ORIGINAL ARTICLE

Contextualizing Evaluation of Performance in Volleyball: Introducing Contextual Individual Contribution Coefficients to Assess Technical Actions

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Abstract

In this study, we propose novel metrics for evaluating volleyball technical performance in relation to the action context. To assess each player'' relative participation, we also introduce relative contextual coefficients. We analyzed 20 games played by the world's top eight teams during the 2019 FIVB Women's Club World Championship, using Data Volley software and Python programming. We evaluated inter- and intra-observer reliability and used binomial logistic regression models to estimate each variable's probability of having contributed to the team's set win. We calculated estimated confidence intervals, standard errors, and Wald values; and we employed Akaike's and Bayesian criteria to evaluate the model's goodness of fit. We identified optimal cut-off points using receiver operating characteristic curves, and we found that the proposed contextual evaluation coefficients prevented overestimation of a player's technical performance in uneven situations. We addressed the issue in which the winning team may be the one that scores the fewest points, and we were able topredict a team's victory with confidence. The proposed coefficients made multiple technical and contextual aspects of the game easily accessible and comprehensible, offering significant beneficial implications for coaches and players.

Keywords Volleyball performance assessment, technical performance, contextual variables, relative participation, Data Volley software, Python programming.

Introduction

Elite sport play is associated with winning team achievements, record-breaking performances, and the identification of a sport's best players (Tener & Franks, 2021). However, a key challenge in performance analysis is determining which variables to evaluate (Glazier, 2017). While past investigators have sometimes focused on the importance of players' anthropometric (Malousaris et al., 2008) and physical characteristics, such as anaerobic and jumping power in volleyball (Martínez, 2017), technical variables have received primary attention, particularly those variables that are directly associated with scoring events, as, for example, in rugby by Novak et al. (2021). In volleyball, terminal actions have been seen as most relevant for generating scores (Giatsis et al., 2022). Yet, continuity actions that do not result in a point are crucially important because they form part of a sequence of actions in volleyball that connect previous quality actions such as reception, dig, or setting that later result in scores (Monteiro et al., 2009; Nikos et al., 2009).

Current approaches to performance analysis are play that is relevant to team victories (James & Henzler, 2002), and they may encompass the utilization of artificial intelligence (AI) models like eigenvector centrality that helps identify game patterns (Laporta et al., 2021), and Social Network Analysis techniques to gauge player interactions (Laporta et al., 2018). AI is particularly noteworthy for its prowess in data analysis (Liu & Lui, 2021) and in uncovering intricate patterns that traditional methods might miss (Van Haaren et al., 2016). Moreover, AI can be trained to forecast performance (Horvat & Job, 2020).

Nonetheless, AI applications in volleyball remain relatively nascent (Rajšp & Fister, 2020), stemming from the challenges associated with accessing extensive data repositories which can hinder the extrapolation and comprehension of the acquired outcomes (Lalwani et al., 2022). The evaluation of volleyball performance is still associated with the generalized use of Data Volley software (Data Volley, 2010) that tracks every technical action performed by each player and provides detailed reports for each set that are highly beneficial to coaches (Zetou et al., 2007).

Coefficients or indices of evaluation recently became popular to establish common metrics enabling player comparisons and improving player contributions to all game actions, independent of scoring. Popular metrics in this domain have been baseball's Wins Above Replacement (Duquette, 2019), and basketball's Player Efficiency Rating (PER) (Kubatko et al., 2007). In volleyball, a popular coefficient is the FIVB Scale (of the Fédération Internationale de Volleyball).

Coefficients measuring player-specific performance, often expressed in percentages or simple mathematical formulas like efficiency or effectiveness ratios (Zidane & Olson, 2017; Bisagno et al., 2019), should consider contextual data such as points played and contacts made, as highlighted by López-Serrano et al. (2022a). Araujo et al. (2010) also emphasized how various playing roles in volleyball, such as wing-spikers compared to middle blockers or liberos, significantly impact each player's participation rates.

Despite some early attention to contextual dynamics, these coefficients often overlook the significance of various game situations. In a study on handball, Oliveira et al. (2012) found that the context in which technical actions are executed determines both their performance value and various interactions between players. Gómez-Ruano et al. (2013) highlighted how home advantage, the crowd, or court familiarity, can psychologically impact players and influence their performance.

