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RESEARCH ARTICLE

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Abstract

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KEYWORDS

Football, Cognitive Neuroscience, Decision Making, Executive Functions, Performance Analysis

1 | INTRODUCTION

Soccer is a complex and dynamic team sport that requires processing a large amount of information in a short period for making decisions (Scharfen & Memmert, 2019a). During a match, there are constant changes between game phases (organization and transition defensive and offensive) that demand different behaviors from athletes. In high-performance, elite athletes need to be efficient in their decision-making under psychological pressure. Decision-making in soccer is a domain-specific ability that emerges from the ongoing interaction between player, environment, and task moment-by-moment. The athletes must analyze multiple alternatives and choose the ideal course of action. Literature has extensively investigated how domain-general cognitive functions measured in decontextualized tasks are related with domain-specific decision making in soccer. The construction of the decision depends on cognitive processes, such as perception, information processing, prior knowledge, and memory (Betsch & Haberstroh, 2004).

Cognitive functions are general mechanisms at our disposal relevant to any goal-directed action in everyday life (Diamond, 2013). There is a distinction between "lower-level" and "higher-level" cognitive functions (Alvarez & Emory, 2006). "Lower-level" refers to basic information processing, such as reaction time, psychomotor performance, and visual perceptual skills (Huijgen et al., 2015; Sánchez-Cubillo et al., 2009). On the other hand, "higher-level" cognitive functions are defined as executive functions, being involved in the control and regulation of "lower-level" cognitive processes, generating goal-directed

Abbreviations: CF, cognitive flexibility; I, impulsivity; VWM visual working memory; SA, sustained attention; TC, tracking capacity; IG, individual goals; CG, conceded goals; GT, goals by teammates; NG, net goals; ML, machine learning; MOT, multiple object tracking; PEBL, Psychology Experiment Building Language; PsychoPy, Psychophysics software in Python; TMT, trail making test; XGBoost, extreme gradient boosting; RF, random forest; LR, logistic regression; KNN, k-nearest neighbors; SVM, support vector machine; GNB, gaussian naive bayes; MLP, multilayer perceptron; ACC, accuracy; BACC, balanced accuracy.

and future-oriented behaviors (Alvarez & Emory, 2006). The executive functions are: (1) cognitive flexibility (CF), defined as changing perspectives or approaches to a problem, flexibly adjusting to new demands, rules, or priorities such as the change of behavior needed in the constant changes of the soccer game phases; (2) working memory, defined as holding information in mind and mentally working with it. In the soccer game that could be important for the identification of game patterns or remembering instructions; and (3) inhibitory or impulsivity (I) control, defined as controlling one's attention, behavior, thoughts, and/or emotions to override a strong internal predisposition or external lure, and instead do what's more appropriate or needed such as controlling when to sprint during the game or the right time for a dribble or risk pass (Diamond, 2013). Another relevant cognitive function is attention, considered a sub-function of human perception that selects relevant aspects from a large number of sensations to efficiently guide actions and thought processes, being considered one of the foundations for executive functions and the decision-making process (Posner, 1980). Furthermore, it is important to acknowledge that competitive level alone does not fully account for inter-individual differences, as metacognitive processes, motivational components and self-regulated learning also play a significant role in youth soccer players' development and performance (Trecroci et al., 2022).

As these cognitive functions are demanded in various sports, scientific literature has sought to understand their relationship with soccer performance (Scharfen & Memmert, 2019a). A recurrent approach is comparing elite athletes with other groups. A systematic review with meta-analysis concluded that elite athletes exhibit superior cognitive functions compared to lower performance level athletes (Scharfen & Memmert, 2019a). Better I control, CF, attention, short-term memory, working memory, processing speed, and meta-cognition were found in young high-performance athletes compared to sub-elite or amateur athletes (Huijgen et al., 2015; Verburgh, Scherder, van Lange, & Oosterlaan, 2014; Verburgh, Scherder, Van Lange, & Oosterlaan, 2016; Vestberg, Reinebo, Maurex, Ingvar, & Petrovic, 2017). Other studies have also highlighted the relationship between cognitive functions and soccer performance. Correlations have been reported between working memory and dribbling skills. The cumulative scores of both cognitive tests and soccer-specific motor skills tests were also found to be correlated among elite youth soccer players (Scharfen & Memmert, 2019b). Additionally, a correlation was observed between cognitive flexibility and both the number of goal assists during the season and game intelligence, measured by coaches' subjective evaluations (Vestberg et al., 2020). These results suggest that the general cognitive functions could be related to how the individual processes the information after/during their perception and may give cues on how they respond to it.

Another approach to describing the relationship between cognitive functions and soccer performance is through prediction attempts. Some studies aimed to classify the athlete's performance level (elite, sub-elite, or amateur) by analyzing cognitive functions (Huijgen et al., 2015; Verburgh et al., 2014). Accuracy rates of 62.5% and 78% were obtained in predictions using statistical methods like discriminant analysis and logistic regression. However, these results were obtained by evaluating the models on the same data used for training, which can result in overoptimistic accuracy estimates, the proper model's validation have already been pointed as a challenge on the application of ML in sports (Souaifi et al.,2025). More robust approaches, such as testing multiple machine learning (ML) algorithms (Claudino et al., 2019) combined with proper dataset partitioning for training and testing the models may provide more reliable results about cognitive functions' predictive power. Predictive modeling with ML techniques demonstrated the ability to capture underlying complex patterns and relationships between variables and can contribute to theory-building by the generation of new hypotheses that can be further investigated in terms of causality (Shmueli, 2010). Besides predictions, ML models have shown the capability to generate insights into how data are associated, indicating which variables' combinations present higher predictive power (Claudino, Capanema, & Santiago, 2022; Murdoch, Singh, Kumbier, Abbasi-Asl, & Yu, 2019).

