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From Tension to Triumph: Design and Implementation of an Innovative Algorithmic Metric for Quantifying Individual Performance in Women Volleyball's Critical Moments

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Abstract: This study introduces the critical individual contribution coefficient (CR-ICC), a novel metric that evaluates player effectiveness in critical moments of the game. We analyzed 16,631 technical actions from the top eight teams across 77 sets of the 2019 FIVB Women's Club World Championship, ensuring data quality through inter- and intra-observer reliability. Traditional variables such as points scored, attack and reception efficiency, and balance were examined. Python programming was utilized to calculate the values of CR-ICC, which consider the contextual variables of set period, score difference, competitive load, and opponent's level. Akaike's and Bayesian information criteria, along with Nagelkerke's coefficient of determination, were employed. Binomial logistic regression and receiver operating characteristic curves estimated the probability of victory associated with each variable. Interactive dashboards were developed, enabling dynamic analysis and data visualization. Statistically significant differences were observed in all variables ($p < 0.05$), except for reception efficiency ($p < 0.05$), at both the team and individual player levels. At the team level, points scored, attack efficiency, and balance exhibited the highest predictive abilities, with CR-ICC also demonstrating a strong predicting ability. The proposed CR-ICC has remarkable potential as a strategic asset for coaches, enabling the identification of players who excel in critical moments of the game.

Keywords: player effectiveness; data analysis; chocking; set victory prediction; Python programming; interactive dashboards

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1. Introduction

Volleyball features a distinctive scoring system where the team with the most overall points does not always secure victory. This phenomenon, also observed in tennis due to its nested scoring structure, is known as the Quasi-Simpson paradox [1,2]. Den Hartigh and Gernigon [3] highlight the significance of critical moments or "momentum" that have a profound impact on the outcome of the match. These critical moments are often overlooked in most studies, where they are considered as mere contextual variables. However, the distinction in the nature of the opponent's level [4] or the type of competition [5] becomes evident when comparing them to other contextual variables such as the competitive load of the set [6], the set period [7], or the score difference [8].

Ferreira et al. [9] identified critical moments in sports as contextual situations closely associated with disruptions in the balance of the game. Some authors refer to these moments as "disturbing factors" [10] due to their significant impact on the outcome. These critical moments are connected to crucial situations, such as the end of the match, where, although each point has the same value, scoring events have the greatest influence on determining victory. Moreover, these moments are often characterized by high levels of stress, which significantly influence athletes' performance. These dynamics underscore the critical impact of such moments on players and their decisive role in determining outcomes [11,12].

In line with this, Ref. [13], in a comparative study involving young elite football and volleyball athletes found that volleyball induced higher levels of competitive stress, particularly towards the end of sets, where mistakes could result in crucial points for the opposing team that were challenging to recover. While all players are affected by these high-stress situations, some experience a sharp decline in performance, commonly referred to as "choking" [14], while others thrive under pressure, taking responsibility and showing no hesitation or wavering when it comes to asking/wanting the ball during crucial moments. This phenomenon is known as "clutch" [12]. Evaluating these players using the same criteria as others may not provide a fair assessment for them.

This study analyzes the dynamics of volleyball during critical moments, rectifying previous oversights and shedding light on the key aspects identified by elite coaches [15]:

- The set period variable, crucial in volleyball, includes the "golden scores" [16] from point 20 onwards, which significantly affects match outcomes. Raymond et al. [17] argue that its impact is intensified when the score difference is small.
- The score difference variable, studied in closed sets, where the difference is <2 points [18].
- The competitive load variable, examining the impact of each set. Molina-Martín [19] suggests that players may see their performance reduced due to increased competitive stress during decisive sets with no margin for recovery to win or lose the match.
- The opponent's level variable, which comes into play primarily when the opponents are of similar level [4].

Additionally, this study considers player roles and positions' impact on performance, influencing their contributions in scoring or defense [20].

We should note here that, in recent years, the evaluation of player performance, in sports other than volleyball, has been revolutionized by the adoption of artificial intelligence (AI) and machine learning (ML) techniques. These are statistical and modern tools that offer objective, accurate, and actionable metrics that go beyond traditional performance statistics, and enable data-driven insights that enhance decision-making processes for coaches, analysts, and players.

Multi-criteria decision analysis (MCDA), for example, is a structured approach that integrates quantitative and qualitative factors to evaluate multiple, often conflicting criteria. In basketball, Dadelo et al. [21] proposed a TOPSIS-based method for player assessment and team formation, while Blanco et al. [22] developed a multi-criteria outranking methodology for ranking players based on efficiency indices. These studies highlight the importance of objective and comprehensive evaluations in sports management. In the area of sports analytics, machine learning models have demonstrated remarkable success in predicting outcomes. For instance, Chakraborty et al. [23] used random forests to achieve an 84.06% accuracy rate in forecasting T20 cricket match winners. Vistro et al. [24] applied support vector machines (SVMs) and logistic regression to analyze player performance and weather conditions, successfully predicting IPL outcomes. Priya et al. [25] refined these approaches by comparing supervised classification algorithms, improving prediction accuracy, and underscoring ML's potential to generate valuable insights for performance.