Among contextual factors that have been studied to date are home advantage (Gómez-Ruano et al., 2013), how an opponent's skill level motivates top level teams (García-de-Alcaraz & Marcelino, 2017), the contribution of the set period to the final periods for the victory (Marcelino et al., 2012), and how score differences ≤ 2 points contribute to a subsequent victory (Dávila-Romero y García-Hermoso, 2015). Other contextual variables are also thought to affect the quality of technical actions, including the game score, the result of the previous set, or the competitive load (López-Serrano et al., 2022b). However, despite ample evidence that contextual variables significantly impact performance indicators in volleyball (García-de-Alcaraz & Usero, 2019), there is currently no model for quantifying this influence or for integrating the impact of multiple contextual variables (López-Serrano et al., 2022b).

Our objective was to provide coaches with efficient decision-making support by devising an innovative algorithm to accurately capture individual player performances during matches while considering contextual data. We sought to formulate a comprehensive and distinct metric to achieve this goal. Thus, in this study, we present several coefficients that evaluate the technical performance of elite volleyball players individually, while considering their specific contributions within the broader context of each action.

Method

Participants

These data were collected via Data Volley Professional 4 software. Data consisted of 16,631 technical actions (excluding setting) performed by the top eight women's volleyball teams during the 2019 FIVB Club World Championship, comprising 77 sets within 20 games. The data analysis was fully approved by the Research Ethics Committee of the Polytechnic University of Madrid (Spain). Since the data were publicly available in game films, there was no need to obtain informed participant consent.

Contextual Evaluation (C-ICC)

Contextual Individual Contribution Coefficient

Also aiming to develop a metric for evaluating player performance in elite volleyball, López-Serrano et al. (2022a), evaluated six technical actions (excluding setting; see Table 1 of López-Serrano et al., 2022a), including three terminal actions (serve - S, attack -A, and block - B) and three continuity actions (reception - R, dig - D, and free ball – F). They categorized these actions into six codes (#, +, !, -, /, and =) and evaluated a player's technical actions numerically with decimal values between -1.0 and 1.0, provided by elite coaches and assigned to the technical actions, based on their importance. In this way, each technical action $A(At,Ac)$ (At=1,…,6 and Ac=1,…,6) was linked to a numerical value $I(At,Ac)$ to indicate its importance (see Table 2 of López-Serrano et al., 2022a).

López-Serrano et al. (2022b), additionally identified the following five contextual variables that were considered to affect individual performance in elite volleyball players: (a) opponent's skill level (*OL*); (b) set period (*SP*); (c) score difference (*SD*); (d) result of previous set (*SetP*); and (e) competitive load (*CL*). Tables 2 and 4 of López-Serrano et al. (2022b) provide detailed explanations and subcategories for these variables, with their Table 4 showing their median values (i.e., importance) as provided by elite experts.

In what follows we mathematically formulated these contextual variables and linked their numerical values of importance as follows:

(a) ***Contextual variable OL***

The contextual variable *OL* is a 1 x 5 matrix, represented by the letters$L_{-}, L_{+}, M_{-}, M_{+}$ and *H*, which correspond to "low level –" (two groups above), "low level +" (two groups below), "medium level-" (one group above), "medium level+" (one group below) and "same (high) level" respectively:

$OL = [L_{-}, L_{+}, M_{-}, M_{+}, H]$.

Table 4 of López-Serrano et al. (2022b), shows the numerical values linked to each category, permitting the expression of importance of the *OL* variable as

$I_{OL} = \left[I_{L_{-}}, I_{L_{+}}, I_{M_{-}}, I_{M_{+}}, I_{H}\right]$,

where $I_{L_{-}}, I_{L_{+}}, I_{M_{-}}, I_{M_{+}}$ and I_{H} are numerical values derived from the median values.

During a particular match, where both the players' team and their opponents do not change, the contextual variable *OL* also maintains a constant numerical value, which belongs to one of the five values included in the matrix I_{OL}. This fixed value, that solely depends on the opponent's level, will be henceforth referred to as the coefficient OL_{coef}.

