Original Article

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Match Outcome Prediction in 3x3 Basketball: Validating Team Performance Index and Benchmarking Against Shooting Efficiency and Shooting Value (Paris 2024 Olympics)

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Abstract: The fast-paced nature of 3x3 basketball requires simple performance metrics that support quick decision-making. This study aimed to validate a new Team Performance Index (TPI) for predicting match outcomes, using data from all 34 men's games at the Paris 2024 Olympics. TPI was defined as points scored divided by a composite error term (missed shots + team fouls + turnovers – offensive rebounds + 1). We compared TPI against two established metrics – shooting efficiency (S-EFF) and a statistical value index (S-VAL) – to evaluate their predictive power using ROC-AUC, classification accuracy (with cross-validation), and effect sizes. Results showed that winning teams had significantly higher TPI (mean 1.11 vs 0.68, p<0.001, very large effect size). TPI achieved excellent discrimination between wins and losses (AUC ~0.91, accuracy ~81%), comparable to S-VAL (AUC ~0.93) and superior to S-EFF (AUC ~0.81). No significant difference in AUC was found between TPI and S-VAL, while both outperformed S-EFF. Preliminary "traffic-light" thresholds indicated that TPI <0.67 (red zone) corresponded to almost certain defeat (0% win rate), 0.67–1.05 (yellow) to an even chance (~50%), and >1.05 (green) to near-certain victory (~94% wins). Sensitivity analysis (MCDA) revealed missed shots and team fouls as the dominant drivers of TPI (~74% combined importance), underscoring shooting accuracy and foul discipline as key success factors. In conclusion, TPI is a practical and interpretable index that effectively signals likely outcomes and supports real-time coaching decisions; however, it's not deterministic and should be further validated in diverse competitions.

Keywords: Performance Analysis; Game Statistics; Technical–Tactical Indicators; Winning Factors; MCDA; Decision–Making.

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INTRODUCTION

Since its debut at the 2010 Summer Youth Olympic Games in Singapore and its inclusion in the 2020 Tokyo Olympics, the 3x3 format has continued to grow in popularity. This was confirmed by Zarubina et al. [1], who showed that the number of tournaments worldwide increased by over 30% before the Games. The sport's rapid growth and promotion are supported by the official FIBA calendar [2], which estimates that around 157 official 3x3 basketball events will be held by the federation in 2025. These include the World Tour, Challengers, World Cup, Asia Cup, Youth Nations League, and Champions Cup. The fast-paced nature of 3x3 basketball—characterized by a lack of traditional offense and the need for quicker decision-making than in regular basketball—has required different tactical and training approaches. In response to its rising popularity, intense research began in the early 21st century to understand its physiological, biomechanical, and motor characteristics. Several features differentiate 3x3 basketball from 5x5, including higher exercise intensity, more frequent inertial movements over short distances, increased cardiovascular demands, and quicker muscle fatigue. Researchers also studied player recovery and physiological parameters such as heart rate, lactate levels, and hemoglobin variability. Simultaneously, studies examined how tournament workload affects muscle contractility and the effectiveness of technical actions, deepening understanding of 3x3 play [3-18]. Match statistics analysis has revealed differences between winning and losing teams, including the number of free throws attempted—winning teams tend to take more [19]. It was also found that winners more frequently cooperate on offense, achieve more assists, set more screens, and execute more pick-and-rolls than losers [20]. Researchers systematically analyzed the technical-tactical actions immediately preceding a three-point shot (a two-point field goal in FIBA 3x3), focusing specifically on both on-ball (direct) and off-ball (indirect) screens. Their findings highlight distinct gender-based patterns in how these screening actions are used before shot attempts, offering key insights for player development and tactical planning at the elite level of 3x3 basketball [21].

Other studies revealed differences between 3x3 and 5x5 variations in the number of 1-point and 2-point shots attempted [22,23]. These studies assessed effectiveness based on the number of shots attempted. In 5x5, a team scores about 1 point per possession on average, while in 3x3, it is around 0.5 points. Since points are scored differently in both variations, a more accurate measure considers the maximum points possible from a single play. Offensive efficiency in traditional basketball is around 35%, whereas in 3x3, it is roughly 27.5%. The lower shooting accuracy in 3x3 partly results from less preparation time. Additionally, the constant switch between offense and defense complicates decision-making, creating an unpredictable environment and requiring more focus than in 5x5 [24].

The issue of spacing between players and their optimal positioning for effective actions is also addressed. The importance of quickly resuming play after a missed shot is highlighted [25]. Efforts were made to compare shooting accuracy between women and men, dividing the study group into juniors (U-18) and seniors. It has been suggested that men's teams outperform women's teams in scoring from beyond the 6.75-meter line (2 points). However, transitioning from youth to senior tournaments may be easier for female players due to the similarity in shot selection between under-18 and senior games. Recently, Chen [27] and Li and Phucharoen [28] conducted detailed analyses of match statistics from the Tokyo 2020 Olympic Games, focusing on specific types of offensive and defensive actions in men's 3x3 basketball. They examined correlations between these actions and match outcomes, showing a positive relationship between the effectiveness of all shot types and success, with successful two-point field goals playing a particularly crucial role [27,28]. Coaching practices rely on simple, single-value indicators that can be monitored after just a few possessions to quickly assess the "direction of the game" and decide what to correct, such as shot selection, turnover risk, or foul discipline. In recent years, 3x3 analysis has commonly used scoring efficiency and game value indicators (e.g., S-EFF, S-VAL) and their team-level equivalents (T-VAL). Research and practical experience demonstrate that these metrics are coach-friendly and useful for rapidly evaluating offensive quality and the impact of a player or team, especially when standardized by possession and interpreted using brief, "tournament-level" samples [19,20,22,23,27,28]. Nonetheless, limitations are evident: sensitivity to small sample sizes, such as in single games or short periods; lack of context regarding shot quality (including pressure and location); and ambiguous definitions of some team metrics in publicly available materials, which make cross-tournament comparisons difficult. In 5-on-5 basketball, a popular metric for overall player evaluation is the Player Efficiency Rating (PER), introduced by John Hollinger and widely used in the NBA. Recent studies suggest that winning teams generally have higher PER values than losing teams. Similarly, in 3x3 basketball, we propose the Team Performance Index (TPI), a new metric designed to overcome the limitations of existing measures and provide a more contextually relevant assessment of team performance. The TPI is a simple team-level metric that helps translate statistical results into coaching decisions, especially when using interpretation thresholds ("traffic lights") and identifying key "levers"—such as 1/2-point field goal balance, turnover control, and scoring efficiency [29].

Therefore, in applied 3x3 analytics, it is important to explicitly define the metrics used in the methodology, standardize per-possession measures, and report clear interpretation thresholds. The Multi-Criteria Decision Analysis (MCDA), as a part of operational research, is widely used in sport management problems. In the literature, MCDA methods have been applied to evaluate the performance of players from different sports disciplines, such as football [30], swimming [31], and basketball [32], among others. Particularly in basketball-related issues, research has focused on selecting Most Valuable Players (MVP) for a sports season [32], assessing team performances [33], developing player selection systems [34], and evaluating players' performance under uncertainty. This range of applications demonstrates that MCDA has gained significant attention in sports management, especially in basketball [35]. However, to our knowledge, MCDA has not yet been combined with box-score–derived efficiency indices to construct and validate a single, team-level performance indicator in 3x3 basketball. This gap motivates the present study, in which we integrate MCDA-based sensitivity analysis with a box-score-derived efficiency index in elite 3x3 basketball.