Although performance in soccer is context-dependent and emerges from the ongoing interaction between player, environment, and task, the current literature indicates that various cognitive functions measured in decontextualized tasks are more developed in elite athletes compared to amateurs or non-practitioners. Furthermore, correlations were found between both motor skills required in soccer and individual performance variables with cognitive functions. These founds indicate that general cognitive functions may be related to the way soccer players interact with the perceptions of affordances and the invitations for actions that arise in the game. The predictive power of general cognitive functions on sports performance remains unclear in the literature, with some authors suggesting that further research is needed with young, skilled athletes (Kalén et al., 2021). Therefore, the present study aimed to explore the role of cognitive functions on the performance of under-17 soccer players on different demands of small-sided games. The cognitive functions of superior and inferior performing players in the different game demands were compared with traditional statistics. The present study also tested the feasibility of using supervised ML algorithms to differentiate soccer players' performance at the same competitive level, using it to identify which algorithms and combinations of cognitive functions present higher predictive power. Based on the literature, the study hypotheses were that general cognitive functions would differ between superior and inferior performance players and that the ML models would present moderate predictive power.

2 | METHODS

2.1 | Participants

Forty-four male soccer players (age: 16.51 ± 0.57 years; soccer experience: 9.41 ± 2.16 years; training per week: 5.59 ± 0.77 days) participated in the present study. These players trained in the under-17 category of [available in final version] and had no injuries that resulted in training absences for a period equal to or greater than thirty days in the last two months from data collection. The experimental procedures were approved by the [available in final version]. Written informed consent was obtained from the participants and their legal guardian(s) and this study conformed to the recommendations of the Declaration of Helsinki.

2.2 | Procedures and Materials

The data collection took place at the training sites of the participants' clubs. Cognitive data was collected in a quiet space during the afternoon, with eight participants per session. The battery consisted of one 40-minute session with a fixed test order as used in a previous study (Scharfen & Memmert, 2021c): (1) multiple object tracking, (2) visuospatial working memory, (3) cognitive flexibility, and (4) impulsivity and sustained attention. The battery included three tasks (Corsi block, Go/No Go, Trail Making) administered using the Psychology Experiment Building Language (PEBL, version 2.0 beta 5) (Mueller & Piper, 2014), and one task (Multiple Object Tracking) administered using the Psychophysics software in Python (PsychoPy, version 2022.2.4) (Peirce, 2007). Dell Inspiron 3501 notebooks were used for the test administration. During the evaluation, instructions were provided and a quiet environment was ensured to maintain standardized testing conditions. All tasks were preceded by standardized, test-integrated instructions and practice trials to ensure participants' familiarity with the procedures. The small-sided game's evaluation was conducted over two mornings, each consisting of 56 minutes of playing time, as detailed below.

2.2.1 | Cognitive functions evaluation

Multiple object tracking (MOT) was assessed with a validated open-source version of the MOT task, available at https://osf.io/qy6nb/ (accessed in July 2025) and translated into 16 different languages (Meyerhoff & Papenmeier, 2020). MOT requires various cognitive functions, such as integration of complex movements, sustained, selective, and distributed attention, and working memory (Faubert & Sidebottom, 2012; Romeas, Guldner, & Faubert, 2016) and has been used in other studies with soccer players (Faubert, 2013; Memmert, Simons, & Grimme, 2009; Romeas, Chaumillon, Labbé, & Faubert, 2019; Romeas et al., 2016; Scharfen & Memmert, 2019b, 2021b, 2021c, 2021a). The test involved a black background screen with eight white circles randomly arranged. Four of them were highlighted in red before returning to their original color. All the circles then move for 8 seconds at a constant speed. Once they stop, the participant must identify the four initially highlighted circles by clicking on them with a mouse. After each attempt, the participants received feedback on the number of correct selections made. The test consisted of five blocks with ten attempts each. The total application time was approximately 15 minutes. The tracking capacity (TC) provided by the test was used for further analysis (Meyerhoff & Papenmeier, 2020).

Visuospatial working memory (VWM) was assessed using the Corsi block test (Corsi, 1972). The computerized task version available in PEBL consists of 9 blue squares on the screen, some of them, one at a time, change to yellow and then return to blue in a certain sequence. The participant must memorize and reproduce this sequence by clicking on the squares in the correct order. The test started with a sequence of two squares, and every two attempts, the sequence to be recalled was increased by one. The test ended when participants made two consecutive errors. This task has been used in other studies with soccer players (Baláková, Boschek, & Skalíková, 2015; Glavaš, 2020). The variable extracted for the test analysis was the Memory Span, calculated based on the total number of correct attempts and the last item with a complete attempt (Scarpina, D'Agata, Priano, & Mauro, 2021).

Cognitive flexibility (CF) was assessed using the Trail Making Test (TMT). The computerized version is available in PEBL and the administered format consisted of two types of tasks. In the first (TMT-A), the participant must click on the numbers from 1 to 26, randomly arranged on the screen, in ascending order. In the second task (TMT-B), individuals must alternate between clicking numbers in ascending order and letters in alphabetical order as quickly as possible. For example, the subject must connect "1-A-2-B-3-C" in this order, alternating between a number and a letter. Both parts, each containing 26 elements to connect, were administered in alternating order for a total of five repetitions each (Piper et al., 2012). The TMT has been used before to measure CF in soccer players (Huijgen et al., 2015; Scharfen & Memmert, 2021a, 2021b, 2021c; Vestberg, Gustafson, Maurex, Ingvar, & Petrovic, 2012). For analysis, the difference between the best completion times for TMT-B and TMT-A (B-A) was used to determine a CF score. Lower values represent greater cognitive flexibility (Sánchez-Cubillo et al., 2009).

Sustained attention (SA) and *Impulsivity* (I) were assessed using the Go/No Go task. This test is a response inhibition task in which participants must execute or inhibit a response to the presented stimulus. The computerized version available in PEBL consisted of a screen with 4 squares arranged in a 2x2 matrix, each containing a blue star. The letter “P” or “R” appeared in one of the squares. In the first block (P-Go), participants were required to respond when the “P” stimulus appeared and inhibit their response to “R”. In the second block (R-Go), participants were instructed to respond when the “R” stimulus appeared and inhibit their response to “P”. Each block consisted of 160 stimuli with the ratio of response to inhibition stimulus of 80:20 (Bezdjian, Baker, Lozano, & Raine, 2009). Go/No Go and similar tasks (e.g., stop signal) have been used to measure SA and I in soccer players (Huijgen et al., 2015; Verburgh et al., 2014, 2016; Shimi, Tsestou, Hadjiaros, Neokleous, & Avraamides, 2021). For analysis, the GO and No Go response accuracy was extracted. Higher accuracy in response to the Go stimulus is considered a better score for sustained attention and higher accuracy in response to the No Go stimulus represents a measure of greater impulsivity control (Bezdjian et al., 2009).

