ORIGINAL ARTICLE

Introducing the Technical Individual Contribution Coefficient: A metric for evaluating performance in elite volleyball

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ABSTRACT

This study introduces a new metric, the Technical Individual Contribution Coefficient, that enables the quantification of the individual technical performance in elite volleyball, from the practical perspective of coaches. Additionally, three Relative Individual Contribution Coefficients provide complimentary information on the players' relative participation.

Data from 20 matches of eight teams during the 2019 Club World Championship were provided by Data Volley software. The numerical evaluation of the players' actions was based on experts' ratings, and all calculations were carried out using Python programming. Binomial logistic regression and the areas calculated under the receiver operating characteristic curves were utilized to predict set outcomes based on team variables. For individual analysis, Spearman's rho correlations and multiple descriptive analyses were conducted, and dynamic visualisations in Power BI were employed to enhance interpretation.

The proposed coefficients efficiently predict both absolute and relative technical performance, across all game actions. This novel metric offers a comprehensive tool for performance evaluation and has significant potential to benefit not only fans and the media, but also coaches and team managers in their decision-making process for player selection. The dynamic visualisations utilized make it easier to understand multiple comparisons and to identify ways for improving performance.

Keywords

Sport analytics, volleyball, team sport, individual assessment, data analysis, python programming

INTRODUCTION

Sports analytics gained momentum after the publication of the book: 'Moneyball: The Art of Winning an Unfair Game' (Lewis, 2003), which benefitted from the use of Artificial Intelligence to measure performance, focusing on the use of new metrics that highlighted the presence of undervalued players (Link, 2017). According to Mortenson et al. (2015), analytics represents a shift from intuition to reason in decision-making. Coaches now rely on quantitative data instead of subjective judgements, such as having a good eye (Cullen et al., 2009), which are considered more objective and reliable (Ramírez-López et al., 2020). In volleyball, the tool that objectivises the coaches' decisions is Data Volley, by recording and assessing each player's contact with the ball.

While the software allows for further analysis on the basis of video, areas or directions, in practice, this perspective takes a personalistic approach to volleyball performance. During competition, it is common to provide coaches with quantitative reports in box-scores, which mainly capture the individual contribution of each player, expressed as scoring data. Box-scores are very useful for coaches as they are available for every set (Zetou et al., 2007), allowing them to efficiently assess each player's contribution in all aspects of the game. The different metrics used in box-scores, according to the action analysed, lead to some confusion and difficulties in making performance comparisons between players (Ducht et al., 2010).

López-Serrano et al. (2022) use the term 'scoring terminal actions' to refer to the terminal actions involving the score of one point. Such actions (and any errors) are shown in the box-scores as raw data of points scored by each player, but also in terms of efficiencies or ratios. In contrast, all those actions which do not score points (i.e. defensive actions), are simply expressed in terms of efficiencies or ratios, despite their influence in conditioning the success of the terminal actions (Nikos et al., 2009). Efficiencies or ratios also aim to demonstrate players' contribution based on their participation (Zidane & Olson, 2017).

Efficiency can be defined as the performance in a skill achieved in relation to the resources employed (García-Sánchez, 2007). Data Volley has spread the efficiency in volleyball regarding the total contacts performed (Data volley, 2010). In summary, efficiency refers to a player's raw performance based on their participation in each skill. More specifically, López-Serrano et al. (2022) emphasize the significance of investigating performance in terms of points played. The participation of each player determines performance, and the players' roles have a fundamental contribution (Araujo et al., 2010), limiting the participation of central players and liberos (replace each other), with wing attackers (opposites and outsider-hitters) being the most requested roles (Milián-Sánchez et al., 2015).

Traditionally, the coefficients in volleyball are based on Fédération Internationale de Volleyball (FIVB) scale. This scale is based on linear weightings of all actions achieved, which simplifies each player's performance to a single number. In volleyball research literature, coefficients have been utilized to evaluate players' performance based on number of contacts they make (Drikos et al., 2021; Marcelino et al., 2008; Palao et al., 2009). The use of the coefficients aims to evaluate and quantify continuity actions that did not result in points. However, their practical use met various obstacles: a) categorisation of actions based on Likert scales without relationship to the actual score of the game that awards a point for a winning action and a point to the opponent for each error (Drikos & Tsoukos, 2018), b) lack of standardisation which leads to coaches using them according to their personal beliefs or needs (Palao & Hernández, 2014). To fully utilize the coefficients for comparing performances using a common metric, López-Serrano et al. (2022) proposed the use of coefficients based on the same metrics used in the score and taking into account coaches' opinions.