In this context, the present study validates a Team Performance Index (TPI) as a simple team-level indicator of victory, explicitly built and tested using multiple complementary analyses (logistic regression, receiver-operating-characteristic curves, accuracy measures, and MCDA-based sensitivity analysis). We assume that the TPI can serve as a practical bridge between box score and coaching decisions, especially when accompanied by decision thresholds ("traffic lights") and the identification of key "levers" (e.g., 1/2-point balance, turnover control, and scoring). Moreover, when real-time data are available, the TPI may function as a dynamic indicator of team effectiveness, reflecting whether a team's current performance trajectory is aligned with successful outcomes even if the immediate scoreline is unfavorable. We also demonstrate this with a case study analyzing the TPI process in one match that does not comply with the rule.

The main goal of this study was to verify, using data from the Paris 2024 Olympic Games (men's tournament), the ability of the newly proposed Team Performance Index (TPI) to differentiate between winning and losing teams statistically, and to see if its structure offers understandable insights into why and under what performance conditions teams succeed or fail. Additionally, the predictive accuracy of the TPI (accuracy/AUC) was compared with that of established indicators such as S-EFF and S-VAL. To achieve these objectives, we used a multi-layer approach that combined discrimination analysis (AUC and accuracy), the development of decision thresholds, MCDA-based sensitivity analysis, and a case-study of a "rule-breaking" game.

The specific aims were to establish preliminary interpretive thresholds for TPI ("traffic lights": green, yellow, red) that can support quick in-game decision-making; to identify the key indicators most strongly influencing TPI growth through sensitivity analysis and Multi-Criteria Decision Analysis (MCDA); to develop practical coaching transfer formats, including a concise 1-page guideline and an A→B→C action plan, enabling immediate application of the findings in match preparation and real-time strategic adjustments; and to analyze a game that does not follow the basic predictive assumption of TPI (i.e., that the team with the higher TPI should win), thereby illustrating its practical limitations and interpretive value in close matches.

MATERIAL AND METHODS

Participants

The study's material included all men's 3x3 basketball games (n = 34) played during the XXXIII Olympic Games in Paris (July 30 – August 5, 2024). Eight national teams participated: the Netherlands, France, Lithuania, Latvia, Serbia, Poland, the United States, and China. The dataset encompassed 28 group-stage games, 2 play-in games, 2 semifinals, the bronze-medal game, and the final. Inclusion criteria were: (i) official status as a men's Olympic 3x3 game and (ii) complete box-score statistics published by FIBA. No games met the exclusion criteria, so all 34 were included. Each match provided two team-game observations (one per team), resulting in 68 team-level records (34 wins and 34 losses). The research relied exclusively on aggregated official FIBA 3x3 Olympic Games box-score statistics (publicly available on the FIBA website), with no access to individual player identities or sensitive personal data. The full team-level dataset, derived from these box scores, is available as a supplementary file and in the public repository at https://doi.org/10.5281/zenodo.15337106

Protocol

Official box-score statistics were the primary data source. For each of the 34 games, team totals for all standard variables were exported from the official FIBA 3x3 Olympic reports into a spreadsheet and then imported into Python for further analysis. Each row in the dataset represented one team in a single game (team-game observation), including points scored, field-goal and free-throw attempts and makes, missed shots, team fouls, turnovers, and offensive rebounds. Using these box-score variables, we calculated two established efficiency indices, S-EFF* and S-VAL**, following the FIBA 3x3 Statisticians' Manual, and developed the new Team Performance Index (TPI) (Figure 1). Missed shots (TMS) were defined as the sum of all unsuccessful 1-point, 2-point, and free-throw attempts; team fouls (TF) as the total number of fouls committed by a team; turnovers (TO) as all recorded ball losses; and offensive rebounds (OREB) as all rebounds collected by the attacking team after a missed shot. Each team-game observation was also labeled as a win or a loss based on the final score. This dataset formed the basis for all subsequent descriptive, predictive, and MCDA-based analyses.

Definitions:
* S-EFF (Shooting efficiency) = PTS / (1PTA + 2PTA + FTA); calculated according to the official FIBA 3x3 statistics formula.
** S-VAL (Shooting Value) = S-EFF × PTS; efficiency factor derived from the FIBA 3x3 Statisticians' Manual.

$$\mathrm{TPI} = \frac{\mathrm{PTS}}{(\mathrm{TMS} + \mathrm{TF} + \mathrm{TO} - \mathrm{OREB}) + 1}$$

TPI - Team Performance Index, PTS – points; TMS – missed shots; TF – team fouls; TO – turnovers; OREB – offensive rebounds. All statistics and parameter descriptions can be found in the supplement.

Analysis stages

The analytical workflow consisted of four stages. First, we performed a descriptive comparison of box-score statistics and efficiency indices between winning and losing teams at the team-game level (N = 68). Second, we validated the discriminatory ability of TPI relative to S-EFF and S-VAL through receiver-operating-characteristic (ROC) analysis and cross-validated logistic regression, and we derived decision thresholds for TPI "traffic lights" linking index values to the probability of winning. Third, we applied a simple multi-criteria decision analysis (MCDA) framework based on one-way sensitivity analysis (±20% changes in TMS, TF, OREB, and TO) to quantify the relative importance of TPI components both globally and for each team. Finally, we used a single close game that did not align with the basic predictive assumption of TPI (the team with the higher TPI should win) as a case study to illustrate the index's dynamic behavior and practical limitations.

Decision thresholds

To develop coach-friendly interpretation categories for TPI, we combined distribution-based and model-based methods. First, we set initial thresholds based on the empirical distribution of TPI using quartiles, which defined three ranges indicating low, intermediate, and high index values. Next, we calibrated these ranges against the probability of winning by applying logistic regression with TPI as a continuous predictor and win/loss as the outcome. For each potential threshold, we examined both observed and model-based winning probabilities. Additionally, the ROC-optimal Youden cut-point was provided as a statistical reference, even if it did not exactly match the most practical "traffic-light" boundaries used in the practical recommendations.

Statistical analysis

All analyses were performed in Python (using pandas, numpy, scikit-learn, and SciPy) within the Google Colab environment to ensure full reproducibility. Descriptive statistics included means, medians, standard deviations, and ranges. Depending on the distribution and homogeneity of variances, differences between winning and losing teams were tested with either parametric or non-parametric methods, with effect sizes reported to enhance practical interpretation. The predictive ability of TPI, S-EFF, and S-VAL was evaluated using ROC analysis, including the calculation of the area under the curve (AUC) with 95% confidence intervals. Pairwise comparisons of AUC values were performed using the DeLong method. Predictive performance (AUC and accuracy) was further assessed via 5-fold stratified cross-validated logistic regression at the individual team-game level (N = 68), maintaining the overall win/loss ratio in each fold; however, folds were not grouped by game ID, so both teams from the same match could be assigned to different folds. Statistical significance was set at $p < 0.05$.

Multi-criteria decision analysis (MCDA) and the sensitivity of TPI

To evaluate the relative importance of the components in the TPI formula, we employed a simple MCDA framework based on one-way sensitivity analysis. For each team-game observation, we recalculated TPI after increasing and decreasing each component by 20%, while holding the other variables constant: missed shots (TMS), team fouls (TF), offensive rebounds (OREB), and turnovers (TO). For each variable, we determined the average change in TPI across all games separately for the +20% and −20% scenarios. These changes were then normalized so that the total absolute effects across the four variables equaled 1, yielding dimensionless importance weights (i.e., MCDA weights) for TMS, TF, OREB, and TO. The analyses were performed both for all team games combined and at the individual team level, allowing us to generate global and team-specific sensitivity profiles. In practice, higher weights indicate that proportional changes in a variable lead to larger shifts in TPI. All sensitivity and MCDA calculations were performed in Python using custom scripts.