2.2.2 | Small-sided games evaluation

The protocol developed by Wilson et al. (2021) (Wilson et al., 2021) was used to evaluate the players’ performance on the field using small-sided games. The protocol measures the athlete’s contributions to the team and overall effectiveness. To set up the games, four fields measuring 30×25 meters were marked with sports cones, with goals 2 meters wide and 1 meter high, indicated with cones, following the validated protocol recommendations (Figure 1). The participants were randomly divided into teams of 3 players each, without a goalkeeper, round by round. The games lasted 4 minutes, and after the time ended, the players were redistributed into different teams for the next round. This time between rounds also served as a rest period. Four games were played simultaneously, allowing 24 athletes to play at the same time. With a high number of games and random team formations, the protocol aims to extract individual performances from collective interactions among players.

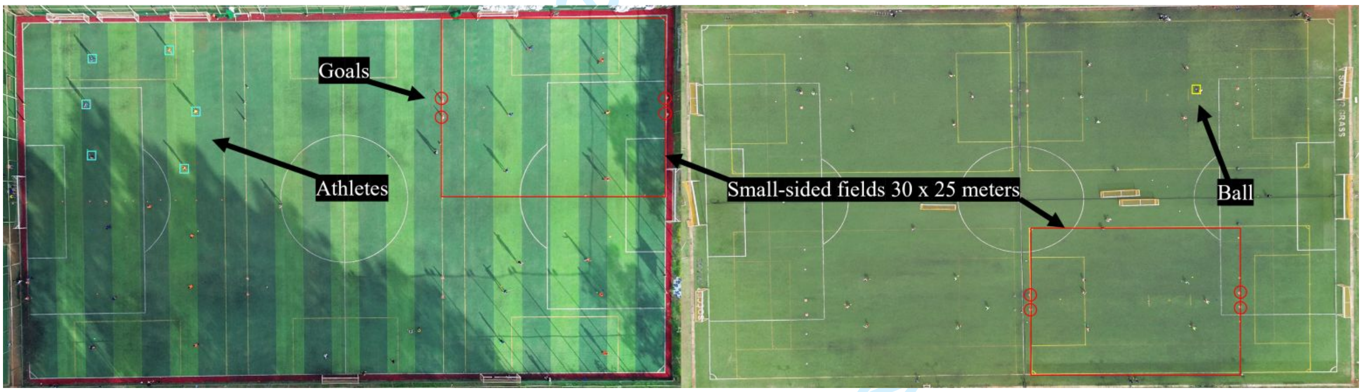


FIGURE 1 Top-view images from the experimental setup of on-field performance evaluation. The image shows small-sided fields and goals marked in red, players highlighted in blue, and the ball indicated in yellow.

The small-sided games were played on artificial grass fields over two consecutive days. 14 rounds were played each day, totaling 28 rounds, which is sufficient to ensure reliability in subsequent analyses (Wilson et al., 2021). Occasional substitutions of players participating in the small-sided games were made due to fatigue or injuries. Only players who participated in at least 22 rounds were considered for the final analysis. In each small-sided game, there was at least one evaluator to assign the members of each team and the game score, and to referee the match. The evaluator was responsible for putting the first ball into play, and after each goal, the athletes restarted the game from their team’s goal line. Throw-ins, corner kicks, and fouls were signaled by the evaluators following official soccer rules with no limit for touches in the ball and allowed verbal encouragement from the evaluators and team staff. The teams were identified by different colored vests. The types of player contributions to the team in the small-sided games were: (1) individual goals (IG) (average number of goals scored per game); (2) conceded goals (CG) (average number of goals conceded per game); and (3) goals by teammates (GT)(average number of goals scored by teammates). The overall effectiveness of the players was calculated by the average net team goals (NG) per game (Wilson et al., 2021).

2.3 | Machine Learning algorithms

To predict on-field performance variables through cognitive function analysis, supervised ML models for classification were used. The analysis compared the performance of seven ML models traditionally used in classification problems: Extreme Gradient Boosting (XGBoost), Random Forest (RF), Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), and Multilayer Perceptron (MLP). The Scikit-learn v.1.6.1 library in Python v.3.12 was used to train the models (Pedregosa et al., 2011).

Features/predictor variables were the results from cognitive functions assessment (SA, I, VWM, CF, and TC), while target variables to be predicted were the players' contributions to the team and overall effectiveness. To categorize players' performance in each game variable (IG, CG, GT, and NG), a non-supervised ML technique, K-means clustering, was used. Each variable was categorized into two levels, separating the players into groups of superior and inferior performance.

2.3.1 | Pre-processing

To infer the combination of cognitive functions with higher predictive power for each on-field performance data, the cognitive variables were mixed to create different datasets used as predictor variables. All possible combinations of the five cognitive functions resulted in 31 different datasets. The VWM data from one participant had an error in the evaluation, to avoid excluding the participant from the sample, his test value was replaced with the group mean. Since the field tests were conducted at two different clubs and their results represented the player's performance relative to other team members, the K-means clustering technique was applied separately to each team sample. This identified players with superior and inferior performance within each team. For training the supervised ML classification models, data from both teams were concatenated (Figure 2). The point of dividing the players into groups was to make a comparison to other studies that investigated the cognitive functions of athletes from different competitive levels such as elite, sub-elite and/or amateurs. The present analysis aimed to investigate if there is a difference in the cognitive functions analyzing superior and inferior performing athletes from the same competitive level in different small-sided game demands.