Obviously, the applications of AI and ML extend far beyond the area of sports. MCDA has gained significant traction in environmental decision-making [26,27] and has been employed in healthcare, energy management, and sustainability [28]. Over the past two decades, MCDA methodologies have evolved to include multi-objective, fuzzy-based, and hybrid approaches, effectively addressing complex scenarios in business, engineering, and public policy [29]. Additionally, models like Markov decision processes (MDPs), reinforcement learning, and computational intelligence techniques have successfully tackled challenges involving uncertainty [30,31]. In the area of intelligent decision support systems (IDSSs), AI tools such as neural networks, fuzzy logic, and intelligent agents have augmented human reasoning in domains including healthcare, marketing, and cybersecurity [32]. Furthermore, advancements in decision theory models, including MDPs, POMDPs, and reinforcement learning, have enabled the development of autonomous agents capable of making optimal decisions under uncertainty [30]. Computational intelligence techniques have addressed challenges in physics, biology, engineering, and social sciences, advancing areas like intelligent control systems, knowledge technologies, and affective computing [31]. Recent studies have extended science decisions into education [33–35]. These approaches aim to provide accurate and comprehensive assessments of teaching quality by integrating multiple attributes and data-driven information.

Although standardized AI and ML methods are widely used, custom-built algorithms designed for specific sports contexts often offer unique advantages. As these approaches incorporate specific knowledge, account for contextual factors, and provide real-time adaptability, in specialized scenarios they frequently outperform the generic methods. For example, Zavadskas et al. [36] introduced the weighted aggregates sum product assessment (WASPAS) method, which combines weighted sum and weighted product models to enhance decision-making accuracy.

The present study demonstrates the significant potential of custom-made AI-driven methodologies in sports performance evaluation, particularly within the dynamic and competitive environment of volleyball. In line with prior research [37,38], we introduce an algorithm designed to evaluate individual volleyball players' performance during critical moments. The algorithm we propose provides a unified metric that quantifies all aspects of the game into a single measure, thus enabling the evaluation of individual performance during the matches' critical moments.

2. Materials and Methods

2.1. Participants

To evaluate the effectiveness of the proposed metric/coefficient, an analysis was conducted on 77 sets played during the 2019 FIVB Women's Club World Championship. A comprehensive examination of 16,631 technical actions performed by the top eight teams worldwide across 20 matches was conducted. It is important to note that actions related to setting were excluded from the analysis.

We prioritized the analysis of high-level matches with competitive balance, selecting competitions that bring together the world's best players and teams. This approach has been used in prestigious studies on elite volleyball [39,40], which employ similar sample sizes.

The research protocol received full approval from the Research Ethics Committee of the Technical University of Madrid (Spain).

2.2. Players' Roles and Playing Positions

The players analyzed in this study were classified according to their specific roles on the court: middle blockers, who primarily operate at the center of the net as main blockers; liberos, defensive specialists who cannot serve or attack; opposites, the main attackers who play on the right side of the court; and wing spikers, the primary receivers of the team who also attack from the left side of the court. These positional roles are essential for understanding the context of their technical contributions and the calculation of the CR-ICC values.

2.3. Technical Evaluation: Technical Variables and Their Numerical Values of Importance

The technical actions considered (see also [37,38,41]) included three terminal actions (serve—S, attack—A, and block—B) and three continuity actions (reception—R, dig—D, and free ball–F), furthermore categorized using the six codes #, +, !, −, / and =. To facilitate mathematical formalization, we used 6×6 matrix A to represent all types of technical actions, excluding setting due to its complexity and singularity (see also [37,38]).

In López-Serrano et al. [41], the technical actions of each player were assessed by assigning importance values to them, expressed as decimal numbers ranging from -1.0

to 1.0. These values were determined based on average ratings provided by elite coaches worldwide. To mathematically represent this evaluation, we defined 6 × 6 matrix I, which contains all the detailed evaluation values from Table 2 of López-Serrano et al. [41]. In this matrix, each action A(t,c) (where t = 1, . . ., 6 and c = 1, . . ., 6) is associated with a specific numerical value I(t, c).

2.4. Critical Evaluation: Critical Variables

According to expert opinions, as mentioned in the Introduction Section and as reported in López-Serrano et al. [15], distinct phases of the game exhibit varying levels of "momentum", giving rise to critical situations characterized by heightened psychological pressure and limited recovery opportunities. In López-Serrano et al. [41], the study identified three variables that significantly influence performance in these critical situations:

(a) The high opposition level, denoted as OL_{CR}.
The variable OL_{CR} is activated exclusively when the opposition level is high. Its numerical value is based on the median values presented in Table 4 of López-Serrano et al. [15], corresponding to matches against high-level opposition.

(b) The high competitive load, denoted as CL_{CR}.
The variable CL_{CR} comes into play only during critical moments of the match, specifically in sets characterized by a high competitive load. Assuming that each set is uniquely identified by an integer number k, ranging from k = 1 to a maximum of k = 5, the variable CL_{CR} is defined for each set k (where k = 1, . . ., k_max with $3 \leq k\_max \leq 5$) and, for each set takes a singular value $CL_{CR}(k)$. The assigned value is associated with the median values shown in Table 4 of López-Serrano et al. [15] for sets with a "high competitive load".