(b) ***Contextual Variable SP***

The contextual variable, set period (SP), can be represented by two 1 x 3 matrices, namely.

$SP = [I, C, F]$ and $SP_5 = [I_5, C_5, F_5]$.

The letters I, C, F and F correspond to "initial period (0–9)," "central period (10-19)," and "final period (≥20)," respectively. On the other hand, I_5, C_5 and F_5 correspond to "initial period during $5th$ set (0–4)," "central period during 5th set (5-9)," and "final period during 5th set (≥10)," respectively. The importance of the *SP* variable, expressed in numerical terms, can be written in the form of two matrices:

$I_{SP}(1, \ldots, 4) = [I_I, I_C, I_F]$ and $I_{SP}(5) = [I_{I_5}, I_{C_5}, I_{F_5}]$

where $I_I, I_C, I_F, I_{I_5}, I_{C_5}$ and I_{F_5} are numerical values derived from the corresponding median values presented in Table 4 of López-Serrano et al. (2022b).

We now define the 6 x 6 matrix $N(k)$, that includes the actions performed by the player under study, during the *k*-th set of the match $= 1, \ldots, k_{max}$ where $3 \leq k_{max} \leq 5$).

The element $N(k)(At, Ac)$ provides the frequency of the *A(At,Ac*) action of this specific player. Each element $N(k)(At, Ac)$ can be further expanded to provide additional details regarding the set period during which the player executes each action. Mathematically speaking, we can write:

$$N_{SP}(1,\ldots,4)(At,Ac) = \begin{bmatrix} N_{SPI} \\ N_{SPC} \\ N_{SPF} \end{bmatrix} \text{ and } N_{SP}(5)(At,Ac) = \begin{bmatrix} N_{SPI5} \\ N_{SPC5} \\ N_{SPF5} \end{bmatrix}$$

where N_SPI is the number that gives the frequency of the *A(At,Ac)* action during the initial period of the k-th set, and so on. Note that there is $N(k)(At,Ac) = \sum_{a=1}^{3} N_{SPa}(k)(At,Ac)$.

Once the numbers $N_{SPa}(k)(At,Ac)$ are determined, the product of I_{SP} and N_{SP} will give the contribution of the contextual variable *SP* to the player's evaluation, for each action and during each set:

$$SP_{coef}(k,At,Ac) = I_{SP}(k) \cdot N_{SP}(k)(At,Ac)$$

(c) ***Contextual Variable SD***

As above, the contextual variable score difference (*SD*) can again be represented by the following two 1 x 3 matrices,

$$SD(1,\ldots,4) = [L,M,H] \; and \; SD(5) = [L_5,M_5,H_5]$$

where the letters L,M and H correspond to "low (0-2)," "medium (3-5)," and "high (>5)," respectively, and the letters L_5, M_5 and H_5 correspond to "low during the 5th set," "medium during the 5th set," and "high during the 5th set," respectively. The importance of the *SD* variable, can be expressed numerically as elements of the matrices

$$I_{SD}(1,\ldots,4) = [I_L, I_M, I_H] \text{ and } I_{SD}(5) = [I_{L_5}, I_{M_5}, I_{H_5}]$$

The values $I_L, I_M, I_H, I_{L_5}, I_{M_5}$ and I_{H_5} are derived from the corresponding median values shown in Table 4 of López-Serrano et al. (2022b).

The same way as before, the number $N(k)(At, Ac)$ gives the frequency of the *A(At,Ac*) action can be further expanded into the following two matrices, to incorporate the effect of score difference:

$$N_{SD}(1, \dots, 4)(At, Ac) \begin{bmatrix} N_{SDL} \\ N_{SDM} \\ N_{SDH} \end{bmatrix} and\ N_{SD}(5)(At, Ac) \begin{bmatrix} N_{SDL5} \\ N_{SDM5} \\ N_{SDH5} \end{bmatrix}$$