Currently, the traditional use of box-scores is obsolete and unable to deal with the quantity, diversity and constant evolution of sports data collection and storage systems (Basole & Saupe, 2016). Understanding the constant flow of sports data requires a change of approach and use of graphics or interactive visualisations capable of providing more personalised, accurate (Casals & Daunis-i-Estadella, 2022) and significant information to players (Araújo et al., 2021). The main objective of the present study was thus to develop a common metric capable of quantifying the individual performance of elite volleyball players in competition. The metric considers all technical contributions (excluding setting, due to its complexity and uniqueness), taking also into account relative participation.

MATERIAL AND METHODS

Participants

The sample included 20 matches and 77 sets, belonging to the eight best teams in the world at the 2019 FIVB Women's Club World Championship. All technical actions were analysed (except setting), with 3,399 serves, 4,963 attacks, 2,062 blocks, 3,081 receptions, 2,735 digs and 391 free-balls.

Technical evaluation (T-ICC)

A1. Technical individual contribution coefficient

The mathematical formulations described below are based on the study of López-Serrano et al. (2022), which presented an evaluation of each of the players' technical actions (excluding setting, due to its complexity and singularity). The values assigned to each technical action were the median values of importance, as they were provided by the world's elite coaches. These values of importance were expressed as decimal numbers within the interval [-1.0,1.0], with one decimal place.

The technical actions considered were: three terminal actions (serve - S, attack -A and block - B) and three continuity actions (reception - R, dig - D and free ball–F). These six technical actions were furthermore categorized by use of six codes #, +, !, −, / and =.

To express the results of López-Serrano et al. (2022) in a mathematical framework, let us first consider the following 6x6 matrix that includes all the technical actions that were evaluated and considered in the study (as presented in Table 1 of López-Serrano et al., 2022):

$$A = \begin{bmatrix} S \\ A \\ B \\ R \\ D \\ F \end{bmatrix} \times [\#, \quad +, \quad !, -, \quad /, \quad =] \,.$$

Each action $A(At,Ac)$ (At=1,…,6 and Ac=1,…,6) is linked to a certain numerical value $I(At,Ac)$ that, as explained above, indicates the importance of this particular action. These numerical values (see Table 2 of López-Serrano et al., 2022) constitute the 6x6 matrix I, that will serve as the basis for the numerical evaluation of the players' technical actions.

Let us now consider the m-th player of a team that takes part in a volleyball match (m=1,…, m_{max}, where $m_{max} = 14$). The actions performed by this particular player during the k-th set of the match (k= $1, \dots, k_{max}$ where $3 \leq k_{max} \leq 5$), after being identified as to their technical quality and categorized, can be stored as elements in the 6x6 matrix $N_m(k)$, in such a way that the element $N_m(k)(At, Ac)$ gives the frequency of the *A*(*At,Ac*) action for the m-th player and during the *k*-th set.

Taking into consideration all the above, a "Technical Individual Contribution Coefficient" of the m-th player can be defined. This coefficient, which will be denoted as "*T-ICC*", will give an evaluation of the *m*-th player's performance during a particular set, and during the whole match, as will be described below.

During the k-th set of the match, the technical individual contribution coefficient can be obtained by use of the following formula:

$$[T - ICC]_m(k) = \sum_{At=1}^{6} \sum_{Ac=1}^{6} N_m(k)(At, Ac) \cdot I(At, Ac)$$

while the total technical individual contribution coefficient $[T - ICC]_m$ that evaluates the performance of the *m*-th player during the whole match can be calculated as the sum of all technical points obtained by the player during all sets:

$$[T - ICC]_m = \sum_{k=1}^{k_{max}} [T - ICC]_m(k)$$

A2. Relative technical indices (T-ICC R1, T-ICC R2 y T-ICC R3)

As reported in López-Serrano et al. (2022), 70% of the expert elite coaches agreed that it is necessary to consider the players' relative participation together with their technical points, to obtain a more complete indication of the players' technical performance during a particular set (or match).