(c) The final period (of all sets) in combination with low score difference, denoted as $SPSD_{CR}$.
In line with the above and in accordance with López-Serrano et al. [15], the variable $SPSD_{CR}$ is defined for each set k but is activated exclusively during the final period of the set and only when the score difference is low (0–2). The actions performed by a specific player during the critical moments of set k, categorized based on their technical quality, can be used to determine the numerical values $SPSD_{CR}(k, t, c)$, where, as previously stated, t = 1, . . ., 6 and c = 1, . . ., 6. These numerical values are derived from the average importance values presented in Table 4 of López-Serrano et al. [15], for the final period and low score difference.

2.5. The Critical Individual Contribution Coefficient (CR-ICC)

By combining the three variables OL_{CR}, CL_{CR}, and $SPSD_{CR}$, a comprehensive numerical evaluation of the player's technical performance during critical moments of the k-th set in a match can be achieved through the utilization of a "Critical Individual Contribution Coefficient". This coefficient, denoted as "CR-ICC", is specifically calculated for each set k. The mathematical expression for calculating CR-ICC that corresponds to the k-th set is as follows:

$$[CR - ICC](k) = OL_{CR} \cdot CL_{CR}(k) \cdot \sum_{At=1}^{6} \sum_{Ac=1}^{6} SPSD_{CR}(k,t,c) \cdot I(t,c)$$

where once again it is reminded that the value $I(t,c)$ is the numerical evaluation of the technical importance of each $A(t,c)$ action. The technical performance of the player during critical moments of the game can be evaluated using the total critical individual contribution coefficient, CR-ICC. This coefficient is obtained by summing all critical points achieved by the player during all sets:

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

Figure 1 illustrates the sequence of data analysis for this study. It outlines the steps involved, starting with the input data, followed by the technical evaluation, critical evaluation, and culminating in the output, which is the critical individual contribution coefficient (CR-ICC). Each step represents an essential component of the analysis, showing how the technical and critical evaluations combine to determine the final performance index.

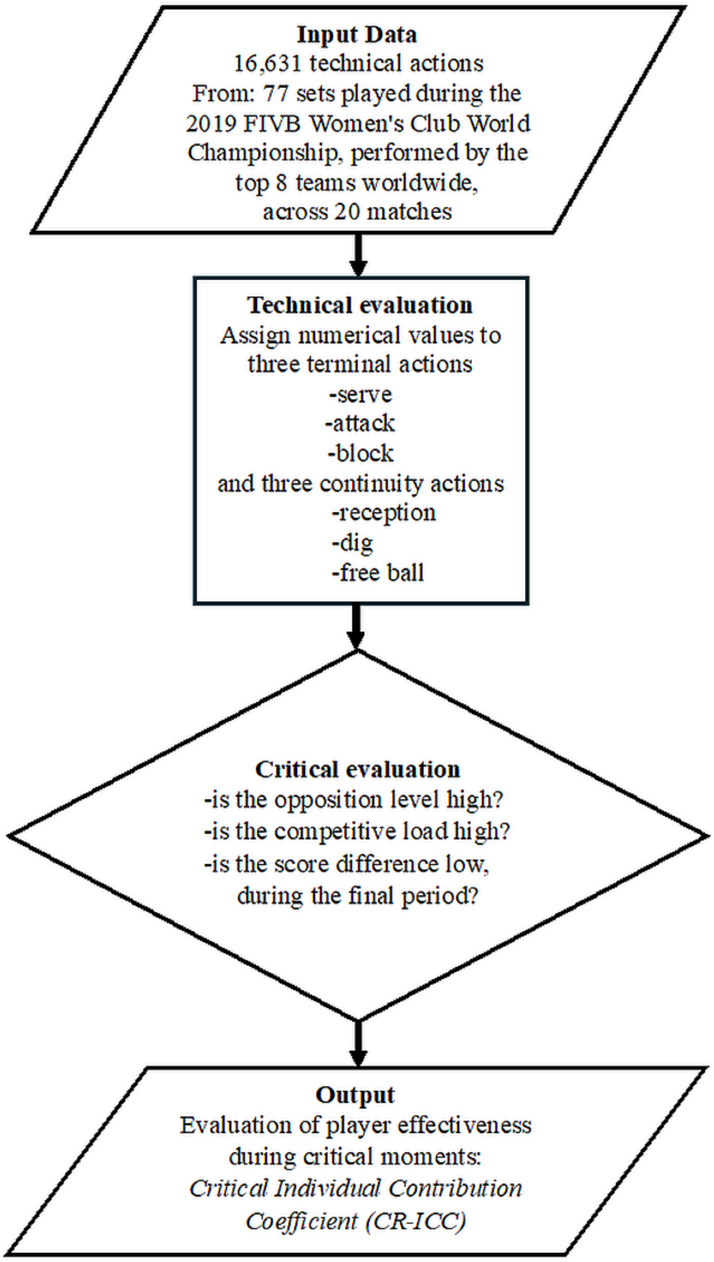

Figure 1. Flowchart of the data analysis sequence, illustrating the steps for the calculation of the critical individual contribution coefficient (CR-ICC).