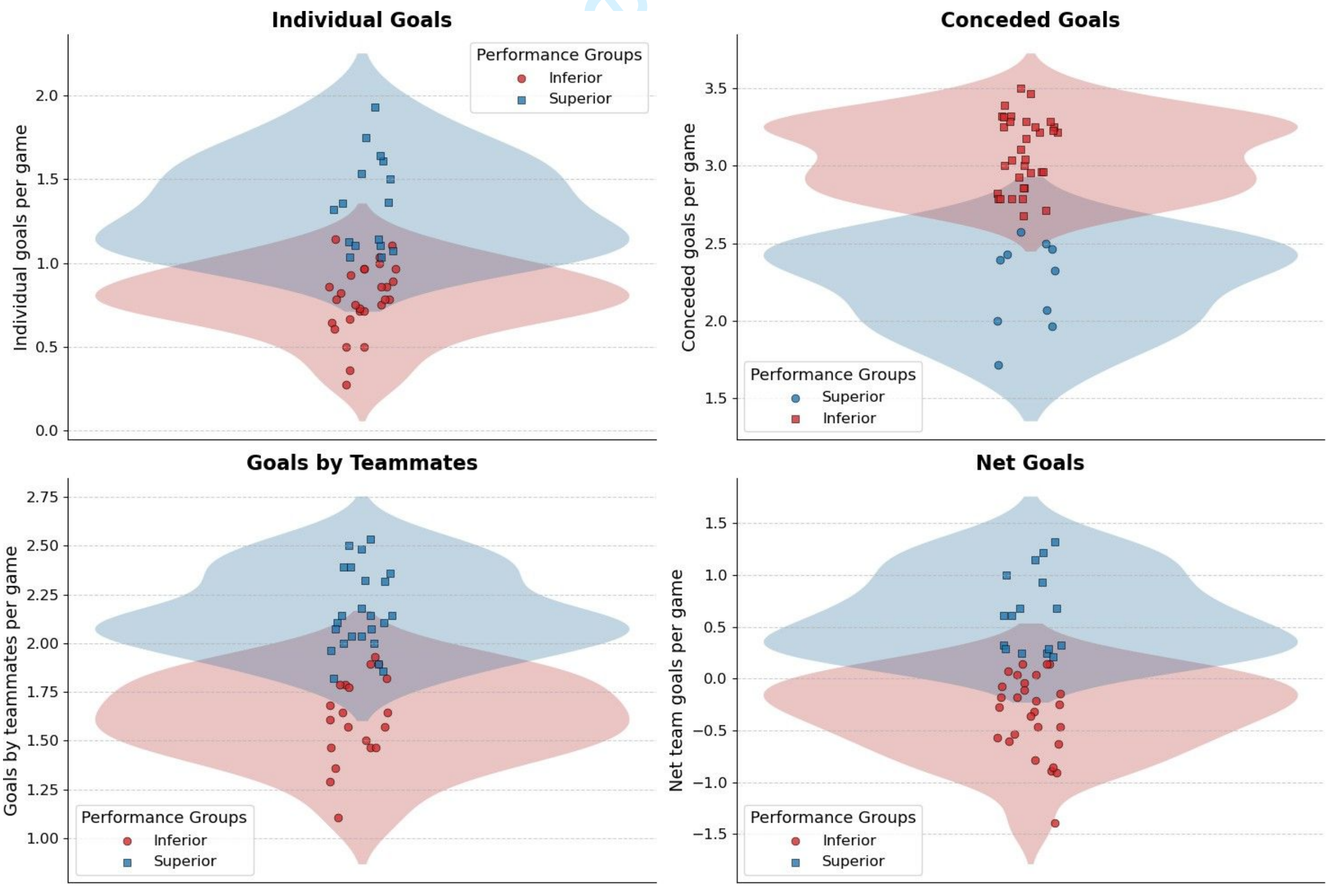


FIGURE 2 Clusters with density of the small-sided games performance variables.

2.3.2 | Models training, comparisson and evaluation

The Grid Search was applied to optimize the ML algorithms' hyperparameters. At this stage of processing, a set of hyper-parameters for each model was defined. The GridSearch technique tested all combinations for each algorithm using 5-fold stratified cross-validation and selected the best combination to optimize Balanced Accuracy and refined it to improve F1 score (Raschka & Mirjalili, 2019). For all evaluations, cognitive function variables were normalized using Scikit-learn's Standard-Scaler, which was fitted on the training data and then applied to the test data. Considering the relatively small dataset to ensure robust model evaluation, after determining the best hyperparameters, each model underwent 30 times repeated 5-fold stratified cross-validation with different random splits in each execution. The three combinations of cognitive functions that showed the best-balanced accuracy values were selected for further comparison of their other metrics (Figure 3).

The metrics for model evaluation were Accuracy (ACC), Balanced Accuracy (BACC), Precision, Recall, and F1-score. BACC was chosen for Grid Search optimization and first model selection and comparison due to the imbalanced dataset, thereby avoiding bias in models that may correctly predict one class more often than another (Raschka & Mirjalili, 2019). All metrics were extracted for each class as well as for the mean. The model's performance was evaluated by averaging the chosen metric across all iterations (Bishop & Nasrabadi, 2006). Due to the imbalanced nature of the dataset (Figure 2), the StratifiedKFold cross-validation technique was used. This technique maintains the class ratio within each fold, which is important to avoid misleading model performance evaluation where some folds may have a significantly different class distribution than the original