Three types of relative technical individual contribution coefficients are considered in this study, for the m-th player, named $[T - ICC]_m$ R1, $[T - ICC]_m$R2 and $[T - ICC]_m$R3. These coefficients are defined by the following relations:

$$[T - ICC]_m \text{ R1} = [T - ICC]_m \times \frac{points\ scored\ while\ player\ in\ the\ field}{total\ points\ scored}$$

$$[T - ICC]_m \text{ R2} = [T - ICC]_m \times \frac{number\ of\ actions\ performed\ by\ the\ player}{total\ number\ of\ actions\ performed\ by\ all\ players}$$

$$[T - ICC]_m \text{ R3} = \frac{[T - ICC]_m}{number\ of\ actions\ performed\ by\ the\ player}$$

Other traditional variables.

Among the traditional variables used to measure individual volleyball performance are the following: a) Points (Ptos), defined as the points scored by the players without considering errors; b) the attack efficiency (Eff A), defined as the difference of attacks achieved less attack errors, divided by the number of attacks made; c) reception efficiency (Eff R), defined as the sum of excellent and positive receptions divided by the amount of receptions made; d) Errors (Err), defined as the total number of errors that end in points for the opponent.

Analysis of reliability

Data were collected by a professional scout (+5 years' experience in professional volleyball teams) though the software, Data Volley Professional 4. Two professional scouts were used to check the consistency of the observations (+5 years professional experience). A test-retest procedure with a 15-day interval was used, applied to a random sample of four matches (20% of the sample according to the literature) (Silva et al., 2016).

Reliability was tested using Fleiss' kappa values, as a more adequate alternative to Cohen's kappa for measuring the degree of agreement among more than three observers (Krippendorff, 2004). Table 1 shows the reliability values, all of which are considered to be substantial (.61–.80) to almost perfect (> .81) (Landis y Koch, 1977), with a higher discrepancy found for free-ball. To guarantee better data quality, the data were presented in sequential order instead of frequencies (Anguera et al., 2011). The data were analysed using the SPSS v.26 statistical package (IBM Corp., Armank, NY, USA).

Insert Table 1

Data analysis

All technical action data were implemented using code written in Python 3. To identify the optimal fit of the proposed models regarding the team's win (using the sum of all team players), the Akaike criterion (AIC) and the Bayesian criterion (BIC) were used. In the same way, a binomial logistic regression was implemented to estimate the probability of the dependent variable being satisfied (Wset; set win).

The Receiver Operating Characteristic (ROC) curve was applied to determine the predictive ability of each quantitative variable, by determining the area under the curve (AUC), which allows us to quantify the success probability of the proposed model. At individual player level, the Kolmogorov–Smirnov test was used to evaluate the normality of the data. Due to the violation of these assumptions of normality, Spearman's Rho correlations were used to determine the strength of association between the different variables suggested, as well as the other traditional variables: Ptos, Eff A, Eff R, Err, regarding Wset. Finally, descriptive analysis was applied to make multiple-variable comparisons, supported charts and tables implemented with Microsoft Excel Office 365 and Microsoft Power BI Office 365.

RESULTS

At the team level, Table 2 indicates the estimator coefficients of the model (Estimator), the standard error, Wald value and p-value of the Wald test. In this case, the constant was not significant, but that the p-value presented as an explicative variable was highly significant ($p < .05$), which would allow us to predict the outcome in percentages from the AUC.

Insert table 2

Table 3 shows the model fit of the technical coefficient (T-ICC) and relative indices (T-ICC R1, T-ICC R2 and T-ICC R3), together with the traditional variables considered**.** These results showed significance for all variables regarding set win ($p < .001$), except for T-ICC R2 ($p < .115$) and Eff R ($p = .445$).

Insert table 3

Table 3 also shows the predictive measures according to the optimal cut-off point, the accuracy, specificity, sensitivity and AUC for each variable. This allows us to know the success percentage of each predictive model suggested. This table shows the precision of the predictive power, represented by the AUC values. In addition, the cut-off point is shown that indicates where sensitivity and specificity together reach the highest point, which would allow us to optimise and maximise both values. Likewise, figure 1 (ROC curves) plotted AUC and its values expressed as a percentage.

Insert Figure 1

At the team level, the model that best predicted a winning set was the scoreboard variable (AUC – 100%), represented by the points on each team's scoreboard in the set, followed by Ptos (AUC – 95.2%) and Eff A (AUC – 94.3%). Among the suggested models, the index T-ICC R1 achieved the best results with an AUC of 89.9%, followed by T-ICC R3 (AUC – 89.1%) and T-ICC (AUC – 87.4%), highlighting the strong predictive power by winning the set.