2.6. Implementation

The technical actions were collected via Data Volley Pro 4 by a professional scout and subjected to a rigorous consistency analysis by two experienced scouts with more than 5+ years of international experience. This process ensured reliable and accurate data for evaluating the proposed coefficient. Python 3 was utilized for its versatility and widespread use to efficiently calculate CR-ICC coefficients, process extensive data, and generate insightful analysis on player performance in evaluated matches (see also [37,38]).

2.7. Reliability Analysis

An assessment of inter-observer and intra-observer reliability was conducted to examine the consistency of the observations. A retest test was administered to four randomly selected matches (representing 20% of the sample according to the existing literature) [42], with a 15-day interval between each test.

A sequential data entry approach was employed to ensure higher data quality [43]. To evaluate agreement among more than three observers, Fleiss' Kappa values were utilized. In all cases, reliability values surpassing the thresholds considered acceptable were obtained: serve (0.958), attack (0.969), block (0.945), reception (0.898), dig (0.943), and free ball (0.701) [44]. The data were analyzed using the SPSS v.26 statistical package (IBM Corp., Armank, NY, USA).

2.8. Statistical Analysis

A binomial logistic regression was conducted to examine the relationship between the calculated CR-ICCs and the team's set victory, both at the team and player levels. Furthermore, the values of traditionally used performance variables in volleyball were investigated. These variables included points scored by each player (Pts), efficiency of attack (Eff A), efficiency of reception (Eff R), and the balance between points scored and errors. The objective was to gain a deeper understanding of the impact of these traditional variables, and the CR-ICC, on the team's set victory.

Binomial logistic regression models have proven successful in prediction studies related to sports outcomes [45]. To assess the goodness of fit for each variable, the Akaike criterion (AIC), Bayesian criterion (BIC), and Nagelkerke R^2_N were considered. The precision of each variable was measured using receiver operating characteristic curves (ROC). These curves allowed for the estimation of the probability of victory in relation with the performance of each variable, using the area under the curve (AUC) as a quantitative measure.

Additionally, a collinearity analysis was conducted in the binomial logistic regression to assess the contextual variables that could affect CR-ICC. The objective was to understand the influence of various predictive factors, such as players' roles, or contextual variables such as the competitive load, the opposition level, the set number, and the final rankings of the teams in which each player participated. Significance was set at $p < 0.05$.

2.9. Presentation of Results Through Interactive Dashboards

This study emphasized the creation of performance reports in the style of coaches using innovative dashboards in Microsoft Power BI. These dynamic dashboards include tables and charts for a novel and better understanding of the data, enabling multiple comparisons for player analysis.

3. Results

3.1. Performance Metrics and CR-ICC

Table 1 displays the findings of the binomial logistic regression analysis conducted at both the team and player levels. Significant differences were observed in the CR-ICC, Ptos, Eff A, and balance variables concerning the team's success in the set ($p > 0.001$). These significant differences were also evident when considering individual player performance. However, no notable differences were found in the Eff R variable ($p = 0.576$ for the team and $p = 0.866$ for the players).

Table 1. Team level vs. player level. Model coefficients and other traditional variables regarding set win.

Team Level							
Predictor	**Estimator**	**SE**	**Z**	***p*-Value**	**OR**	**95% CI**	
						Inf	**Sup**
Constant	0.093	0.349	0.268	0.789	1.098	0.554	2.178
CR-ICC	−0.1925	0.0523	−3.684	<0.001	0.825	0.825	0.914
Constant	−0.0092	0.408	−0.022	0.982	0.991	0.445	2.204
Ptos	−0.661	0.164	−4.034	<0.001	0.516	0.374	0.712
Constant	−0.352	0.397	−0.088	0.929	0.965	0.443	2.10
Eff A	−17.107	4.12	−4.144	<0.001	3.72×10^{-8}	1.14×10^{-11}	1.21×10^{-4}
Constant	−0.203	0.266	−0.761	0.447	0.816	0.484	1.38
Eff R	−0.710	1.269	−0.559	0.576	0.492	0.040	5.92
Constant	0.139	0.309	0.449	0.654	1.15	0.626	2.11
Balance	0.089	0.023	−4.227	<0.001	1.09	1.04	1.15
Player Level							
Predictor	**Estimator**	**SE**	**Z**	***p*-Value**	**OR**	**95% CI**	
						Inf	***Sup***
Constant	−0.206	0.0838	−2.46	0.014	0.814	0.690	0.959
CR-ICC	0.102	0.0202	5.07	<0.001	1.108	1.065	1.152
Constant	−0.224	0.0967	−2.32	0.020	0.799	0.661	0.966
Ptos	0.110	0.0287	3.83	<0.001	1.116	1.055	1.180
Constant	−0.1341	0.0789	−1.70	0.089	0.874	0.749	1.02
Eff A	0.0090	0.0020	4.52	<0.001	1.009	1.005	1.01
Constant	0.0303	0.0876	0.345	0.730	1.03	0.868	1.22
Eff R	3.37×10^{-4}	0.0019	0.169	0.866	1.00	0.996	1.00
Constant	0.018	0.069	0.262	0.793	1.02	0.889	1.17
Balance	0.160	0.030	5.341	<0.001	1.17	1.107	1.25

Note. Estimators represent the log odds of "Win set = False" vs. "Win set = True"; SE—standard error; Z—Wald value; *p*-value—*p*-value of of the Wald test; OR—odds ratio; IC 95%—confidence intervals for the odds ratio; significance (bilateral): $p < 0.05$.