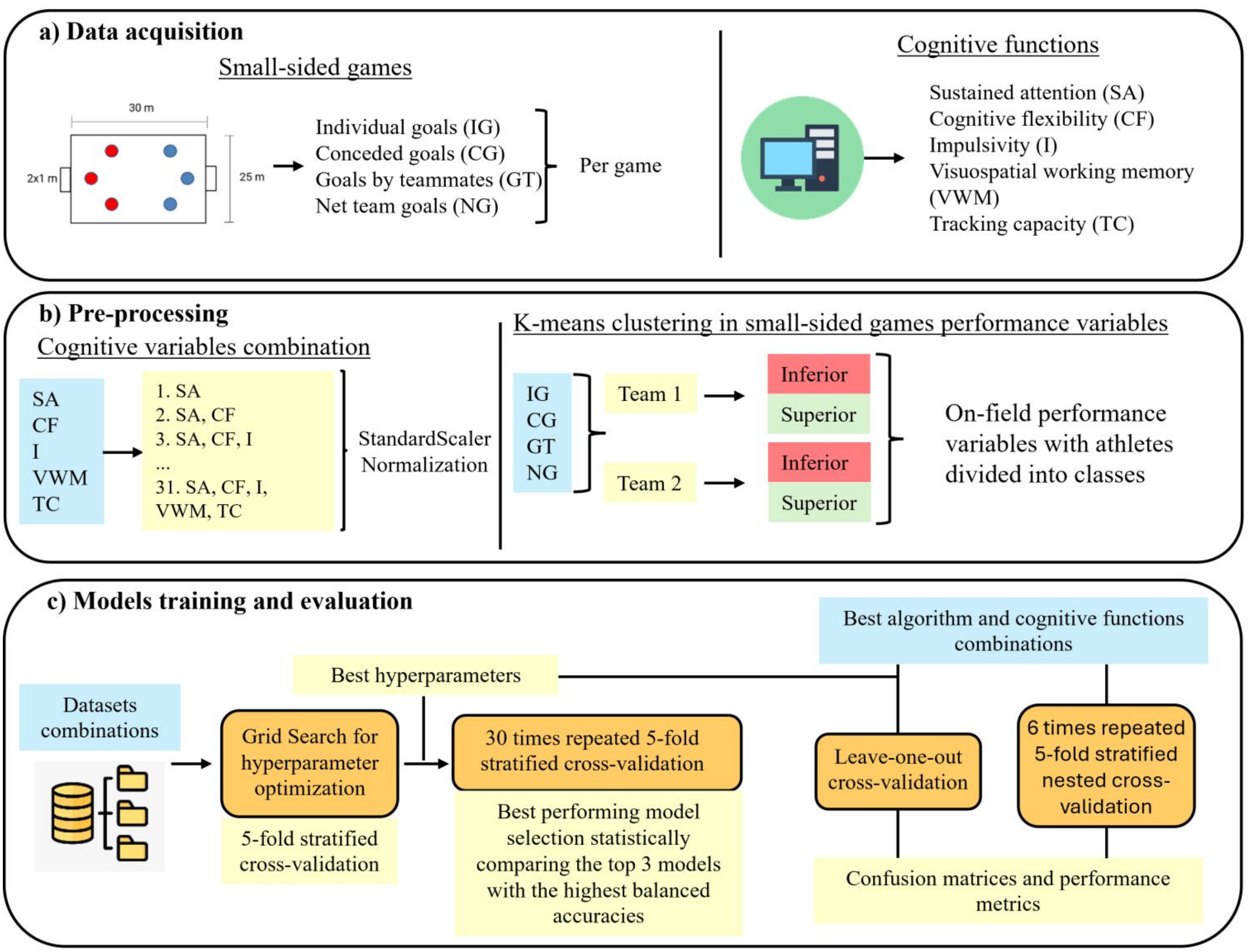


FIGURE 3 Methodology used for training and evaluating supervised machine learning classification algorithms. a) Data acquisition; b) Pre-processing; and c) Models training and evaluation.

dataset (Raschka & Mirjalili, 2019). To ensure the test set is representative of the entire dataset, a random split (shuffle) technique was used to shuffle the data before splitting it into training and test sets. A fixed Random State value was used for reproducibility and to compare the performance of different models using the same test set. Other techniques such as synthetic minority over-sampling technique and different k-fold cross-validation strategies were tested but discarded for the final analysis.

For each on-field performance metric, the top three models with the highest balanced accuracies were statistically compared, and the best-performing model was selected for the final evaluations. Two analyses were conducted for the final models' performance estimation. The first one consisted of using the best combinations of cognitive functions and the optimal hyperparameters obtained through Grid Search to perform Leave-One-Out cross-validation. In this approach, the model is repeatedly trained on the entire dataset minus one sample, which is then used for testing. Confusion matrices were generated for each best model, reporting precision and recall for each class (Figure 7). This approach is recommended with small datasets but has limitations in the present study due to a bias involved in selecting the best hyperparameters using the whole dataset.

That leads to the second analysis conducted for final evaluation. It consisted of a 6 times repeated 5-fold stratified nested cross-validation applied with the best combination of cognitive functions and the algorithm with best performance. In this approach, Grid Search with cross-validation is performed within each fold of the outer cross-validation loop, ensuring that the hyperparameter tuning process is completely isolated from the final test set evaluation. This process was repeated six times, resulting in a total of 30 different train-test splits, to obtain a more robust estimate of the models' generalization performance by reducing the variability caused by a single data partitioning, providing more stable and reliable performance metrics. The predictions from the 30 folds were summed for each class to produce the aggregated confusion matrices and to calculate the corresponding performance metrics (Figure 8).

2.4 | Statistical analysis

The data normality was checked using the Shapiro-Wilk test. As some variables did not show normal distribution, Spearman's correlation coefficient (r) was used to describe the relationship between the variables. Additionally, the p-value was provided to indicate correlation significance. Cohen's d was calculated for each correlation to describe the effect size, derived from Spearman's r, where values of 0.2, 0.5, and 0.8 represent small, medium, and large effects, respectively (Cohen, 1988), as used in other studies exploring the relationship between cognitive functions and performance in soccer (Scharfen & Memmert, 2019b, 2021b). The Mann-Whitney U test was used for comparison of the cognitive functions between superior and inferior performance player groups across each on-field performance metric.

The metrics described in the model evaluation section for the top-three combinations of cognitive functions that presented the best balanced accuracy for each on-field performance variable were compared for choosing the best models for final evaluations. Normality and homogeneity were verified using the Shapiro-Wilk and Levene tests. As some data distribution was not normal and homogeneous, the metrics were compared using the Kruskal-Wallis test with Dunn's post-hoc test and Bonferroni adjustment. In all cases, the significance level considered was $p < 0.05$. The analyses were performed using Python 3.12 algorithms.

3 | RESULTS

3.1 | Correlations and differences between groups

The Spearman's correlations between all variables are presented in Figure 4. Regarding the relationship between different cognitive functions, a direct proportional correlation was found between VWM and TC ($r = 0.34$; $p = 0.024$; $d = 0.72$). In terms of the variables related to on-field performance, IG showed a negative correlation with GT ($r = -0.4$; $p = 0.007$; $d = -0.87$) and a positive with NG ($r = 0.42$; $p = 0.004$; $d = 0.93$). CG exhibited a negative correlation with NG ($r = -0.78$; $p < 0.001$; $d = -2.48$). GT showed a positive correlation with NG ($r = 0.31$; $p = 0.04$; $d = 0.65$). No significant correlation was found between cognitive variables and on-field performance variables. The differences between the cognitive functions of the superior and inferior performance players group in each on-field performance are presented in Figure 5. The Mann-Whitney test revealed no significant differences in any of the comparisons ($p > 0.05$).