The lowest performance was achieved by the Eff R (AUC – 56.1%) and T-ICC R2 (AUC – 73.6%), showing the weakness of reception efficiency in predicting winning, as well as informing on the defensive players' performance. At the individual level, Table 4 shows the correlation between the different variables regarding winning the set. Following Fleiss' scale (1986), this correlation was null ($r < .30$). In this regard, the unique variables that were not correlated with winning were the Eff R, Err and the Role.

Insert table 4

The following link presents a dynamic data visualisation elaborated on the Power BI (Microsoft) platform:
https://app.powerbi.com/view?r=eyJrIjoiOGU2MTg3MDktNjJlMS00YzI1LWEwY2ItNWRlNWRhZGRlMTA4IiwidCI6IjZhZmVhODVkLWMzMjMtNDI3MC1iNjlkLWE0ZmIzOTI3YzI1NCIsImMiOjl9

Beginning with the initial navigation front page, it allows us to make comparisons between multiple variables (suggested new metrics and/or traditional variables). Choosing which variables we want to filter and representing them in tables and/or graphs facilitate the comparison and understanding of multiple data. Tab 1 (General) presents all variables in two separate tables which would enable the simultaneous comparison between groups of players. The right-hand column contains filters, which allow you to delimit the information more precisely.

Tab 3 (T-ICC) allows comparing the T-ICC values per player versus some of the most relevant traditional variables. Tab 5 (per ROLES) shows the T-ICC values per set versus points and according to the playing role. The graphs show that the T-ICC allows to evaluate the liberos who achieve neither Ptos nor Eff A (Tab 9).

Tab 7 (relative indices) provides technical indices information, noting that the T-ICC R1 coincides fully with the T-ICC values for those players who played all the points in the set. T-ICC R1 and T-ICC R2 are led by wing-speakers player's role, being the players who most participated in the team's game and who made more contact. Finally, Tab 8 (relative index R3), points to a trend change, which was clearly being led by the players in the role of the libero. However, it overestimates players whose participation was very low and of high quality.

DISCUSIONS

The aim was to develop a common metric capable of quantifying the individual performance of elite volleyball players in competition, from all their technical contributions, while also taking into account relative participation. At team level, the study revealed the high predictive accuracy of T-ICC (87.4% AUC) in determining the probability of a team winning. By including these traditional metrics, the study aimed to compare the performance of the suggested coefficients to the variables traditionally used in volleyball. The results indicated a strong predictive power for the Ptos (94.9%), the Eff A (94.3%) or Err (−89.5%).

The findings indicated that scoring events had a stronger predictive power compared to coefficients and technical indices, consistent with previous research, suggesting that the terminal actions (particularly the attack), were strongly associated with winning (Drikos et al., 2021; Marcelino et al., 2008). Similarly, it is also common to report errors in relation to scoring events given to the opponent (Laios & Kountouris, 2005). Regarding the defensive actions' metrics, the Eff R obtained a low predictive power (56.1%). This result is paradoxical, as it is the main classical metric used to indicate the effectiveness of players performing continuity actions, which are determinants in facilitating attacking actions (Costa et al., 2011; Palao et al., 2009).

Despite its frequent use in elite volleyball, the relationship between reception quality and attack effectiveness does not appear to be directly proportional (Papadimitriou et al., 2004). Mercado-Palomino et al. (2022) discovered that reception effectiveness did not predict the final ranking of teams in the 2010 Men's World Championship. While good reception certainly aids the setter and ensures all attackers are readily available, what ultimately determines victory is the setter's ability to generate successful attacks even with imprecise receptions (Millán-Sánchez et al., 2020).

In short, both the Ptos and Eff A only report terminal actions and attack, respectively, ignoring the important predictive power of reception or defence in winning (Conti et al., 2018), as they allow the attack to be organised. Giatsis et al. (2022) indicated that the fundamental issue is to achieve a balance between all of them, something these traditional metrics ignore. Measuring the individual performance of each player, the results showed a correlation with a set win, but reported a poor correlation for all models, with a slightly higher correlation of T-ICC than Eff A. Hvattum (2019) argued that the analytical approach to performance is a simplistic vision that isolates a player's performance from players' and opponents' interactions. In this regard, Vilar et al. (2012) indicated that, to be correct, these individual performance indicators should be highly associated with winning.Determining individual player performance is challenging to determine due to many qualitative and quantitative factors involved (Bisagno et al., 2019). The teamwork essence determines that the individual performance of each player does not determine the success of the team, but it is a precondition given that the best players tend to contribute the most points and experience (Flores-Szwagrzak & Treibich, 2020). It is frequently noted that 'superstars' have a huge impact on their teams, yet the precise extent of their impact remains undetermined (Duch et al., 2010). The perplexing aspect lies in understanding why remarkable individual accomplishments by players are not regarded as exceptional performances when their team does not secure a victory.