The fit for each variable was subsequently assessed using the AIC, BIC, and Nagelkerke R2 coefficient (Table 2). The results indicated that all variables demonstrated a better fit at the team level, displaying lower AIC and BIC values and higher Nagelkerke coefficients compared to the individual results for each player. Notably, the variables Pts (R^2_N = 0.714), Eff A (R^2_N = 0.690), and CR-ICC (R^2_N = 0.547) stood out with high Nagelkerke R^2_N values, suggesting that they could account for 71.4%, 69%, and 54,7%, respectively, in explaining a team's set victory. The CR-ICC coefficient yielded an R^2_N value of 0.547. In contrast, Eff R exhibited a considerably low R^2_N value of 0.006, indicating its limited explanatory power of only 6% in relation to set victory.

Table 2 displays the optimal cutoff points for each variable, which maximize the values of sensitivity and specificity. In addition, the table includes the area under the ROC curve (AUC) values, which represent the probability for each model.

Figure 2 illustrates the ROC curves, showcasing the best predictions achieved for the variables of Pts (AUC—93.9%), Eff A (AUC—93.0%). The critical coefficient CR-ICC also showed significant predictive value (AUC—87.1%). However, Eff R exhibited low predictive capacity (AUC—56.0%).

Table 2. Binomial logistic regression for the fit of each model and predictive analysis according to the cut-off point.

Team Level											
Model	**AIC**	**BIC**	$\mathbf{R^2_N}$	**Global Model Test**			**Cut-Off Point**	**Accuracy**	**Specificity**	**Sensitivity**	**AUC**
				χ^2	**g.l.**	***p*-Value**					
CR-ICC	58.2	62.5	0.547	33.6	1	<0.001	0.41	0.797	0.80	0.786	0.871
Ptos	43.0	47.3	0.714	48.7	1	<0.001	0.50	0.859	0.889	0.821	0.939
Eff A	45.5	49.8	0.690	46.2	1	<0.001	0.51	0.875	0.889	0.857	0.930
Eff R	87.4	95.7	0.006	0.31	1	0.575	0.44	0.547	0.556	0.536	0.560
Balance	67.4	71.8	0.423	24.3	1	<0.001	0.54	0.688	0.714	0.667	0.823
Player level											
Model	**AIC**	**BIC**	$\mathbf{R^2_N}$	**Global Model Test**			**Cut-Off Point**	**Accuracy**	**Specificity**	**Sensitivity**	**AUC**
				χ^2	**g.l.**	***p*-Value**					
CR-ICC	1167	1177	0.042	27.5	1	<0.001	0.49	0.575	0.565	0.584	0.607
Ptos	1179	1189	0.023	15.2	1	<0.001	0.51	0.559	0.646	0.475	0.567
Eff A	1173	1182	0.033	21.6	1	<0.001	0.49	0.552	0.551	0.553	0.588
Eff R	1194	1204	4.45×10^{-5}	0.0287	1	0.866	0.51	0.487	0.580	0.397	0.502
Balance	1164	1173	0.046	30.7	1	<0.001	0.52	0.569	0.710	0.434	0.604

Note. AIC—Akaike criterion; BIC—Bayesian criterion; R^2_N—R^2 de Nagelkerke; χ^2—goodness of fit; g.l—degrees of freedom; *p*-value—significance value; CR-ICC—critical coefficient; Ptos—difference in points scored by all players of both teams; Eff A—attack efficiency; Eff R—reception efficiency.