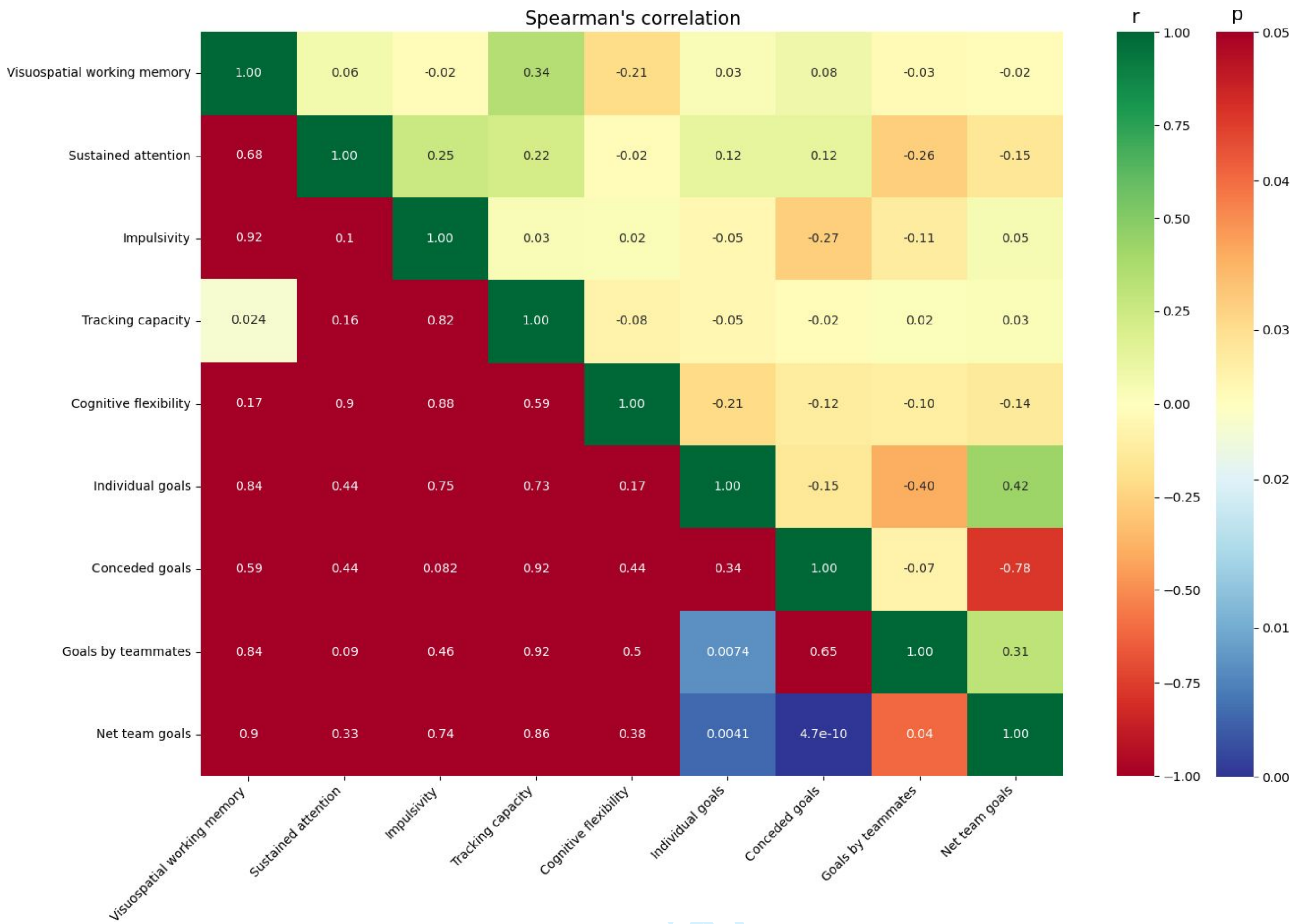


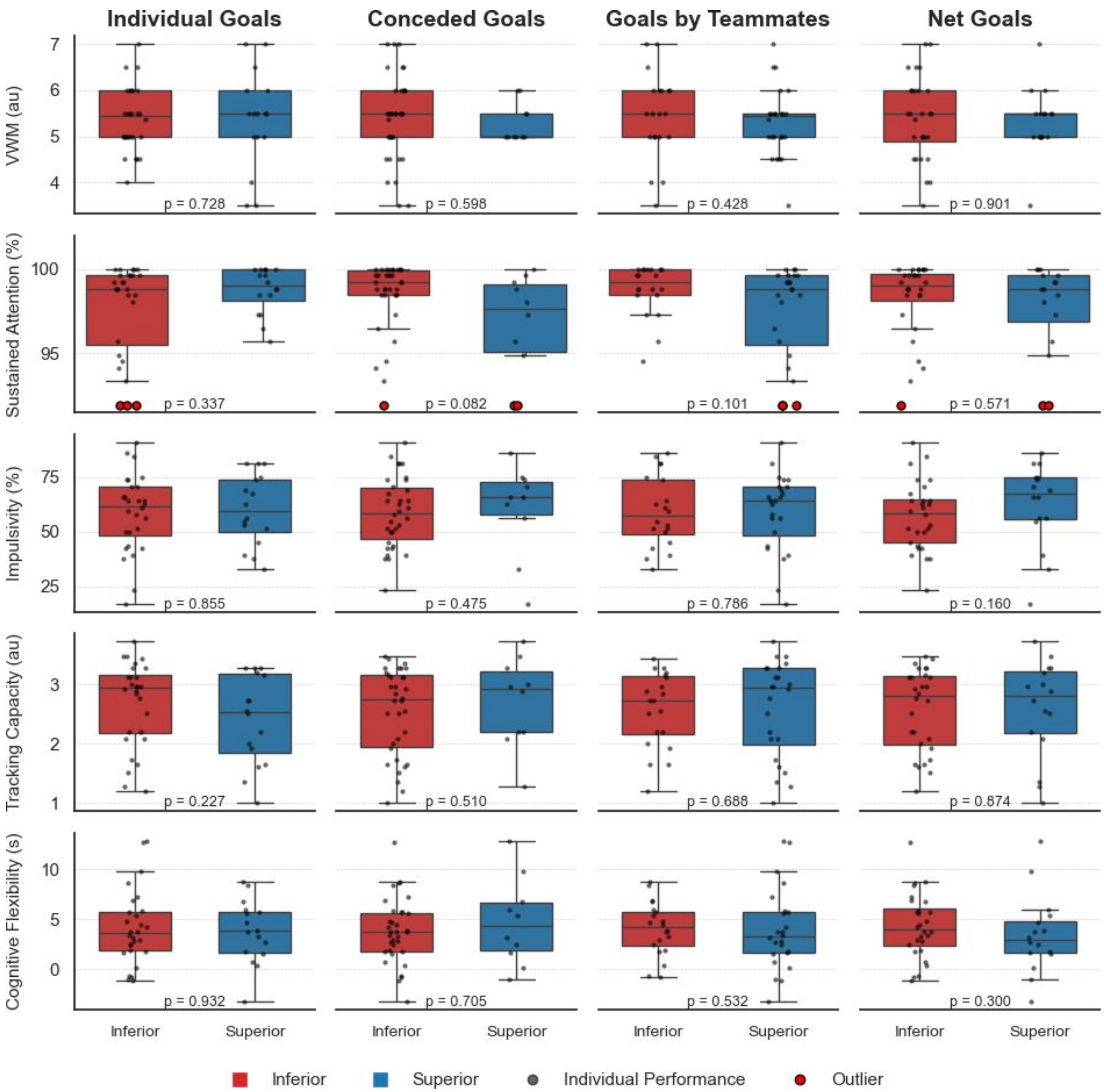
FIGURE 4 Spearman's correlation (r) and p-value between all variables.