It is worth observing that, as in the case of SP, there is

$$N(k)(At, Ac) = \sum_{a=1}^{3} N_{SDa}(k)(At, Ac)$$

In this way, the contribution of the score difference as a contextual variable can be included in the value of the coefficient $SD_{coefficien}$, which is dependent on the type and code of the *A(At,Ac*) action and the set *k*:

$$SD_{coef}(k, At, Ac) = I_{SD}(k) \cdot N_{SD}(k)(At, Ac)$$

(a) Contextual variable SetP

The contextual variable *SetP* which corresponds to the result of the previous set depends only on the set k, and can be written as

$$SetP = [W, L]$$

where the letter "W" refers to "previous set won" and the letter "L" refers to "previous set lost". The values of importance of this variable, evaluated by the experts can be found in Table 4 of López-Serrano et al. (2022b). Utilizing these values and the notation described above, we can construct the matrix,

$$I_{SetP} = [I_W, I_L]$$

The contribution of the result of the previous set as a contextual variable can be expressed, as before, in the form of a coefficient $SetP_{coefficient}(k)$. During the k-th set, the value of the $SetP_{coef}(k)$ will be equal to one of the two values that constitute the matrix I_{SetP}.

(b) Contextual variable CL

Finally, the contextual variable of the competitive load (CL) can also assume two distinct values and can be mathematically expressed as

$$CL = [A, HCL]$$

where the letters "A" and "HCL" refer to "attenuated load" and "high competitive load", respectively. The importance values of this variable can be found in table 4 of López-Serrano et al. (2022b), similarly as with the rest of the contextual variables. Utilizing these values, we construct the matrix

$$I_{CL} = [I_A, I_{HCL}]$$

Similar to the aforementioned contextual variables, the contribution of the competitive load as a contextual variable can be expressed as the coefficient $CL_{coef}(k)$ such that, during the k-th set, the value of the $CL_{coef}(k)$ will be equal to one of the two values of the matrix I_{CL}.

© ***Contextual Individual Contribution Coefficient***

Considering all the information mentioned above, the "Contextual Individual Contribution Coefficient" (denoted as "*C-ICC*") can be defined. This coefficient numerically evaluates the technical performance of the player during the *k*-th set of the match, in combination with all five contextual variables.

The formula for obtaining the C-ICC during the *k*-th set of the match is given by:

$$[C-ICC](k) =$$

$$= OL_{coef} \cdot SetP_{coef}(k) \cdot CL_{coef}(k)$$

$$\cdot \sum_{At=1}^{6} \sum_{Ac=1}^{6} SP_{coef}(k, At, Ac) \cdot SD_{coef}(k, At, Ac) \cdot I(At, Ac)$$

where it should be reminded that the value *I(At,Ac)* represents a numerical evaluation of the technical importance of each *A(At,Ac)* action.

The player's overall performance throughout the match, considering the impact of the defined contextual variables, can be measured by the total contextual individual contribution coefficient *C-ICC*. The *C-ICC* coefficient is computed by adding up all the contextual points earned by the player during every set:

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

The illustration in Figure 1 below depicts how the *C-ICC* is defined and the conditions under which it is calculated.

[Insert Figure 1 about here.]

Relative Contextual Individual Contribution Coefficient

Three relative contextual individual contribution coefficients can be defined by use of the formulas shown in in Figure 2.

[Insert Figure 2 about here.]

Other Traditional Variables

To test the potential of the proposed coefficients as performance evaluators, we compared them to the traditional variables commonly used to measure performance of volleyball players. The traditional variables were: (a) Points (Ptos); scored per player (errors excluded); (b) attack efficiency (Eff A), defined as the ratio between the attack balance (attacks scored minus attacks missed) to the number of attacks made; (c)reception efficiency (Eff R), defined as the ratio of excellent and positive receptions to the total number of receptions,; (d) Errors (Err), which are the total number of errors that result in the opponent's points.

Reliability Analysis

Inter-observer and intra-observer reliability were assessed to evaluate observation consistency. A professional scout picked up all the technical actions, using the Data Volley software. Two other professional scouts, each with more than five years of international experience, analyzed the consistency of the observations, using a test-retest method applied to four randomly selected matches (20% of sample, as suggested in the literature) (Drikos et al., 2018) after a 15-day period.