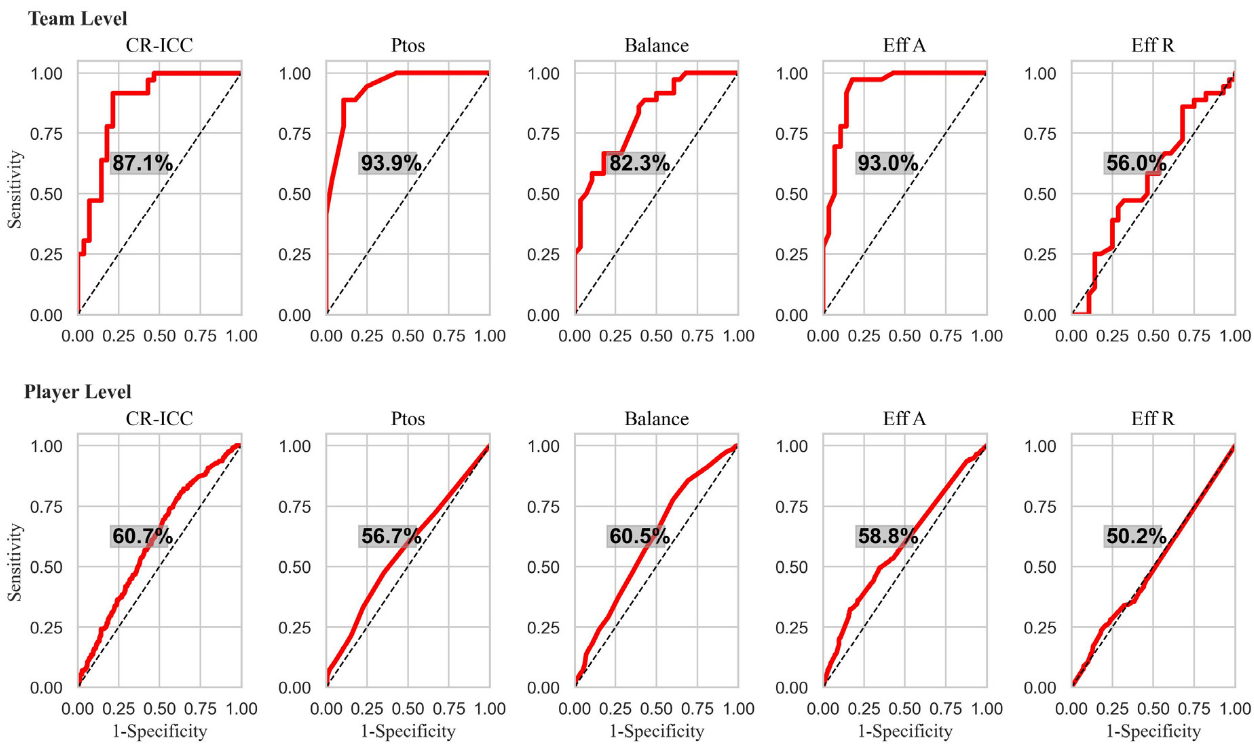

Figure 2. Predictive ability of each variable, represented by the ROC curves and area under the curve (expressed as a percentage). AUC—area under the curve ROC; CR-ICC—critical coefficient; Ptos—points scored by each player (errors excepted); balance—difference between points and errors; Eff A—attack efficiency; Eff R—reception efficiency.

When considering individual players, all variables yielded very low prediction values close to 50%, indicating results similar to random. Notably, CR-ICC (AUC—60.7%) and balance (AUC—60.5%) exhibited the highest values, followed by Eff A (AUC—58.8%).

On the other hand, the results obtained for the CR-ICC covariate based on various contextual factors (Table 3) demonstrated statistical significance ($p < 0.001$). Furthermore, a positive estimate of 0.136 was observed, with a 95% confidence interval for OR > 1. This indicates that the probability of winning the set increases by 1.143 times, when the values of CR-ICC are high. Regarding the contextual factors, significant differences were found in the final sets, i.e., in the third set ($p < 0.001$) and in the fourth and fifth sets ($p < 0.05$), using the critical coefficient. Additionally, the competitive load variable CL_{CR}, which identifies these crucial sets, also showed significance ($p < 0.05$).

Table 3. Player level. Model coefficients and other traditional variables regarding set win. Collinearity statistics of the contextual variables.

Predictor	Estimator	SE	Z	*p*-Value	OR	95% CI		Collinearity Analysis	
						Inf	*Sup*	VIF	Tolerance
Constant	0.932	0.2928	3.182	<0.001	1.293	1.430	4.507		
CR-ICC	0.136	0.0228	5.966	<0.001	1.143	1.095	1.198	1.13	0.884
Rol								1.02	0.983
Middle blocker–libero	0.242	0.206	1.172	0.241	1.274	0.849	1.911		
Opposite–libero	−0.039	0.227	−0.173	0.862	0.961	0.615	1.502		
Wing spiker–libero	−0.111	0.197	−0.563	0.574	0.895	0.607	1.318		
Competitive load (CL)								2.48	0.404
High Load–attenuated load	0.957	0.325	2.994	0.003	2.652	1.406	5.022		
N° SET								1.27	0.788
2–1	0.142	0.177	0.803	0.422	1.153	0.814	1.633		
3–1	−1.131	0.314	−3.594	<0.001	0.323	0.174	0.598		
4–1	−1.177	0.403	−2.921	0.003	0.308	0.139	0.679		
5–1	−0.825	0.419	−1.967	0.049	0.438	0.192	0.997		
Opposition level (OL)								1.08	0.927
Mid level–high level	−0.159	0.154	−1.034	0.301	0.852	0.629	1.154		
Low level –high level	−0.135	0.242	−0.560	0.575	0.873	0.542	1.404		
Ranking								1.02	0.979
2–1	−0.591	0.265	−2.228	0.026	0.554	0.329	0.931		
3–1	−0.415	0.261	−1.590	0.112	0.660	0.395	1.101		
4–1	−0.993	0.249	−3.983	<0.001	0.370	0.227	0.604		
5–1	−1.196	0.254	−4.696	<0.001	0.302	0.183	0.498		
6–1	−1.674	0.261	−6.407	<0.001	0.187	0.112	0.313		
7–1	−2.263	0.280	−8.076	<0.001	0.104	0.060	0.180		
8–1	−1.733	0.279	−6.197	<0.001	0.177	0.102	0.306		

Note. Estimators represent the log odds of "Win set = False" vs. "Win set = True"; SE—standard error; Z—Wald value; *p*-value—*p*-value of of the Wald test; OR—odds ratio; 95% CI—confidence intervals for the odds ratio; VIF—variance inflation factor ($1/(1 - R^2)$). Tolerance: proportion of variance (1/VIF); significance (bilateral): $p < 0.05$.