RESULTS

All three indices were consistently higher in winning teams (table 1). Across the 34 games, winners had noticeably higher average values for S-EFF (0.70 vs 0.56), S-VAL (14.68 vs 8.94), and TPI (1.11 vs 0.68) compared to losers. The medians show a similar pattern, with the median TPI for losing teams (0.67) near the lower end of the distribution and the median for winning teams (1.05) close to its upper limit. Minimum and maximum values further reveal that, although individual losing teams sometimes reached moderate or even high index values, their typical performance was significantly below that of winners. Overall, Table 2 demonstrates that S-EFF, S-VAL, and TPI all distinguish between winning and losing teams, with the scale of TPI subsequently used to define “low,” “intermediate,” and “high” performance zones in the traffic-light interpretation.

Group comparisons confirmed statistically significant differences between winners and losers for all three indices ($p < 0.001$). Effect sizes were very large for S-VAL ($d \approx 1.96$), TPI ($d \approx 1.60$), and S-EFF ($d \approx 1.28$), indicating substantial practical differences in shooting-related performance between the two groups. Although S-VAL showed the largest standardized difference, TPI combined a clear positive mean difference (+0.43) with a directly interpretable scale that is later linked to winning probability. Together, Tables 1 and 2 demonstrate that TPI aligns consistently with S-EFF and S-VAL in distinguishing winners from losers, while providing a convenient basis for establishing decision thresholds for coaching applications. Smoothed density plots revealed clear separation between winners and losers across all indices (Figure 2A and 2B). In the original units (Figure 2A), mean TPI was higher in winning teams (1.11) compared to losing teams (0.68). Similar differences were observed for S-EFF (0.70 vs. 0.56) and S-VAL (14.68 vs. 8.94). When standardized to a 0–1 scale (Figure 2B), the relative shifts remained consistent, with winners consistently displaying higher mean values than losers. These findings confirm that TPI, along with S-EFF and S-VAL, systematically distinguishes between match outcomes, with the distribution of TPI showing exceptionally stable separation across games.

Table 1. Descriptive statistics of efficiency indices by match outcome (Win (1) vs Loss (0)).

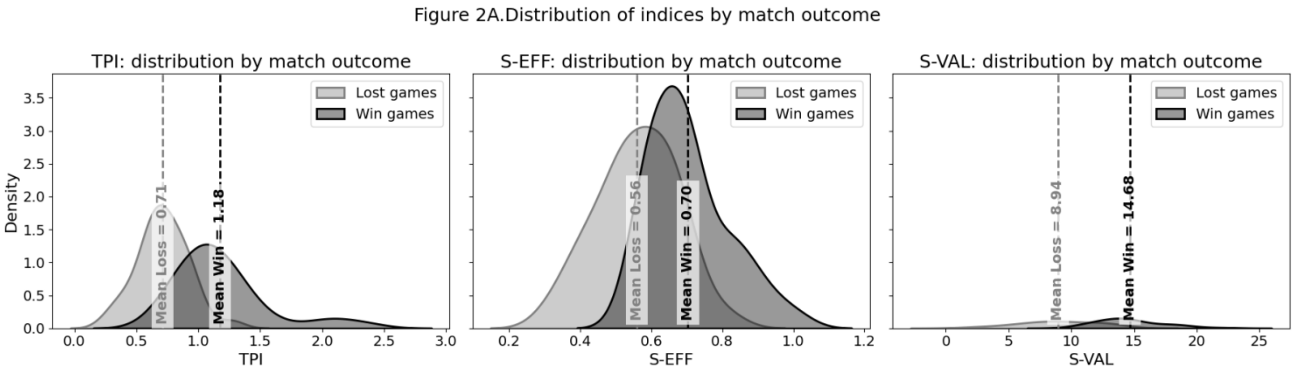
metrics	S-eff - lost (0)	S-eff - win (1)	S-val lost (0)	S-val - win (1)	TPI - lost (0)	TPI - win (1)
count	34.00	34.00	34.00	34.00	34.00	34.00
mean	0.56	0.70	8.94	14.68	0.68	1.11
std +/-	0.11	0.11	3.17	2.68	0.19	0.33
median	0.56	0.68	9.20	14.23	0.67	1.05
min	0.32	0.56	1.89	10.45	0.26	0.68
max	0.81	1.00	13.79	22.00	1.19	2.10

S-EFF – (Shooting efficiency), S-VAL - (Shooting Value), TPI – (Team Performance Index); Win (1) / Loss (0) – match outcome groups; count – number of cases; mean, std, median, min, max – descriptive statistics for each group.

Table 2. Group comparisons between winning and losing teams with effect sizes (Mann-Whitney test).

Metric	Mean_Win	Mean_Loss	Diff	p	Effect_d
S-EFF	0.70	0.56	0.14	<0.001	1.28
S-VAL	14.68	8.94	5.74	<0.001	1.96
TPI	1.11	0.68	0.43	<0.001	1.60

S-EFF – (Shooting efficiency), S-VAL - (Shooting Value), TPI – (Team Performance Index); Mean_Win / Mean_Loss – average values for winners and losers. Diff – difference (Win – Loss); p – p-value for group difference; Effect_d – effect size (Cohen's d or rank-biserial r).



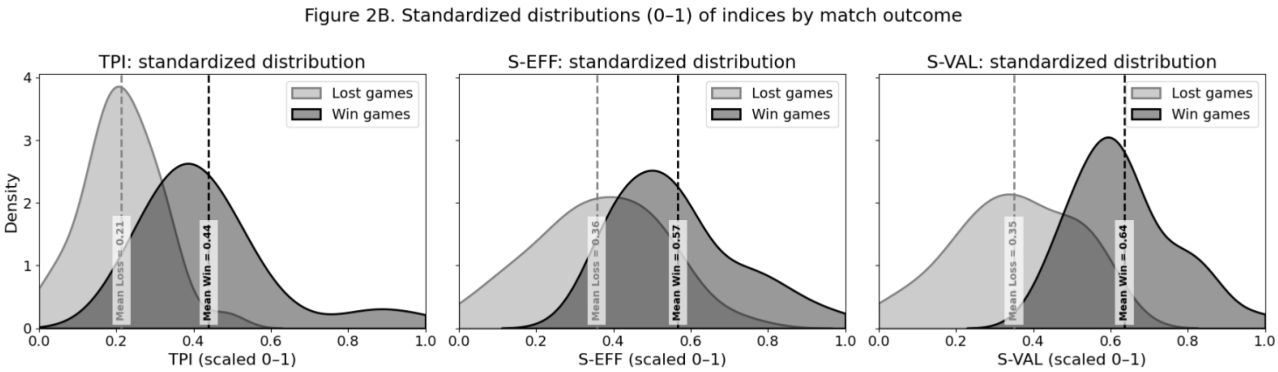


Figure 1A and B. Smoothed distributions of efficiency indices (TPI, S-EFF, S-VAL) by match outcome in original units (A) and after min–max standardization to 0–1 (B).