We applied sequential data recordings to guarantee a higher data quality (Anguera et al., 2011). We used the Fleiss Kappa values to determine the agreement over three observers (Krippendorff, 2004). The reliability values in all cases were higher than: Serve (.958), Attack (.969), block (.945), reception (.898), dig (.943) and free ball (.701), all considered adequate (Landis y Koch, 1977).

Data Analysis

We analyzed all data using the Statistical Package for the Social Sciences (SPSS, v.26; IBM Corp., Armank, NY, USA)The data we collected from the Data Volley software was processed using Python code for subsequent analysis and for the numerical calculation of the coefficients.

We used binomial logistic regression models to estimate the likelihood of each variable contributing to the team's set win (Wset), calculating the estimator and its confidence intervals, standard error, and the Wald value. In addition, we used Akaike's criteria (AIC) and Bayesian criteria (BIC) to determine the model's goodness of fit. Previous studies also used regression models in the prediction of sports (Ievoli et al., 2021).

Finally, we used receiver operating characteristic curves (ROC) to identify the optimal cut-off point, where sensitivity and specificity were balanced. Additionally, we employed the area under the curve (AUC) to assess the predictive capacity of each variable, thereby facilitating the interpretation and comparison of their performance.

Results

We initially estimated the fit for each model variable (Table 1), for predicting the team-wide set win. Results indicated significant relationships ($p < .001$), for all variables. C-ICC, C-ICC R1 y R3, with traditional variables, being slightly but significiantly less for C-ICC R2 ($p < .005$). Reception Efficiency was the only variable that was not statistically significant in the regression ($p < .445$).

[Insert Table 1 about here.]

According to the *p*-value of the estimators considered in each model (Table 2), we found that the constant was not significant, but that the explanatory variable was highly significant ($p < .001$), except for the Scoreboard, which is one's own set victory, also C-ICC R2 and Reception Efficiency. The high significance of the models shows that the AUC (area under the curve) percentage can be used as a predictor of outcome for each model.

[Insert Table 2 about here.]

Table 3 indicates the values of the specificity and sensitivity curve, as well as cut-off point, and whose values will allow us to maximize both curves.

From this cut-off point and the respective specificity and sensitivity values, it is possible to determine the AUC values, shown in Figure 3, as prediction percentages for each traditional model and the variables.

[Insert Table 3 and Figure 3 about here.]

The proposed models showed a high ability to predict team success in the set. The highest values were found for the contextual coefficient C-ICC R3 (AUC – 89.8%), followed by the contextual coefficient itself (AUC – 88.9%), and for C-ICC R1 (AUC – 88.1%). In contrast, the C-ICC R2 showed the worst performance among all the coefficients proposed, with values of (AUC – 77.8%).

When comparing these data against the predictive power of the variables traditionally used to measure performance in volleyball, we found that the Scoreboard logically had an absolute predictive power for winning the set (AUC – 100%). Next, Points (AUC – 95.2%) and Attack Efficiency (AUC – 94.3%), showed higher predictive power than the coefficients. Nevertheless, the Reception Efficiency (AUC - 56.2%), showed just slightly better predictive power than the randomness.

At the individual level, the Rho spearman correlations only revealed null correlations ($r < .30$) (Fleiss, 1986) of all variables, with the set victory. High significant correlations were found between the C-ICC with C-ICC R1 y R2 ($r > .900$). There was no significant correlation found for traditional variables Reception Efficiency, Errors and the RoI with Set Win.

[Insert Table 4 about here.]

We developed dynamic visualizations using the Microsoft PowerBI platform to explore the potential of the coefficients. These visualizations enabled comparisons of multiple variables in graphical form, facilitating an understanding of the results:

https://app.powerbi.com/view?r=eyJrIjoiOTFhM2Q1OWMtNjJhMi00NWE4LWJkMDgtNWY3MzNkZjMzYzFjIiwidCI6IjZhZmVhODVkLWMzMjMtNDI3MC1iNjlkLWE0ZmIzOTI3YzI1NCIsImMiOjl9