The ranking analysis revealed significant differences between all teams compared to the top-ranked team ($p < 0.001$), except for the third-ranked team. It is worth noting that the two teams classified as having a high opposition level, indicating the highest level of competition, occupied the third and first positions, respectively. Therefore, no significant differences were found in the influence exerted by variations in CR-ICC values among teams with higher opposition levels.

The collinearity analysis of all variables, with variance inflation factor (VIF) values below 2 and tolerance greater than 0.1 (see Table 3), indicated the independence of the variables, ensuring higher accuracy in predictions by avoiding the inclusion of redundant variables and issues of variance inflation.

3.2. Interactive Dashboards

Dashboard has multiple tabs with graphs and tables analyzing player tournament performance, for example (accessed on 9 February 2023):

https://app.powerbi.com/view?r=eyJrIjoiYmRlZTI5NjYtNDRjYi00YzE4LTkwZTAtYTQyMjljMGE3ZDZjIiwidCI6IjZhZmVhODVkLWMzMjMtNDI3MC1iNjlkLWE0ZmIzOTI3YzI1NCIsImMiOjl9

The Tab Index navigates reports, featuring interactive charts and data-filtering options. Tabs 1–2 compare CR-ICC values among teams. Tab 3 contrasts CR-ICC with other variables; Tab 4 presents a bubble chart analyzing CR-ICC/Set. Tab 5 correlates average CR-ICC with points by player roles; Tab 6 displays comparative team CR-ICC statistics. Tab 8 explores CR-ICC versus points by player roles.

Finally, Tab 7 compares CR-ICC values of two players, revealing their contributions to technical actions. This tab compares two standout players from the championship: 18E.P (designated as the most valuable player) and 11H.I (designated as the best opposite).

The data reveal that player 18E.P was more decisive in critical moments, with a CR-ICC of 67.11 and a CR-ICC per set of 5.16. Furthermore, she achieved 89.43% of her points through attacking actions, despite playing three sets less than her rival and having a lower total point production (123 points compared to 127 points of 11H.I).

4. Discussion

The main objective of this study was to introduce the CR-ICC, a unified metric capable of quantifying performance in critical moments, facilitating the evaluation of individual contributions in decisive scenarios [15].

Our results show that the CR-ICC is a useful metric for evaluating performance in critical moments, with significant predictive capacity (AUC—87.1%), though lower than Ptos (AUC—93.9%) and Eff A (AUC—93.0%). This may be because these metrics focus on terminal events directly related to the score, which have a strong correlation with victory [8]. However, the CR-ICC also incorporates continuity actions and contextual aspects, making it less predictive in absolute terms but valuable for identifying performance patterns under pressure in decisive situations.

This can be explained by the fact that Ptos and Eff A focus on terminal events directly related to the score. According to [8], terminal metrics have a stronger correlation with victory due to their immediate and visible impact. In contrast, the CR-ICC also integrates continuity actions and contextual aspects, making it less predictive in absolute terms but more useful for identifying performance patterns under pressure.

Compared to Eff R (AUC—56.0%) and balance (AUC—82.3%), the CR-ICC stands out by capturing the contextual impact of players. Eff R, although key for organizing attacks and providing more options for the setter with quality receptions [46], depends heavily on subsequent actions. Costa et al. [47] point out that receptions are merely the foundation for offensive plays, whose effectiveness depends on the tempo and type of attack. Silva et al. [48] add that, even with good receptions, decision-making and execution under pressure are crucial to scoring points. On the other hand, balance, although measuring net contributions, does not include the competitive context, where the CR-ICC excels in evaluating performance in critical moments [49].

At an individual level, the results show a more limited predictive capacity for all metrics, with AUC values close to randomness. The CR-ICC, with an AUC of 60.7%, outperforms Eff A (58.8%) and balance (60.5%), demonstrating its utility in capturing key contributions. However, Ptos, highly predictive at a team level (AUC—93.9%), significantly declines at an individual level (AUC—56.7%), reflecting the importance of collaborative context in volleyball, conditioned by specific roles that influence team dynamics [20,50]. According to Taylor and Bendickson [51], success depends on standout talents who can keep the team afloat under pressure [52]. The CR-ICC identifies these exceptional players in key contexts, capturing their greater involvement during critical moments [49]. This approach complements the belief in "superstars" capable of influencing outcomes [53] and helps to identify talents with impact in decisive moments [54].

When analyzing player roles, we observe that the CR-ICC favor's key offensive roles. According to Table 3, opposites (Opposite) stand out in critical contexts with positive coefficients compared to liberos (OR = 1.274, p = 0.241), while middle blockers and wing spikers have a relatively lower impact. This finding aligns with Conti et al. [54], who highlight the offensive importance of opposites, especially in decisive moments, and with Araújo et al. [20], who emphasized their ability to execute effective attacks even against double blocks or in high-pressure contexts.