TPI – Team Performance Index; S-EFF – Shooting Efficiency; S-VAL – Statistical Value (unitless); Curves: Kernel density estimates (KDE) for winning and losing teams; Colors: Black = Win (1), Gray = Loss (0); Dashed lines: Group means, with numeric labels indicating the mean value for each outcome; Axes: X – index value (original units in A; scaled 0–1 in B); Y – density; Interpretation: A consistent rightward shift of the brack curve relative to gray indicates systematically higher index values for winning teams.

Both TPI and S-VAL showed excellent discriminatory power (AUC > 0.90), with similar accuracy (0.81 vs 0.84). S-VAL recorded the highest values numerically, but the difference from TPI was small and within the confidence intervals overlap. S-EFF performed much weaker (AUC = 0.81, ACC = 0.74), confirming its lower predictive value compared to the other two indices.

Pairwise analyses confirmed that both TPI and S-VAL more effectively discriminated game outcomes than S-EFF. The differences were positive, and their confidence intervals did not include zero (TPI vs S-EFF: ΔAUC ≈ +0.10; S-VAL vs S-EFF: ΔAUC ≈ +0.12). No significant difference was found between S-VAL and TPI (ΔAUC ≈ +0.02, 95% CI including zero), supporting their comparable predictive capabilities. These findings reinforce that TPI achieves discrimination levels similar to the top index (S-VAL), while being easier to compute and interpret.

ROC curve analysis confirmed that all three indices provided significant discrimination between winning and losing teams (Figure 3). TPI achieved an AUC of 0.91 (95% CI: 0.83–0.97), which was comparable to S-VAL (AUC = 0.93, 95% CI: 0.87–0.98) and superior to S-EFF (AUC = 0.81, 95% CI: 0.71–0.90). Pairwise comparisons showed no significant difference between TPI and S-VAL, while both clearly outperformed S-EFF. These results confirm that TPI offers robust discriminatory power, nearly matching the best available index (S-VAL) while remaining simpler to compute and interpret in applied contexts.

The traffic-light system based on TPI quartiles showed that teams in the red zone never won a game, while teams in the yellow zone had about a 50% chance of winning. Teams in the green zone won nearly all of their games (~94%). This confirms that TPI is a useful and simple way to distinguish between winning and losing teams.

The one-way sensitivity analysis (±20%), based on data from the Paris 2024 Olympic Games men's tournament as described in the Methods section, showed that missed shots (TMS) are the most influential factor, making up 48% of the overall sensitivity of TPI. This percentage reflects the specific performance characteristics of the analyzed dataset and may vary slightly in other tournaments due to differences in playing style, competition level, or sample makeup. A 20% decrease in missed shots raised TPI by about +0.14, while a 20% increase reduced it by approximately −0.10, indicating a slight asymmetry in effect. This asymmetry suggests that improving shooting accuracy provides greater benefits than the negative effects of similar declines, emphasizing the importance of limiting missed shots to achieve success. Team fouls (TF) contributed an additional 26% to the total sensitivity. Reducing fouls by 20% increased TPI by +0.07, whereas increasing fouls by 20% lowered it by –0.06. This highlights the importance of foul discipline, especially in the 3x3 format, where penalties escalate rapidly after the 7th and 10th team foul. Offensive rebounds (OREB) explained about 16% of TPI sensitivity. Increasing OREB by 20% improved TPI by +0.04, while decreasing OREB had the same impact in the opposite direction. Despite their smaller weight, offensive rebounds offer valuable “second chance” opportunities. Turnovers (TO) had the least influence, with a normalized importance of 11%. Changing turnovers by ±20% affected TPI by only ±0.03. Although their effect is minor, turnover management may be crucial in close endgame situations. Additionally, for team fouls (TF), offensive rebounds (OREB), and turnovers (TO), the effects of a 20% reduction and increase were nearly symmetrical, indicating that fluctuations in these factors do not significantly change the overall TPI result compared to shooting efficiency. Collectively, the findings show that TMS and TF account for nearly three-quarters of the TPI sensitivity. Enhancing shot selection and accuracy, along with maintaining foul discipline, are the most effective strategies to improve TPI and boost winning chances. Meanwhile, offensive rebounding and turnover control act as secondary but still important factors (Figure 4).

Per-team MCDA Analysis of TPI

To explore team-specific profiles, a one-way sensitivity analysis (±20%) was performed separately for each team participating in the Paris 2024 Olympic men’s 3x3 tournament. (Figure 5) presents a heatmap of deviations in normalized importance weights relative to the tournament average profile (TMS ≈ 0.48, TF ≈ 0.26, OREB ≈ 0.16, TO ≈ 0.11). Positive values (red) indicate that a variable is of above-average importance for a given team, while negative values (blue) indicate that it is of below-average importance.

Table 3. Discrimination metrics of efficiency indices: ROC-AUC and cross-validated accuracy

Metric	AUC	95%CI_low	95%CI_high	ACC_mean	ACC_sd
S-VAL	0.93	0.87	0.98	0.84	0.05
TPI	0.91	0.83	0.97	0.81	0.10
S-EFF	0.81	0.71	0.90	0.74	0.07

Metric – efficiency index under evaluation (S-VAL, TPI, S-EFF); AUC – area under the ROC curve; 95% CI low/high – 95% confidence interval for AUC (DeLong method); ACC_mean – mean classification accuracy from 5-fold stratified cross-validated logistic regression; ACC_sd – standard deviation of cross-validated accuracy.

Table 4. Pairwise comparisons of AUC values between efficiency indices

Comparison	Delta_AUC	95%CI_low	95%CI_high
S-VAL vs TPI	0.02	-0.04	0.08
S-VAL vs S-EFF	0.12	0.06	0.19
TPI vs S-EFF	0.10	0.01	0.20

Comparison – pair of indices compared; ΔAUC – difference in AUC (first index minus second; positive values indicate higher AUC for the first index); 95% CI low/high – 95% confidence interval for ΔAUC. All ΔAUC estimates and confidence intervals were obtained using the DeLong method.

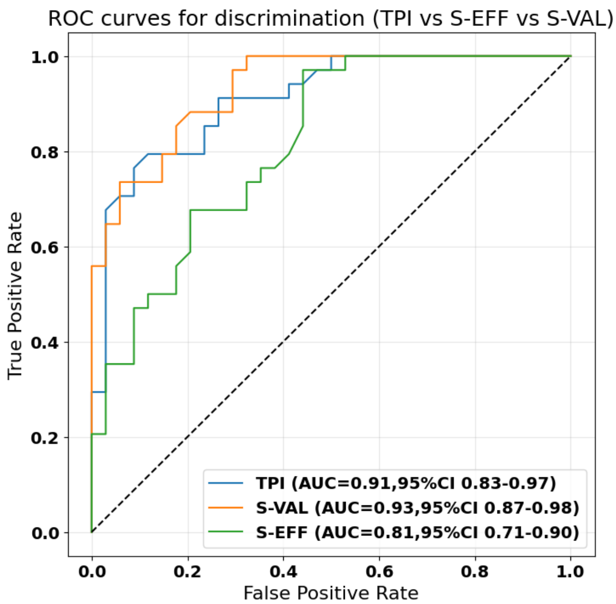


Figure 2. ROC curves for discrimination between winning and losing teams (TPI, S-EFF, S-VAL).
ROC curve – the relationship between TPR (True Positive Rate; sensitivity) and FPR (False Positive Rate; 1-specificity) for a given metric; AUC – area under the ROC curve; higher = better discrimination; Colored lines – ROC curves for: TPI (blue), S-VAL (orange), S-EFF (green); Dashed line – random classifier (AUC = 0.50); X-axis (FPR) – false positive rate; Y-axis (TPR) – true positive rate.