With its various possible comparisons, this report facilitated an organized and graphical data analysis . It offered countless comparisons, according to needs of the researcher/practitioner. The different tabs displayed graphical examples of various comparisons, with Tab 1 (Coefficient Table) showing all the values of each variable in two separate tables andallowing for comparisons between two players by selecting filters from the column on the right; withTab 2 (Graph C-ICC) graphically displaying the absolute and average values of C-ICC per set played by each player andallowing for filtering by players, teams, game role, and team classification; with Tab 3 (C-ICC) allowing for graphical comparisons of C-ICC values with other traditional variables such as Points, Errors, and Balance (positive and negative contact difference); with Tab 4 (Bubble chart C-ICC) highlighting the players with the highest C-ICC values and averages per set, considering the number of sets played by each one (determined by the size of the bubble); With Tab 5 (per role) presenting the average C-ICC/set versus the average points variable (Ptos/set), both globally and distributed by roles (and the same occurring in Tab 9 [C-ICC vs Eff] but comparing absolute C-ICC data versus Attack Efficiency [except for Reception Efficiency for liberos); with Tab 6 (Team Coefficients) showing the different coefficients per team, and filtering this information according to team, players, and role; and withTabs 7 (Relative indices) and Tab 8 (Relative index R3) allowing for the exploration of each of the relative indices R1, R2, and R3, distributed in two tables that would favor visually opposing two different options.

Discussion

This study marked the first attempt to develop a coefficient for quantifying the individual performance of elite volleyball players, while considering the game context in which each technical action occurred and the specific relative contribution made by each player toward victory determinations.

Although previous studies have acknowledged the significant impact of contextual factors on technical performance (Lago-Peñas et al., 2020), there has been no means of quantifying and integrating the most relevant contextual variables with a performance coefficient (López-Serrano et al., 2022b). The capacity to capture this contextual influence could differentiate this metric from such other measures as the PIR (Performance Index Rating) used by the International Basketball Federation for assessing player performance (Pérez-Toledano et al., 2019).

Our total sample included 77 sets played across 20 games featuring the world's top eight teams at the 2019 FIVB Women's Club World Championship. We deliberately selected a high-level competition, analyzing all twenty matches with the aim of obtaining the most precise representation of elite-level volleyball.

Our primary findings revealed that traditional variables, Points (AUC = 95.2%) and Attack Efficiency (AUC = 94.3%), were the most effective predictors of victory. These results are consistent with prior research that showed the high influence of points scored upon victory (Drikos et al., 2021) and, more specifically, points from attack actions or attack efficiency (Conti et al., 2018).

Unsurprisingly, the Scoreboard variable demonstrated the highest predictive power, with an AUC of 100%. This is because it directly reflects the points scored by each team and is a perfect indicator of winning a set. As anticipated, the negative results for Errors were notably negative, indicating an AUC of -89.5%. These findings emphasize the significant role of Errors in impeding a team's chances of winning (Drikos et al., 2009).

It is important to highlight the limited predictive power of Reception Efficiency (AUC = –56.2%) that bared exceeded random predictive power (50%). These results are inconsistent with the importance given to continuity actions (such as reception or even dig), that were previously strongly associated with the subsequent generation of more effective attacks (Costa et al., 2016; Monteiro et al., 2009), and are also essential to win games (Drikos et al., 2020).

Our results suggest that the contextual C-ICC coefficient had a high ability to predict team victory (AUC = 88.9%). These data are just slightly below traditional offensive metrics such as Points and Attack Efficiency, but far above defensive metrics such as Reception Efficiency. Previously we have mentioned the importance of reception or defensive actions to win matches (Drikos et al., 2020) to maximize later attack (Costa et al., 2006; Monteiro et al., 2009). Based on these results, the C-ICC coefficient is an innovative performance metric that effectively captures the significance of both offensive and defensive metrics. This characteristic of the C-ICC coefficient ensures that players who contribute defensively are not overlooked and that their performance is not overshadowed, as can happen with traditional performance statistics (Duch et al., 2010). Also, using a single metric facilitates comparisons between players (Franks et al., 2016). At the same time, the C-ICC is not just focused on measuring the performance of all technical volleyball actions. Instead, it quantifies their value in accordance with the moment or context of the game in which each action happens.