3.2 | Machine learning models evaluation

The ML models that presented best BACC after the repeated 30 times cross-validation for each cognitive function combination are presented in Figure 6. The top-three models with higher BACC for each on-field performance metric prediction were selected for further comparison. These models are described in terms of mean and standard deviation of ACC, BACC and F1 in Table1.

Regarding IG prediction, model 2 using CF, VWM, and TC as predictor variables and the MLP algorithm showed higher mean ACC compared to algorithms 1 ($p < 0.001$) and 3 ($p < 0.001$), and higher F1 compared to algorithm 3 ($p = 0.04$). Algorithm 1 also outperformed algorithm 3 in terms of F1 ($p = 0.049$). Considering the results, algorithm 2 was selected for the final evaluations. For CG prediction, model 2 using VWM as predictor variable and the KNN algorithm showed higher mean ACC compared to algorithms 1 ($p < 0.001$) and 3 ($p < 0.001$), and also higher F1 compared to algorithms 1 ($p = 0.03$) and 3 ($p < 0.001$). Algorithm 1 also outperformed algorithm 3 in terms of ACC ($p < 0.001$) and F1 ($p = 0.009$). With that, Algorithm 2 was chosen for final evaluations.

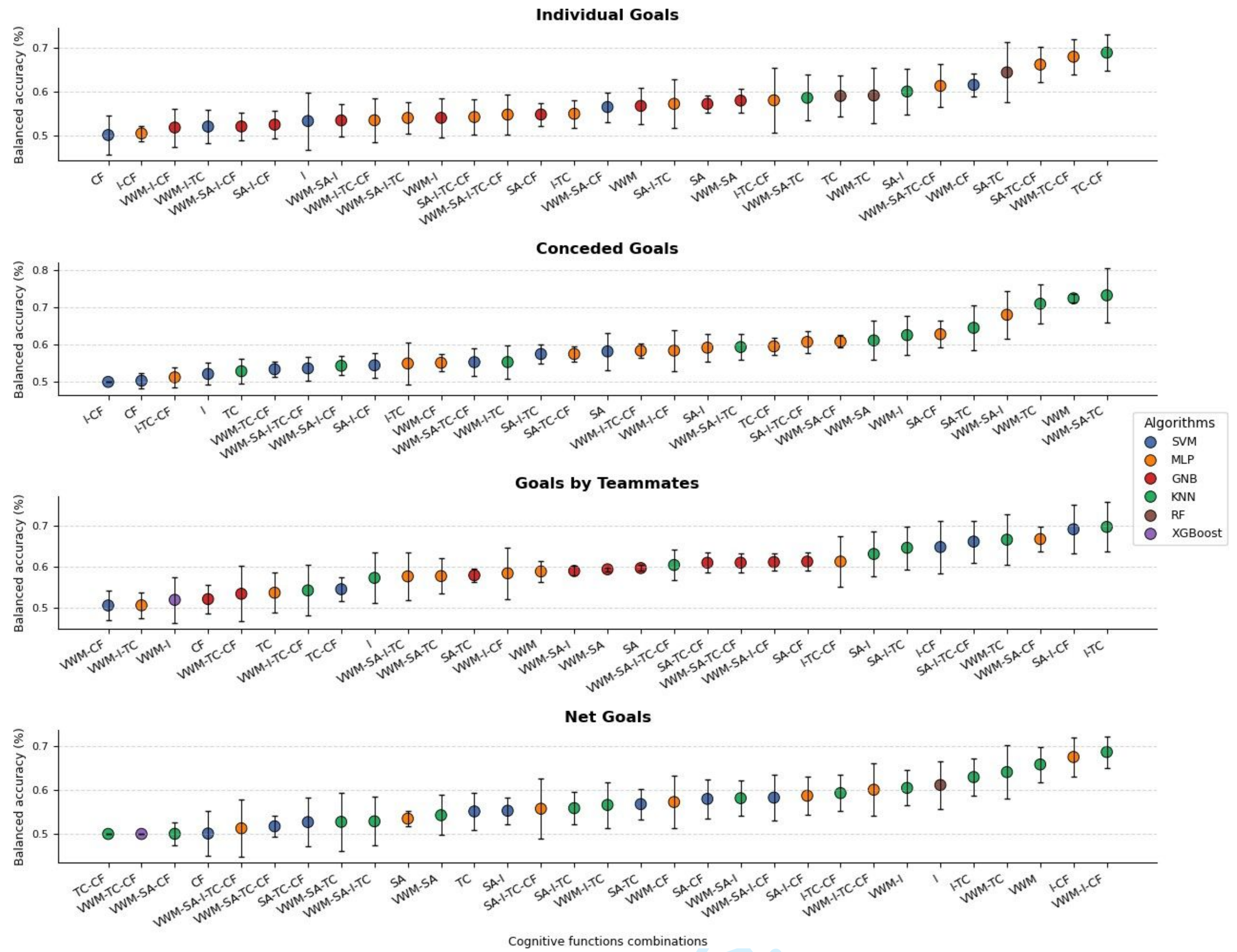
Regarding GT, model 1 using I and TC as predictor variables and the KNN algorithm presented higher mean ACC compared to algorithm 3 ($p = 0.009$), and higher F1 also compared to algorithm 3 ($p = 0.02$). Algorithm 2 outperformed algorithm 3 in terms of BACC ($p = 0.048$). Considering the results, algorithm 1 was chosen for final analysis. For NG prediction, model 1 using CF, I and VWM as predictor variables and the KNN algorithm showed higher mean BACC ($p = 0.03$), ACC ($p < 0.001$) and F1 ($p < 0.001$) compared to algorithm 3. Algorithm 2 also outperformed algorithm 3 in terms of ACC ($p < 0.001$) and F1 ($p = 0.01$). Algorithm 1 was selected for final evaluations. The final evaluations results are presented in Figures 7 and 8, which show the confusion matrices and performance metrics such as ACC, BACC, and per-class precision and recall.