Differences relative to tournament average:

Throughout the Paris 2024 men's tournament, the average importance weights for the TPI components were approximately: TMS ≈ 0.48, TF ≈ 0.26, OREB ≈ 0.16, and TO ≈ 0.11. These values show how much each factor typically influences TPI. For missed shots (TMS), teams with weights above 0.50 rely even more on shooting accuracy than the tournament average (e.g., Serbia), while teams with weights below 0.45 may compensate with other factors, such as fouls or rebounding (e.g., the USA relying more on foul discipline). For team fouls (TF), weights above 0.30 indicate that foul control is a key focus (as in France or the USA), whereas weights below 0.20 suggest a more physical approach, with the team seeking advantages in other areas. For offensive rebounds (OREB), weights above 0.20 indicate a stronger focus on second-chance possessions (e.g., Lithuania and Latvia), while weights below 0.10 indicate little emphasis on offensive rebounding. For turnovers (TO), weights above 0.15 suggest that ball losses pose a significant risk (as in Poland), whereas weights below 0.08 are typical of a "clean" style of play where turnovers are less decisive (for example, Serbia).

Typical pattern and team differences

All teams identified TMS as the most important factor, confirming that shooting efficiency is the main driver of success in 3x3. However, how teams deviate from the average profile varies. In the USA and France, team fouls (TF) are notably above the tournament average, so foul discipline plays a larger role than usual. Lithuania and Latvia stand out for their higher OREB importance, highlighting rebounding as a key element of their styles. Poland shows a higher-than-average importance of turnovers (TO), indicating that ball security is more critical to their TPI than to other teams'. Serbia exhibits a "classic" profile, with shooting dominating and other factors falling below average; their style is the purest and most shooting-focused.

Table 5. Traffic-light thresholds for TPI and empirical win probability.

Percentile	TPI_zone	TPI_range	N	Win probability	Interpretation	Explanation
<Q25	Red (low)	TPI < 0.67	17.0	0.0	Almost certain defeat	Red zone: TPI below Q25 (0.67) → 17 cases and no wins.
Q25–Q75	Yellow (mid)	0.67 ≤ TPI ≤ 1.05	34.0	0.53	Uncertain outcome (~50/50)	Yellow zone: Q25–Q75 (0.67 to 1.05) → 34 cases, with ~53% matches won.
>Q75	Green (high)	TPI > 1.05	17.0	0.94	Almost certain victory	Green zone: TPI above Q75 (1.05) → 17 cases, with ~94% matches won.

Zone – traffic-light categories based on quartile thresholds of TPI: Red (low) = <25th percentile, Yellow (mid) = 25th–75th percentile, Green (high) = >75th percentile; N – number of team-games in the given zone; Win probability – proportion of games won in each zone; Interpretation - Quick Tip; Explanation - Practical Description

Table 6. Practical sensitivity of TPI - simplified "if–then" rules for coaches

Indicator (variable)	If it changes by 20%…	Effect on TPI (average)	Practical interpretation
Missed shots (TMS)	↓ 20% fewer misses	+0.14	Biggest gain – every 1 of 5 shots less missed boosts TPI clearly.
	↑ 20% more misses	–0.10	Strong drop in TPI, most dangerous factor.
Team fouls (TF)	↓ 20% fewer fouls	+0.07	Discipline pays – cutting 2 out of 10 fouls improves TPI moderately.
	↑ 20% more fouls	–0.06	Extra fouls lower TPI (free throws for rivals).
Offensive rebounds (OREB)	↑ 20% more OREB	+0.04	Each "second chance" adds a small but valuable boost.
	↓ 20% fewer OREB	–0.04	Losing offensive boards hurts a bit.
Turnovers (TO)	↓ 20% fewer turnovers	+0.03	Smallest effect, but still meaningful in close games.
	↑ 20% more turnovers	–0.03	Extra mistakes lower TPI slightly.

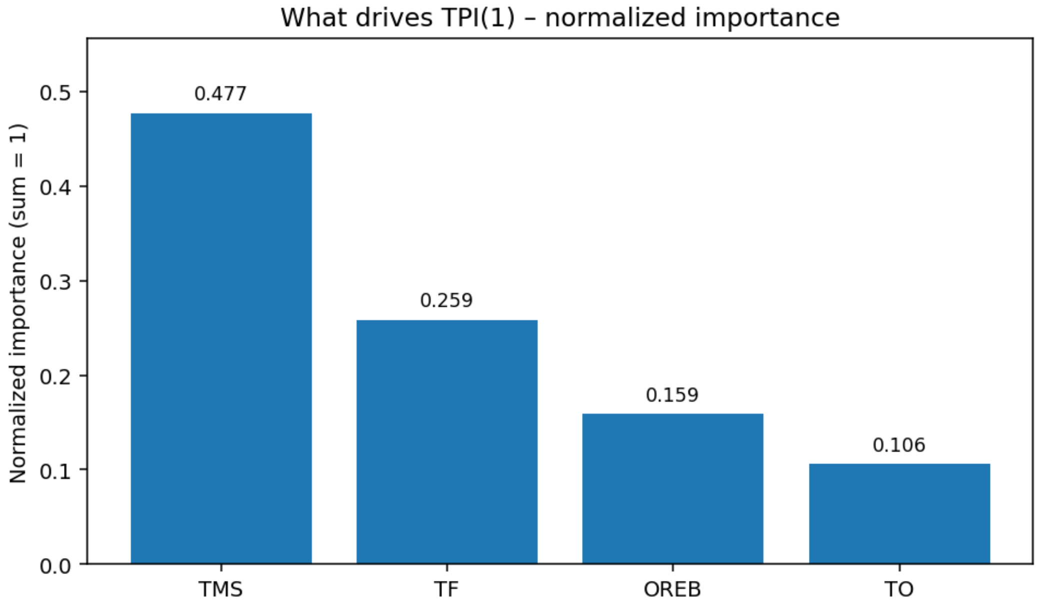


Figure 3. Sensitivity/MCDA – What Drives TPI (MCDA — TPI importance +/- 20%)

Legend: Normalized importance weights (sum = 1) show the contribution of each variable to TPI. Higher bars indicate stronger impact. TMS = missed shots; TF = team fouls; OREB = offensive rebounds; TO = turnovers.

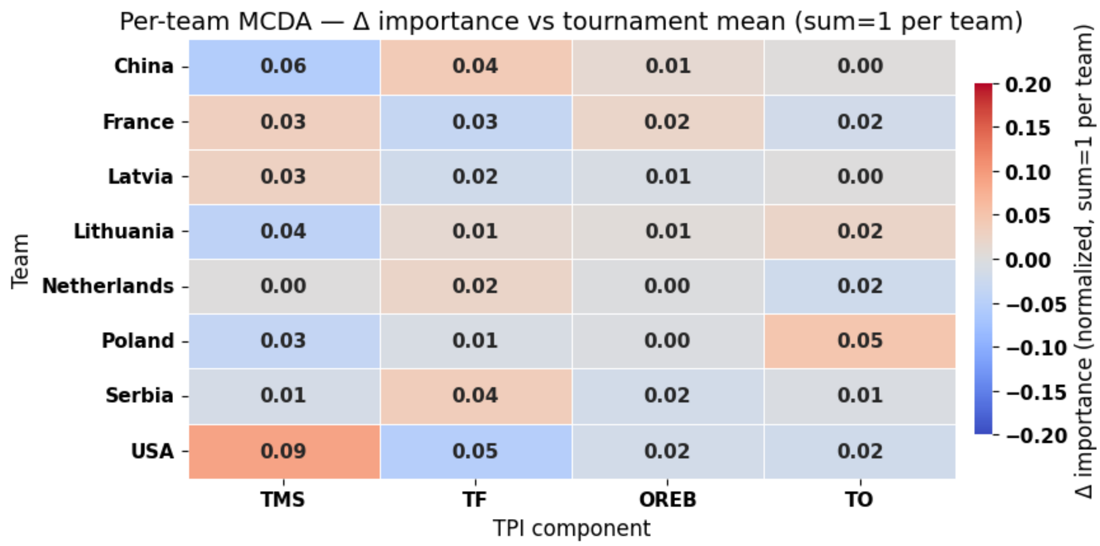


Figure 4. Heatmap of per-team deviations (Δ) in TPI importance relative to tournament mean.