The T-ICC is a performance metric which is easily available in every set for coaches (Zetou et al., 2007), and in contrast to traditional variables, includes offensive and defensive actions, facilitating estimation of a player's full potential (Kizielewicz & Dobryakova, 2020). This characteristic is evidence of the sequential nature of volleyball, where previous continuity actions have a great influence on later scoring actions (Monteiro et al., 2009; Nikos et al., 2009).

Several studies point out that individual performance depends directly on tactical interactions with teammates and opponents (Marcelino et al., 2008; Silva et al., 2016). In volleyball, actions are recorded according to the scoring opportunities given to the opponent or teammates (Palao et al., 2015). Therefore, the volleyball method itself involves some interaction with teammates and opponents. Similarly, some authors suggest that the individual skills of volleyball players (mainly in attacking and serving actions), could be more transcendental than any interaction or game system (Laporta et al., 2021), because in volleyball a defender cannot interrupt the execution of any technical action. This could make sense of the fact that individual statistics in volleyball continue to be used so often by coaches (Drikos et al., 2021).

Including relative indices responds to elite coaches' opinions that consider it important to adjust performance based on the participation of players in points played or contacts made (López-Serrano et al., 2022). This way, we avoid inflating the performance values achieved by players who play many points/contacts more than others. The T-ICC R1 measures the T-ICC performance in terms of points played by the player and has the best predictive power at team level (AUC – 89.9%). Next is T-ICC R3 (AUC – 89.1%), excluding the T-ICC R2 due to its low predictive power. At individual level, the low correlation of the relative indices highlights the difficulty of associating individual performance with team victories.

T-ICC R1 provides a more accurate measure of players who play the most points per set, preventing the overestimation of players who have less participation in the game (e.g. players replaced, middle blockers, liberos). It gives the T-ICC performance in relation to player-specific contributions. In basketball, player efficiency rating (PER) is a reference measure of each player's production per minute of play. Bisagno et al. (2019) expresses the need to have a volleyball performance measure that is able to inform on the 'time' played by each player, to avoid exaggerating game statistics. In basketball, only the players who play more than 40 minutes per game are included in the statistics (Kubatko et al., 2007).

T-ICC R3 aims to evaluate the efficacy of each player based on all contacts they made (reason for being expressed as a percentage). The efficacy of each player is a metric frequently used in the sport, related to the number of attempts by each player. In basketball, it is common to report two-point and three-point shooting percentages based on the number of attempts (Lorenzo et al., 2019). However, this metric tends to overestimate players with fewer attempts, which might benefit from high percentages with a low number of interventions.

Finally, we were unable to identify a similar metric in the literature to the T-ICC R2, which aims to determine the most utilized players in a team. However, the results may be biased as players with high participation, but negative results may be at a disadvantage compared to those who participated less. An additional limitation worth highlighting pertains to the analysis of the setter position. For a more comprehensive understanding, this role should be studied using an expanded dataset that encompasses both genders and various levels of expertise.

CONCLUSIONS

We conclude that:

- The T-ICC technical coefficient is able to unify the technical performance of the players in a single digit and has a strong power for determining set wins.
- The relative T-ICC R1 index provides a more accurate measure of technical performance, based on the player's specific participation, with an even stronger predictive power.
- The T-ICC R3 is a highly sensitive metric for players in the libero role, although the 'inflated' statistics of players involved in few contacts should be monitored.
- The T-ICC R2 shows similar performance to R1, but with lower predictive power.
- Consequently, the proposed coefficients and relative indices provide a viable alternative for evaluating individual player performance. Although their predictive power maybe slightly lower than Ptos or Eff A, it is still above Eff R. This provides a more comprehensive and complete understanding of player performance.
- Finally, the use of dynamic visualisations allows synthesising the relevant information to be presented in a more understandable way.

CONFLICT OF INTEREST STATEMENT

No potential conflict of interest was reported by the authors.

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