In high-pressure contexts, such as decisive sets, the CR-ICC excels. Our data show that performance under pressure is higher in final sets (OR = 1.143 for third, fourth, and fifth sets), validating its ability to identify outstanding players in these moments. This finding aligns with the literature that highlights the importance of situational and psychological factors in performance under pressure [49].

Regarding alternative approaches such as MCDA or machine learning, these present significant technical advantages but face practical barriers. MCDA methods are effective in combining multiple criteria and analyzing complex situations, but their implementation requires specialized knowledge and advanced tools, limiting their applicability in coaches' daily contexts [55]. Similarly, machine learning models can identify dynamic patterns and improve real-time predictions, but their development and interpretation often exceed the expertise of coaches [56]. In contrast, the CR-ICC is simple to calculate and interpret, allowing for coaches to apply it easily for quick decision-making during matches without requiring advanced technical knowledge [37].

The CR-ICC metric offers valuable insights on how to optimize the contributions of such pivotal players during key moments, ultimately leading to set victories. To illustrate this, let us consider an example from our findings. In the analyzed semifinal match 18 (VAK vs. IMO) (please refer to tab9), player 18E.P (IMO) stands out as the most decisive player in the fifth set, achieving an impressive CR-ICC of 9.68. Conversely, the star player of the opponent team (VAK), 11H.I, exhibits a lower performance with a CR-ICC of −1.38. This sheds light on how a team, despite displaying an overall inferior performance throughout the match (53.8 CR-ICC for the IMO team compared to 118.2 CR-ICC for the VAK team), can end up winning the match, thanks to the exceptional performance of their star player during critical moments.

The findings of this study demonstrate the robustness and reliability of the CR-ICC metric in capturing the dynamics of performance in volleyball. The inter-observer and intra-observer reliability assessments ensure consistency in observations, while statistical techniques such as binomial logistic regression and ROC curve analyses provide a rigorous evaluation of predictive precision. Additionally, collinearity analysis accounts for the influence of contextual variables, such as players' roles, competitive load, opposition level, set number, and team rankings, ensuring a comprehensive evaluation of the proposed metric.

However, it is essential to consider that the robustness of these findings might be influenced by variations in competitive environments, player interactions, or sample sizes. Metrics like the CR-ICC may exhibit fluctuations when applied to different populations or under varying match conditions, highlighting the dynamic nature of performance assessment. These considerations emphasize the importance of interpreting the CR-ICC within the specific context of its application, while recognizing its potential adaptability to diverse scenarios. Such adaptability underscores the coefficient's utility, even as further research may refine its application across broader contexts.

In summary, the CR-ICC complements traditional metrics by offering a comprehensive view of performance in high-pressure contexts and specific roles, excelling in its ability to capture contextual and dynamic contributions. Furthermore, its accessibility and ease of use make it a valuable tool for coaches aiming to optimize their players' performance without relying on complex technologies or methodologies.

5. Conclusions

This study introduced the critical individual contribution coefficient (CR-ICC) as a novel and effective metric to evaluate individual performance during critical moments in volleyball. Our findings indicate that, while traditional metrics such as points scored (Pts) and attack efficiency (Eff A) exhibit a higher absolute predictive capacity for set victories, the CR-ICC stands out for integrating the technical, contextual, and dynamic contributions of players under high-pressure situations. This enables the identification of key performance patterns, particularly for offensive roles such as opposites.

The CR-ICC provides a comprehensive approach to analyzing the impact of key players, demonstrating a remarkable ability to capture contextual and dynamic contributions in decisive moments. Its simplicity and ease of implementation make it a valuable tool for coaches, complementing traditional metrics and enhancing strategic decision-making in real time.

6. Limitations and Future Research Directions

This study has limitations that open new avenues for research. While the CR-ICC incorporates technical and contextual aspects, it does not consider how interactions between players and opponents influence individual performance, an essential topic for future studies. The data analyzed focused exclusively on women's matches, limiting its generalizability; therefore, it is necessary to include men's competitions to explore potential gender differences.

Additionally, the data were derived from a single event, highlighting the need to validate the model across multiple competitions. Psychological factors such as anxiety, which impact performance under pressure, were also not addressed and could enrich future analyses. Finally, exploring advanced tools such as multi-criteria decision analysis (MCDA) and machine learning could complement the CR-ICC by integrating more criteria and dynamic patterns, improving its predictive precision and applicability.

7. Practical Applications

The CR-ICC provides an innovative approach to analyzing volleyball performance, facilitating strategic decisions and valuing individual contributions in critical moments of the game. One of its main advantages is balancing recognition between offensive and defensive roles. Traditionally, individual awards and player status focus on those excelling in scoring points. However, the CR-ICC also highlights the importance of defensive and continuity actions, often undervalued. This promotes a fairer and more equitable acknowledgment of players who make key contributions beyond scoring.

Moreover, the CR-ICC allows for coaches to identify player strengths and areas for improvement, design specific training to optimize performance under pressure, and analyze opposing teams to neutralize key players. Its intuitive design and ease of use make it a practical tool not only for individual and collective development but also highly accessible for coaches, who can apply it during matches without requiring advanced computing knowledge.

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