TMS – missed shots; TF – team fouls; OREB – offensive rebounds; TO – turnovers. Colors indicate differences relative to the tournament average profile (TMS ≈ 0.48, TF ≈ 0.26, OREB ≈ 0.16, TO ≈ 0.11): Red shades → above-average importance (variable is more critical for this team); Blue shades → below-average importance (variable is less critical for this team). 0 (white) → equal to tournament average. Numeric values inside cells represent the absolute deviation from the mean (Δ), rounded to two decimals. Rows = national teams, columns = performance indicators.

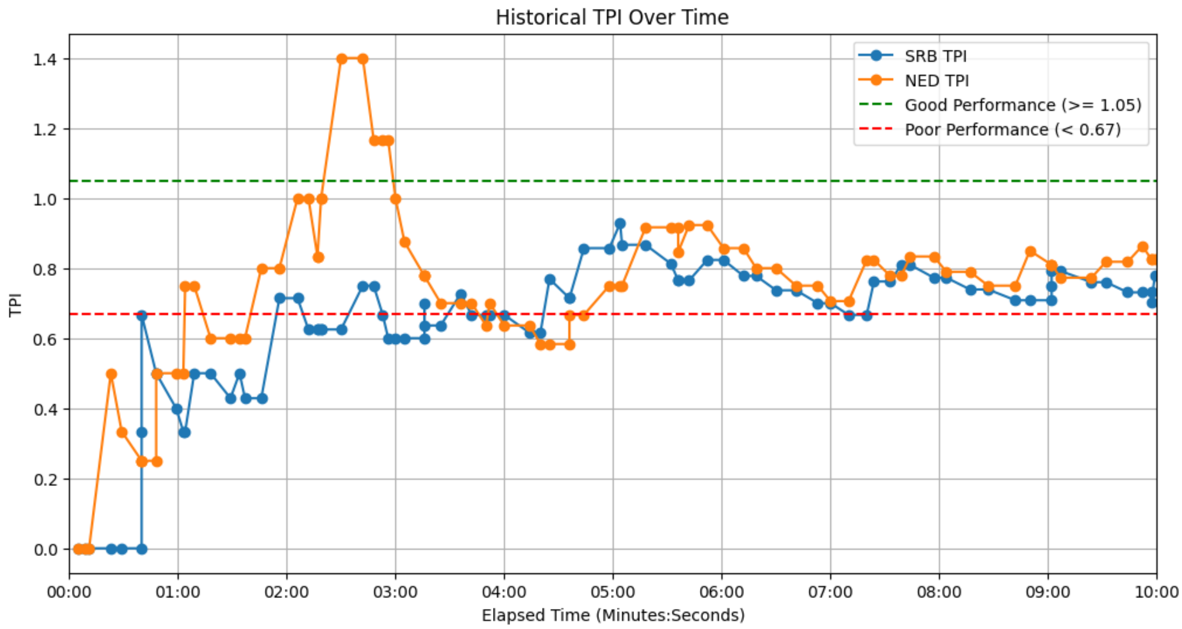


Figure 5. TPI trajectory over Game 9 (Serbia–Netherlands, Paris 2024 Olympics). Vertical lines: fouls; shaded bands: bonus thresholds. The plot shows periods of high Dutch TPI advantage, and it dips after misses; a contested 2-point at the buzzer ultimately ends the game 21–19.

Practical implications for coaches

For all teams, shooting accuracy (TMS) remains the top priority. In the Paris 2024 dataset, TMS also exhibited the most tremendous variability (0.42–0.57), indicating significant differences in shooting performance across teams. Team fouls (TF) varied within a narrower range (around 0.21–0.30), offensive rebounds (OREB) were relatively stable (0.14–0.18), and turnovers (TO) showed moderate variation (0.05–0.13). These patterns suggest that improving shot selection and execution offers the greatest potential for gains, while changes in fouls, rebounds, and turnovers tend to be smaller and more team-specific. From a practical standpoint, this means each team should monitor its own profile relative to the tournament averages. For the USA and France, controlling fouls should be a primary tactical focus. Lithuania and Latvia should protect their advantage on the offensive glass and continue to build second-chance opportunities. For Poland, limiting turnovers is a key goal because they have a greater impact on TPI than other teams. For Serbia, the main objective is to maintain high-quality shot creation and conversion, as their style is already heavily reliant on shooting.

MCDA view and simple three-step use of TPI

From the MCDA perspective, TMS and TF together make up about three-quarters of the total impact on TPI, but individual team profiles vary from the tournament average. Each team, therefore, has its own “red lights” that need special attention in training and match preparation. In practice, TPI can be used in three simple steps. First, coaches evaluate the current situation by checking the TPI value during a game and seeing whether it falls into the red, yellow, or green zone. Second, they compare this value to the thresholds based on the Olympic data: values below 0.67 typically indicate losing performances (red), values from 0.67 to 1.05 represent balanced games (yellow), and values above 1.05 suggest winning performances (green). Third, they address the root issues by focusing on the components that lower TPI: reducing missed shots with better shot choice, improving foul discipline to avoid the 7th and 10th team foul, enhancing offensive rebounding to gain extra possessions, or simplifying the offense to minimize turnovers. This way, TPI helps turn a complex box score into a small set of clear priorities for coaching actions.

Exploratory case study: Game 9

The Serbia–Netherlands game at the Paris 2024 Olympics was essentially a one-possession battle. Serbia won 21–19, although the overall TPI showed a slight Dutch edge (0.83 vs 0.78). We use a mismatch as an example to explore when and why a simple advantage index might differ from the final score despite strong discrimination at the tournament level. Serbia fouled nine times, meaning the next foul would have awarded two free throws plus possession for the Netherlands under 3x3 rules. With 4:24 left, Serbia had already committed seven team fouls and then committed a double foul and an offensive foul. Neither led to Dutch free throws—the offensive foul was recorded as a turnover—but each foul still reduced the team-fouls component in TPI, lowering Serbia's index without giving the Netherlands immediate points. Although Serbia had more fouls, the Netherlands attempted three free throws compared to Serbia's five, showing that Serbian fouls did not translate into a clear scoring advantage for the Dutch.