A fundamental aspect of the C-ICC is its potential to address the hierarchical scoring system in volleyball, similar to tennis. This is known as the Quasi-Simpson paradox (Lisi et al., 2019) whereby the team with the lowest score can still win the match. Hence, not all points have the same importance, and the context of each event can make it more or less crucial for winning the match (Croucher, 1986). The C-ICC coefficient considers this context and provides a more comprehensive measure of team performance. In addition, the C-ICC has the potential to address the issue of overestimating performance values in very unequal situations, against far weaker opponents or when matches are almost decided (Deshpande & Jensen, 2016). For example, in sets where the score difference is wide, the C-ICC could prevent players from raising their own statistics by assigning them lower values in these unequal contexts (López-Serrano et al., 2022b).

The analysis of contextual coefficients revealed that the relative coefficient C-ICC R3 had a higher predictive power (AUC = 89.9%) than the global contextual coefficient C-ICC. This finding is consistent with Sampaio et al. (2010), who found that having more opportunities to take field shots in basketball led to better performance outcomes.

These coefficients would represent 'contextual effectiveness,' when dividing the contextual performance into the total contacts made by the player. Player efficiency is one of the most widely implemented metrics in Sports. For example, in basketball, it is common to report the 2-point or 3-point shooting percentage based on the number of attempts (Lorenzo et al., 2019). But, as a metric expressed in percentages, it tends to overvalue players who make fewer attempts (e.g., high percentages of players receiving just 2-3 actions). To avoid this, in sports such as basketball or baseball, players who do not achieve a minimum participation rate (e.g., playing at least 36 minutes in basketball - White & Sheldon, 2013) are excluded from comparisons.

Although the C-ICC R1 coefficient (AUC = 88.1%) showed slightly lower values, this reduction may be trivial considering its potential to measure players' performance based on their time played. Kubatko et al. (2007), White and Sheldon, (2013) and Martínez, (2012) have highlighted the importance of standardizing performance values based on each player's relative participation. This standardization should consider factors such as points played and/or contacts made (López-Serrano et al., 2022a) and, in volleyball, sets played (Bisagno et al., 2019).

The predictive values of the relative coefficient C-ICC R2 (AUC = 77.9%) were considered acceptable, albeit lower than those of other coefficients, and no similar metrics have been identified in the literature. In contrast, where C-ICC R3 emphasizes the significance of each player's contacts, C-ICC R2 assesses a player's contact ratio in relation to their team's total contacts. Although C-ICC R2 provides insight into each player's involvement within their team, it does not fully capture their contribution to the team's success. Notably, unlike the relative coefficients C-ICC R1 and C-ICC R2, the enhanced predictive power of C-ICC R3 can sometimes lead to the overvaluation of highly effective players with limited participation, mainly due to its representation in percentages. At an individual level, we found a poor correlation between Set Win and victory, both in the coefficients and relative coefficients, as well as for the rest of the traditional variables. Duch et al. (2010) recognized that the real individual performance was 'masked' by the team's play (e.g., perfect receptions or setting), while other authors also raised doubts regarding these individual metrics (Carling et al., 2013), claiming that they ignored player-to-player interactions (Link, 2007). Nevertheless, there may still be usefulness to measuring each player's individual contribution, as these metrics are the ones the coach demands during sets (Zetou et al., 2007).

Palao et al. (2004) correlated attacking and blocking performance with team level, understanding team performance to be a sum of individual contributions.

The pivotal contributions of the team's key players should not be underestimated (Duch et al., 2010). This game unfolds on a divided court, where there are no direct player interactions, and it is characterized by alternating ball possessions (Parlebas, 1992).

Thus, some authors have argued that individual skills (mainly attacking actions) may be more important than any player interactions or than the game itself (Laporta et al., 2021), because, in volleyball, no defender can disrupt any technical action.

We should note that an analysis of male players' performance could yield distinct outcomes. As indicated by Palao et al. (2009), men's volleyball emphasizes powerful attacks, whereas women's volleyball exhibits a more balanced combination of attack and defensive play (Palao et al., 2009). Hilenio et al. (2023) observed that sets last longer in women's than in men's volleyball, (Drikos et al., 2020). Thus, scoring skills, especially offensive ones closely tied to set victories, are more evident among male players (Drikos et al., 2021). This suggests that exploring the predictive capacity of these proposed coefficients in women's volleyball is more challenging, due to the greater balance in the evaluation of their actions.

