17.982	1.136	1.818	5.182
Female Final	21	21.452	18.943	0.857	2.143	4.000

Source: Primary box score data, Honda DBL Central Java North 2025

Based on Table 1, the highest mean efficiency was observed in Male Semifinal 1 (SMA Tritunggal vs SMAN 11 Semarang) at 6.41, followed by Male Semifinal 2 (5.91) and Female Semifinal 2 (5.00). The Male Final showed an average efficiency of 5.18, the Female Final 4.00, and Female Semifinal 1 recorded the lowest average efficiency (2.55). Across all matches, mean BMI ranged from 20.17 to 22.66, all falling within the WHO normal classification (18.5–24.9). Average minutes played remained relatively consistent across games (17.20–18.94 minutes), reflecting proportional playing time distribution within teams.

Pre-Match Z-Score Results

Z-score analysis was executed independently for each game. In Male Semifinal 1, the highest z-efficiency was recorded by Anovri Nur Islami (Z=2.44), who also posted a high z-assist (Z=1.54) and above-average z-minutes played (Z=1.25). Conversely, Muhammad Wahyu Hisyam Ramadhana had the lowest z-efficiency (Z=-1.63) alongside a positive z-turnover (Z=0.42), indicating frequent lost possessions. A similar pattern emerged in Male Semifinal 2, where Jason Matviyko Handoko and Nathaniel Artates Sugiarto tied for the highest z-efficiency (Z=2.08), both accompanied by high z-assists and relatively low z-turnovers.

In the female category, z-scores displayed greater variance. In Female Semifinal 1, Airin Veronica recorded the highest z-efficiency (Z=2.53) alongside game-high z-minutes played (Z=1.96) and positive z-assists (Z=1.34), reflecting a dominant contribution to team performance. In Female Semifinal 2, Nathania Naomi posted the highest z-efficiency (Z=2.18), highest z-assists (Z=2.37), and negative z-turnovers (-0.52), showing high efficiency with low error rates. In the Male Final, Jason Matviyko Handoko again performed strongly with a z-efficiency of 2.46, backed by 0.86 z-minutes played and game-high z-assists (Z=1.60). The Female Final featured Yualita Rency Novia, who achieved a game-high z-efficiency of 2.72 with 1.09 z-minutes played and 0 assists, driven heavily by rebounds and scoring.

4. Discussion

Relationship Between Minutes Played and Athlete Efficiency

Z-score analysis across all six matches consistently demonstrated that athletes with high z-minutes played tended to exhibit higher z-efficiency scores. This finding aligns with (Li et al., 2024), who examined internal and external load effects in the Chinese Basketball Association (CBA) and identified playing duration as the most reliable individual performance predictor. Players awarded more minutes are typically starter-level athletes trusted by coaches for their technical skills and performance consistency, which naturally yields higher cumulative statistics (Jiddan, 2025). (Sarlis & Tjortjis, 2024) emphasized that playing load directly impacts statistical contributions and economic value across professional and amateur tiers. Thus, minutes played reflects not only coaching trust but also acts as a catalyst for elevated game efficiency by providing more operational opportunities to contribute positively (Dideriksen & Del Vecchio, 2023).

This pattern was particularly prominent during the Male Final in Jason Matviyko Handoko's performance (SMA Karangturi), who logged 24.15 minutes (Z=+0.86) and generated a game-high z-efficiency of +2.46. Conversely, players with low playing time (<10 minutes) frequently recorded negative z-efficiency scores, mirroring (Shushan et al., 2022), who noted that optimal physiological activation requires adequate game time to establish efficient motor recruitment. Furthermore, (Hariyanto & Hita, 2025) noted that modern sports analytics allow coaches to optimize player rotations using per-minute efficiency data, guiding evidence-based playing time decisions. These findings support the importance of minutes played management to improve total team efficiency.