In terms of possession volume, the Netherlands secured one additional offensive rebound, effectively gaining one extra possession and one more field goal attempt; however, they also missed more shots overall (13 vs 12 for Serbia), which offset the potential gain in a simple event balance. These dynamics help explain why TPI slightly favored the Netherlands. Across extended phases of play, the Dutch generated a cleaner event profile—more second-chance opportunities and fewer fouls that led to opponent free throws—locally boosting their TPI. Moreover, the uniform weighting of fouls in TPI penalizes seven double or offensive fouls that carry no immediate free-throw cost, contributing to the modest divergence from the 21–19 result. Time-series analysis aligns with this interpretation. Early in the segment analyzed, after an offensive rebound and a made two-point shot, the Netherlands, for example, stood at seven points with two team fouls, one turnover, two misses, and one offensive rebound. A single subsequent miss lowered their TPI from about 1.40 to 1.17, yet the advantage persisted until a contested two at the buzzer decided the game for Serbia, 21–19. The visualization of changes in the index during the competition is presented in Figure 6. In interpretation, TPI summarizes the advantage in simple events; it does not deterministically predict the winner of a single close game. In one-possession finishes, high-leverage plays—the final shot in this instance—can override the prevailing advantage profile. Here, TPI appropriately signals a Dutch edge in event quality, but conversion at decisive moments determined the loss, 19–21. In practice, coaches and players should manage fouls, emphasizing avoidance of those that yield free throws or possession, recognizing that not all fouls carry equal point-value risk. Second-chance opportunities created by offensive rebounds must be converted to realize their expected value. Finally, an advantage in TPI should be treated as an opportunity rather than a guarantee; decision quality and execution in the closing possessions ultimately decide outcomes.

DISCUSSION

This study aimed to validate a simple, box-score–based Team Performance Index (TPI) for predicting match outcomes in Olympic men's 3x3 basketball and to compare it with two established shooting-based metrics (S-EFF and S-VAL). The key findings are as follows. First, TPI values were significantly higher in winning teams than in losing teams, with very large effect sizes, confirming its ability to differentiate between wins and losses. Second, the predictive accuracy of TPI was excellent (AUC ≈ 0.91; cross-validated accuracy ≈ 0.81) and statistically comparable to S-VAL, while clearly outperforming S-EFF. Third, quartile-based "traffic-light" thresholds translated TPI into intuitive performance zones that aligned well with empirical win probabilities (<0.67: almost certain defeat; 0.67–1.05:

roughly even odds; >1.05: near-certain victory). Fourth, MCDA-based sensitivity analysis identified missed shots and team fouls as the main drivers of TPI, emphasizing shooting efficiency and foul discipline as key areas for coaching adjustments, while offensive rebounds and turnovers played more supporting roles. Finally, a play-by-play case study of a close game demonstrated that TPI captures the underlying event advantage but does not fully determine the final outcome, especially in one-possession finishes. Overall, these results largely support our hypotheses that TPI would (1) distinguish winners from losers at least as effectively as existing indices, (2) provide interpretable thresholds linked to win probability, and (3) reflect the combined influence of key box-score variables in a practical way for coaches. From a statistical perspective, the ROC and logistic regression results indicate that TPI is not only strongly associated with the final outcome but also a reliable predictor. An AUC near 0.90 means that, in most cases of randomly paired teams, the team with the higher TPI is also the winner, aligning with the intended interpretation of the index. The cross-validated logistic models further demonstrate that this relationship remains consistent across various data samples and is not influenced by a few extreme games. Therefore, the statistical analyses support the idea that TPI can serve not only as a descriptive measure of event dominance but also as a practical tool for estimating the probability of winning during or after a game.

Across sports, consensus on a single dominant factor influencing performance is rare. Long-term studies in individual sports like swimming have shown that sprint results come from the combined effects of morphology, aerobic and anaerobic capacities, and technical skill rather than any single element [36]. Similar multidimensional factors have been identified in team sports, where technical skill, tactical organization, and physical attributes all contribute to game results. Our finding that shooting efficiency, team fouls, offensive rebounds, and turnovers all significantly influence the Team Performance Index aligns with this broader understanding: TPI acts as a composite measure of multiple underlying abilities rather than just a pure shooting or rebounding metric. This validates using TPI not only as a straightforward efficiency indicator but also as an integrated decision-support tool that combines various aspects of 3×3 performance into a single, understandable value for coaches and analysts.

As researchers specializing in data-driven work closely aligned with the real needs of 3x3 basketball, we evaluate results through the lens of in-game usability. Therefore, the new parameter our team introduces, called TPI, aims to achieve two main objectives: simplicity and interpretability, along with strong predictive power compared to point benchmarks (S-EFF, S-VAL). From a multi-criteria perspective, TPI consolidates key decision-making stimuli (TMS, TF, OREB, TO) into a single metric, consistent with MCDA logic, indicating that the "score` reflects a compromise among multiple criteria rather than a single measure [37]. Our sensitivity analysis confirms that TMS (missed shots) plays the primary role, and this influence is asymmetrical: improving shot selection and execution results in a greater TPI gain than a similar decrease causes a loss. Meanwhile, TF, OREB, and TO behave almost symmetrically, suggesting they may serve as "second-order levers"—useful for fine-tuning the game plan. In the predictive analysis, the AUC for TPI is high relative to S-VAL and clearly outperforms S-EFF. These findings align well with recent research and the depicted context of elite play: 2-point shooting efficiency varies depending on factors like sectors, pressure, and shot clock, and shooting policies should be based on "if-then" rules rather than static percentage tables (for 3-point shooting behavior in 3x3) [21,38]. In practice, we can directly integrate this with TPI by labeling shot analysis as in the cited works, e.g., (sector × pressure × seconds on the clock), and update the Shooting Value in real time. This could produce a different dynamic in TPI fluctuations. Within this MCDA framework, missed shots (TMS) stand out as the most influential component of TPI, followed by team fouls (TF), with offensive rebounds and turnovers contributing smaller but still significant effects. This pattern reflects a concept-driven form of feature selection: instead of relying solely on automatic algorithms, we identified a focused set of theoretically meaningful variables and assessed their relative importance. Practically, this means proportional changes in TMS have the largest impact on TPI, so small improvements in shot selection and execution can significantly alter the index and the estimated likelihood of winning.

The example analysis of Game 9 demonstrated that a play-by-play time-series analysis, which considers additional weights such as a team's 7th and 10th fouls, can help identify key moments of play and correlate them with thresholds that define the lights (green/yellow/red) and the estimated probability of maintaining the lead until the end of the game, ultimately leading to a win. Therefore, we believe that the TPI remains an indicator of advantage rather than an absolute predictor. Based on the analysis of Game 9, we suggest that incorporating a gradation of fouls into the formula (offensive/double fouls without shots versus defensive fouls with bonus fouls) could further enhance its effectiveness, which has already been demonstrated in 33/34 games. This is especially relevant in the final stages of the game, where gaining one additional possession can significantly increase the chances of victory—particularly when the TPI variant includes the option to vary foul penalties based on the accumulating consequences, such as after a team's 10th foul.

It is also worth noting that increasingly sophisticated and effective AI systems are emerging daily, with automatic detection processes becoming more accurate. It is only a matter of time before these systems are equipped with additional algorithms that identify on-field behaviors related to game flow recognition and classify individual player actions. This is supported by ongoing work in automation, where live data combined with computer vision (detection, tracking, and event recognition) forms the basis of low-cost, real-time TPI [39], utilizing a human-in-the-loop model for complex cases. TPI will not replace traditional match statistics; instead, it highlights which factors may be more crucial to winning, allowing for targeted filtering and emphasis on the most important statistics rather than all available data. This approach gives three key statistics the power to influence game outcomes: reducing missed shots, which relates to the strategy and skill of each player—comparable to the quality of action selection and execution, whether offensive or defensive—and maintaining a foul count of 7/10, which indicates tactical discipline and teamwork in defense. Such discipline can positively impact the game and reduce turnovers. Research also clearly shows that attacking the backboard after a missed shot remains an attractive and highly valuable trait in any team's playing style.