Finally, it is important to acknowledge that involving elite-level coaches in assigning numerical values to player actions can be insightful; yet it carries the risk of introducing subjective biases and potential assessment variations. In football, the integration of AI and machine learning (Davis et al., 2022; Robberechts et al., 2023) has proven beneficial in understanding various dimensions of performance, uncovering trends, strategic insights, and even predicting performance. A possible introduction of concepts akin to Expected Goals (XG) would enhance the weighing of actions and explore interactions (Hewitt & Karakuş, 2023). Such approaches could lead to a more comprehensive and unbiased assessment in volleyball, ideally complementing coaches' expert opinions with a data-driven methodology. However, volleyball's slower AI adoption, possibly due to limited extensive data (Rajšp & Fister, 2020), prompted us to focus our study, not on result prediction, but on comprehending player performance and amplifying practical methodologies. Our approach, integrating algorithms, logistic regressions, and predictability studies, aimed to validate their contextual effectiveness in predicting volleyball outcomes . Also grounded in prior research (Zhang et al., 2021), we based our analysis on expert opinions.

Limitations and Directions for Further Research

We acknowledge that we excluded an analysis of the actions of the setters, due to the complexity of such actions, despite their significant relevance in the development of the game. The setter holds a central role in most player interactions and playstyle configuration.

To enable a better understanding of the potential of the proposed coefficients to measure the individual performance of elite players, future researchers might:

- Incorporate larger match samples to enhance the statistical validation of the proposed coefficients;
- Explore players' gender differences, to either corroborate or challenge existing scientific evidence, which has suggested that men's volleyball might exhibit a stronger predictive capability due to their inclination towards aggressive attacks;
- Examine potential discrepancies across various competition levels, spanning from the lowest elite categories to the amateur and even training levels;
- Incorporate setter performance; and
- Apply artificial intelligence tools, that could enhance our algorithm's predictive capabilities by introducing new variables like player interactions and game styles (though we should note that, without analyzing the setter's actions, these variables might lack context and significance).

We also recommend the development and use of dynamic visualizations, as they can synthesize large amounts of information, allow for multiple comparisons, and facilitate player comprehension and learning by use of their graphical layout.

Conclusion

In this study, we presented the first game context quantifications of elite volleyball players' technical performances. We designed an algorithm that assigns weights to various contextual factors, including opponent level, set period, score difference, previous set result, and competitive load. To validate our evaluation approach, we applied this algorithm to data from the leading women's teams during the 2019 FIVB Club World Championship. This strategic choice not only ensured data quality but also capitalized on the wider spectrum of actions that often occur in women's volleyball in contrast with men's volleyball, which tends to be more attack-focused, resulting in less balanced range of actions.

Our findings represent an innovative approach to obtaining performance values that are context-dependent and encompass all technical actions (not just scoring actions). When evaluating individual performance in elite volleyball, the C-ICC and its relative contextual coefficients R1, R2 and R3 demonstrated high ability to predict the team's victory during each set. The C-ICC R1 identified wing-spikers as the players with the highest participation; while, based on the C-ICC R3 values, liberos demonstrated higher efficiency. However, players with minimal participation might have been overvalued in this approach.

The C-ICC R2 had lower predictive power and can be replaced by the C-ICC R1.

Coaches can benefit from having access to such accessible and easy-to-understand performance metrics that encompass numerous technical and contextual facets of the game. Such metrics could be instrumental in training novice players. The proposed algorithm holds promise in providing substantial aid to coaches during their decision-making, particularly in lower-level categories or at training stages, as it prevents the undervaluation performances of certain players.

Last, we should highlight the importance of the dynamic visualizations, which offer valuable tools that effectively illustrate and summarize player performance, thereby enabling comparisons across variables, even those integrated into the algorithm. This facilitates the exploration of player performance across diverse scenarios, allowing for real-time adaptations in strategies during matches to enhance overall performance and secure victories. Identifying the strengths and weaknesses of both individual players and the team within different contexts also aids in designing more efficient training sessions. Ultimately, these dynamic visualizations significantly enhance coaches' decision-making during both training sessions and actual games.

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