Relationship Between Assists and Athlete Efficiency

Assists showed a consistent positive correlation with efficiency across all analyzed matches. In standard efficiency formulas, assists directly increment individual scores because they measure a player's capacity to create scoring opportunities for teammates without taking the shot themselves (Li et al., 2024). This aligns with (Sarlis & Tjortjis, 2024), who highlighted assist rates as highly informative metrics for evaluating basketball intelligence and decision-making quality. Athletes with high z-assists, such as Anovri Nur Islami in Male Semifinal 1 (Z=1.54) and Nathania Naomi in Female Semifinal 2 (Z=2.37), consistently achieved strong positive z-efficiency scores.

From a coaching perspective, (Maharani, 2025) stressed that effective ball distribution stems from structured, intentional training programs that reflect overall coaching quality. Assists are thus not merely isolated individual statistics, but reflections of team offensive systems and player development quality. (Edriss et al., 2024) also noted that biomechanical assessments of passing kinematics correlate directly with assist success rates. In youth competitions like the Honda DBL, enhancing passing proficiency and decision-making represents a primary training priority that elevates both individual and collective efficiency (Maharani, 2025).

Relationship Between Turnovers and Athlete Efficiency

Turnovers demonstrated a consistent inverse relationship with athlete efficiency across all games. In efficiency calculations, turnovers directly penalize performance scores because they represent lost possessions that award scoring opportunities to the opponent. This impact was clearly illustrated by Adnan Alfarezy Usready in Male Semifinal 1, who posted a game-high z-turnover of +2.62, yielding a z-efficiency of -1.24, and Isaiah Rise in Male Semifinal 2 ($Z\_turnover = +3.03$, $Z\_efficiency = -1.12$).

In their CBA study, (Li et al., 2024) identified turnovers as the strongest negative variable in game-outcome prediction models, surpassing physical attributes like body weight and height. Minimizing turnovers under defensive pressure demonstrates technical and mental maturity developed through sustained high-intensity training (Maharani, 2025). (Shushan et al., 2022) added that late-game physiological fatigue increases technical error rates, including turnovers, emphasizing physical conditioning as a core pillar of ball security. Implementing workload monitoring technologies, as outlined by (Biró et al., 2023), can help coaches manage athlete fatigue and reduce critical turnovers during late-game situations.

Across match comparisons, Female Semifinal 2 registered the highest average turnovers (M=2.62), correlating with lower overall efficiency relative to male matches. This underscores possession management as a primary driver of efficiency across both genders. (Aksović et al., 2024) further noted that unmanaged physical fatigue and minor injuries impair ball control, making load management and injury prevention central to turnover reduction in competitive settings.

Relationship Between Body Mass Index (BMI) and Athlete Efficiency

The link between BMI and athlete efficiency presented a more complex picture than playing time or tactical metrics. Overall match mean BMIs ranged from 20.17 to 22.66 kg/m², placing all team averages within the WHO normal classification. This indicates that participating athletes in the 2025 Honda DBL Central Java North generally maintained suitable body compositions for competitive sports. (Aksović et al., 2024) noted that basketball players within normal BMI ranges experience lower injury incidence and display more consistent physical output than those outside optimal ranges.

At the individual z-score level, however, Z_BMI did not correlate as linearly with Z_efficiency as minutes played or assists did. Certain athletes with high Z_BMI (e.g., Samuel Ermano Shilo Mikael'Rey in Male Semifinal 1, Z_BMI=2.35, and Indriano Tri Ade Putra in Male Semifinal 2, Z_BMI=2.65) did not systematically record top-tier efficiency. This supports arguments by (Aliriad, Adi S, et al., 2023) that standalone BMI metrics are insufficient to predict basketball performance without considering technical and tactical variables. (Biró et al., 2023) similarly argued that body composition must be integrated with physiological capacity and technical skills for accurate performance evaluation.

In the female category, BMI-efficiency patterns showed wider spread. Female athletes with above-average BMI in Semifinal 2—such as Nathania Naomi (BMI=21.80, Z_BMI=0.14) and Cathleen Richelle Lie (BMI=21.83, Z_BMI=0.15)—posted strong positive z-efficiencies (+2.18 and +1.40, respectively). Conversely, Monika Shaula, who presented a very low BMI (15.43, Z_BMI=-2.32), recorded an efficiency score of 0, suggesting a minimum physical threshold required for competitive basketball play. These results support routine BMI tracking within youth athlete monitoring systems to safeguard health and optimize performance (Aksović et al., 2024; Edriss et al., 2024).