Study Limitations

This study has several limitations to consider when interpreting the findings. First, it is a small-scale investigation based on a single men’s tournament (the Paris 2024 Olympic Games) with 68 team observations (34 wins and 34 losses). Therefore, the conclusions should be validated with data from multiple competitions. Second, although the data source is public and standardized, it lacks contextual details such as shot location, defender pressure, and the 12-second shot clock. As a result, the TPI does not directly account for shot quality or opponent strength. Third, the current version of TPI treats all fouls equally and does not distinguish between the penalty-point effects of different foul types (e.g., offensive or double fouls occurring simultaneously), which may reduce its accuracy in late-game situations. Finally, the traffic-light thresholds calibrated on quartiles are practical and coach-friendly, but they may need recalibration between tournaments and as more match data becomes available. They should also be refined in future research.

Future research directions

Future research should expand on the current work in several ways. A primary focus is to reevaluate TPI performance while including weightings related to different foul rules, especially in late-game situations. Examining real-time monitoring of TPI is also crucial to identify decisive moments during matches and to link changes in the index with shifts in winning probability. Additional studies should be carried out with coaches to assess the usefulness, interpretability, and decision-making value of TPI in real-world settings. From a technical perspective, the index could be integrated with automated video and image-recognition systems to enable fully or semi-automated calculations during games. Incorporating contextual data such as time, court location, and the opponent's ranking or style of play would help develop more detailed models. Ultimately, expanding the database to include women's 3x3 basketball would improve the generalizability of the findings and support sex-specific analysis applications.

Practical Application

In live match analysis, TPI can be incorporated into an intuitive dashboard that features traffic-light style markings alongside the estimated probability of winning. During the game, coaches can monitor whether the index remains in a favorable zone and identify which components require attention. When the number of team fouls (TF) approaches the seventh or tenth foul, it is advisable to reduce overly aggressive defensive actions to avoid giving away free throws. If the missed-shot rate (TMS) increases, it signals the need to improve shot selection and execution, while a low number of offensive rebounds (OREB) indicates that the team should attack the boards more aggressively.

In scouting and game-plan preparation, analysts can use TPI and its components to build an MCDA-based profile of the opponent and determine what is necessary to win—such as maintaining a TPI above 1.05, committing fewer than seven team fouls, or keeping turnovers below a certain threshold. Based on these benchmarks, coaching staff can design schemes and rotations that exploit the opponent's weaknesses in shooting, foul discipline, rebounding, or turnover management.

For training, evaluation, and planning, post-game diagnostics based on TPI and its components help coaches identify specific deficiencies in key performance indicators (KPIs) like shot selection (TMS), fouls (TF), offensive rebounds (OREB), and turnovers (TO). These areas can then be targeted in training to improve shot quality, maintain foul discipline, and enhance quick, accurate decision-making. Progress in these areas can be monitored week by week through repeated assessments of TPI and its components.

CONCLUSION

The data from the men's 3x3 basketball tournament at the Paris 2024 Olympic Games show that the Team Performance Index (TPI) effectively distinguishes between wins and losses, with an AUC of around 0.91 and a cross-validated accuracy of approximately 0.81. In terms of discrimination and predictive performance, TPI is comparable to S-VAL (AUC ≈ 0.93; cross-validated accuracy ≈ 0.84) and clearly surpasses S-EFF (AUC ≈ 0.81). Quartile-based traffic-light thresholds provide a straightforward, coach-friendly way to interpret TPI: values below 0.67 suggest an almost certain loss, values between 0.67 and 1.05 indicate roughly even odds, and values above 1.05 suggest a high likelihood of victory.

The sensitivity and MCDA analysis revealed that missed shots (TMS) and team fouls (TF) are the main contributors to variability in TPI, highlighting the importance of shot selection, shooting accuracy, and foul discipline as key factors for in-game adjustments. Offensive rebounds and turnovers also play meaningful but supporting roles. A detailed case study of game number 9 showed that play-by-play TPI trajectories accurately reflect the underlying competitive advantage over the opponent, but they do not guarantee the final outcome, as foul dynamics and their scoring effects can temporarily disconnect event profiles from match results. Overall, TPI offers a simple, clear, and practical tool for translating game events into decision guidance, ready to be used in real time through a lightweight dashboard.

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Ethics committee: This study used publicly available, anonymized data. No ethical approval was required.

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SUPPLEMENTARY MATERIALS

Table 7. Operational definitions of key game indicators according to the FIBA 3x3 Statisticians' Manual (2024)

Abbreviation	Definition (FIBA 3x3)	Example situation
TO (Turnover)	An action in which a player loses possession of the ball to the opponent without a shot attempt. Includes passing errors, traveling, offensive fouls, 5-second or 12-second violations.	Bad pass intercepted, traveling violation, offensive foul.
TMS (Missed shot)	Any field goal attempt (1-point or 2-point) that does not result in a score.	Missed 2-point shot from behind the arc.
OREB (Offensive rebound)	A rebound collected by the offensive team after a missed field goal attempt, creating a new possession.	Player secures the ball after his own missed shot.
TF (Team foul)	A personal foul committed by any team member that is charged against the team total. In 3x3, after 7 fouls, opponents receive 2 free throws, and after 10 fouls, 2 free throws plus possession.	Defensive foul during a shot attempt.

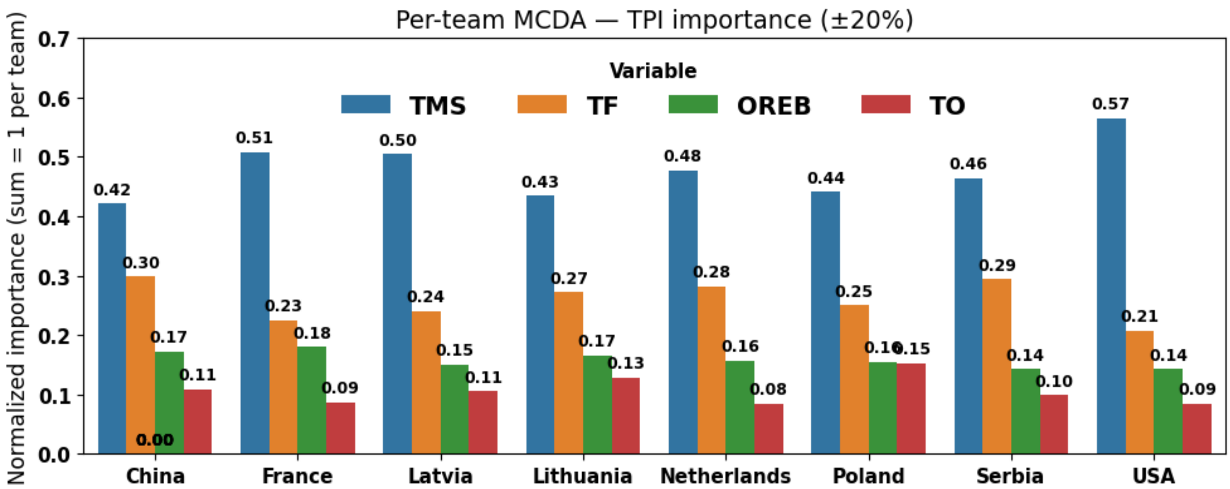

Figure 6. Per-team MCDA (±20%) for TPI.

Complete statistics from the 3x3 Men's Olympic Basketball Tournament - Paris 2024 (Excel)