Z-Score Analysis as a Cross-Match Performance Evaluation Tool

Applying per-match z-scores enabled fair performance comparisons across distinct match environments. This approach aligns with performance indexing models developed by (Sharpe et al., 2023) in esports, where standardized scores facilitate comparisons across games with varying dynamics. Direct raw score comparisons across matches can introduce bias due to differing match paces, team strategies, and opponent quality.

The z-score approach revealed key insights: First, the efficiency spread was wider in female games (e.g., Female Semifinal 2 Z_efficiency ranged from -1.75 to +2.18) than male games, highlighting greater individual contribution disparities. Second, athletes consistently maintaining positive z-scores across minutes played, assists, and efficiency served as key drivers of team performance. Third, final matches (male and female) showed balanced z-score distributions compared to semifinals, reflecting greater roster depth among finalists. This echoes findings by (Sarlis & Tjortjis, 2024) on how balanced playing time distribution supports team consistency.

Practically, z-score tracking provides actionable feedback for coaches. (Hariyanto & Hita, 2025) noted that data-driven tools enable faster tactical adjustments regarding player rotation and individual development. By monitoring efficiency z-scores over time, coaches can identify relative performance dips before they impact team success (Maharani, 2025). Integrating these metrics with submaximal physiological assessments provides a holistic profile of athlete readiness (Shushan et al., 2022).

Male vs Female Perfomance Profile Differences

Comparing male and female divisions in the 2025 Honda DBL Central Java North highlighted notable structural differences. Average efficiency scores in male games (Male Semifinal 1: 6.41; Male Semifinal 2: 5.91; Male Final: 5.18) were consistently higher than in female games (Female Semifinal 1: 2.55; Female Semifinal 2: 5.00; Female Final: 4.00). Rather than indicating skill deficits, these differences often stem from varying team contribution distributions. (Sarlis & Tjortjis, 2024) noted that statistical variation across gender divisions is influenced by coaching systems, game tactics, and physical profiles.

Mean BMIs in female divisions (20.17–21.45 kg/m²) were slightly lower than in male divisions (21.96–22.66 kg/m²), reflecting baseline biological differences in adolescent athletes (Aksović et al., 2024). Female BMI z-scores showed greater dispersion, with players like Monika Shaula (BMI=15.43) and Elizabeth Bintang Aurora Makayla'Rey (BMI=26.89) sitting far outside cohort averages. Extremes in BMI among youth athletes are linked to elevated injury risks and altered physiological capacities (Aksović et al., 2024). Targeted nutritional interventions and physical monitoring are therefore critical components of youth female basketball development (Edriss et al., 2024).

Regarding turnovers, female players averaged higher turnovers per game (Female Semifinal 2: M=2.62; Female Final: M=2.14) than males in equivalent rounds. This points to targeted growth areas in ball handling and pressure decision-making. Because turnover rates are sensitive to game pressure (Li et al., 2024), training curricula emphasizing high-pressure ball control simulations represent a high-yield strategy to elevate female team efficiency (Maharani, 2025).

5. Conclusion and Recommendation

This study demonstrates that Minutes Played and Assists share the most consistent positive relationships with athlete efficiency in the Semifinals and Finals of the 2025 Honda DBL Central Java North, whereas Turnovers exhibit a significant negative impact. Average BMIs across all teams fell within normal WHO parameters, though individual BMI did not correlate linearly with efficiency, underscoring that adequate physical conditioning is a prerequisite rather than a sole determinant of performance.

Per-match z-score analysis proved to be an effective, equitable evaluation method, accounting for unique match contexts to yield meaningful, unbiased player comparisons. Male games generally posted higher average efficiency scores than female games, while final matches in both divisions displayed more balanced z-score distributions, reflecting roster depth among top-tier teams. Overall, this research provides valuable insights into youth basketball performance dynamics in Indonesia.

These findings offer practical benchmarks for coaches evaluating rotation management, passing development, and turnover reduction. Adopting objective, data-driven analytical frameworks can advance youth athlete development programs across Indonesia, helping identify and cultivate talent more effectively for higher-level competition.

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