F I G U R E 5 Boxplots and standard deviations of cognitive functions comparing superior and inferior performance player groups across each on-field performance metric. Individual data points are shown, and outliers are marked in red. P-values from the Mann-Whitney U test are provided for each comparison. VWM = Visual Working Memory.

4 | DISCUSSION

The present study aimed to explore the role cognitive functions in the performance of under-17 soccer players on small-sided games. Exploratory and descriptive analyses included correlations among all variables and comparisons of each cognitive function between the groups. Supervised ML algorithms were employed to predict whether players belonged to a group of superior or inferior performance based on variables extracted from a protocol of multiple small-sided games (Wilson et al., 2021). The results identified which algorithms achieved higher accuracy in predictions and which combinations of cognitive functions presented higher predictive power for each on-field performance variable. The discussion was divided into four sections, presenting the findings of the study and comparing them with relevant literature: (1) Correlations and group comparisons; (2) Machine learning predictions; (3) Limitations; and (4) Future directions.



F I G U R E 6 Mean and standard deviations of the Machine learning models' best balanced accuracies for each cognitive functions combinations across the on-field performance metrics. The color of each point represents the algorithms with best performance for that feature combination. CF = Cognitive Flexibility; I = Impulsivity; SA = Sustained Attention; TC = Tracking Capacity; VWM = Visuospatial Working Memory; KNN = K-nearest neighbors; MLP = Multilayer perceptron; SVM = Support Vector Machine; GNB = Gaussian Naive Bayes; RF = Random Forest; XGBoost = Extreme Gradient Boosting.

4.1 | Correlations and group comparisons

The Spearman's correlation indicates whether as one variable increases or decreases, the other shows a similar behavior. A moderate to strong correlation, with a medium to large effect size, was found between TC and VWM, representing the only significant correlation among cognitive functions. This finding is consistent with the literature, as MOT tasks require sustained, selective, and distributed attention, as well as working memory (Faubert & Sidebottom, 2012; Romeas et al., 2016). Analyzing correlations between performance data in small-sided games, the reliability of these metrics is supported by their consistency with the protocol validation results (Wilson et al., 2021). Specifically, all individual performance variables (IG, CG, and GT) presented moderate to strong correlations with NG, but not necessarily among themselves. These shows that the players could present good overall effectiveness result (NG) by having a good performance in any contributions to team metrics. Only IG showed a negative correlation with GT.

TABLE 1 Accuracy, Balanced accuracy and F1 mean and standard deviation of the top-three models with highest Balanced Accuracies. The models selected for final evaluations are highlighted in bold.

Predicted variables	Classification	Combinations	Algorithms	BACC (%)	ACC (%)	F1 (%)
Individual Goals	1	CF - TC	KNN	68.9 ± 4.2	69.9 ± 4.3	67 ± 4.9
	2	**CF - VWM - TC**	**MLP**	**67.9 ± 4**	**73.9 ± 3.3**[*1,3]	**67.2 ± 4.6**
	3	SA - CF - TC	MLP	66.1 ± 3.9	68.8 ± 3.4	64.4 ± 4.2[*1,2]
Conceded Goals	1	SA - VWM - TC	KNN	73.1 ± 7.2	73 ± 4.6	66.9 ± 6.5
	2	**VWM**	**KNN**	**72.3 ± 1.1**	**79.1 ± 1.7**[*1]	**70.8 ± 2.2**[*1]
	3	VWM - TC	KNN	70.9 ± 5.2	67.2 ± 5.3[*1,2]	62.5 ± 5.4[*1,2]
Goals by Teammates	**1**	**I - TC**	**KNN**	**69.7 ± 6**	**70.2 ± 6.3**[*3]	**68.8 ± 6.6**[*3]
	2	SA - I - CF	SVM	69.1 ± 6	68.1 ± 5.9	66.9 ± 6.2
	3	SA - VWM - CF	MLP	66.7 ± 2.9[*2]	65.8 ± 2.8	64.8 ± 3
Net Goals	**1**	**CF - I - VWM**	**KNN**	**68.7 ± 3.6**	**72.9 ± 3.5**	**68 ± 4**
	2	CF - I	MLP	67.6 ± 4.5	72.3 ± 3.4	66.3 ± 5.3
	3	VWM	KNN	65.9 ± 4[*1]	64.2 ± 3.5[*1,2]	62.5 ± 4.4[*1,2]

CF = Cognitive Flexibility; I = Impulsivity; SA = Sustained Attention; TC = Tracking Capacity; VWM = Visuospatial Working Memory; KNN = K-nearest neighbors; MLP = Multilayer perceptron; SVM = Support Vector Machine.
[*]$p<0.05$ post-hoc Dunn with Bonferroni adjustment.
[1,2,3]Indicates the model for which there is a statistical difference.

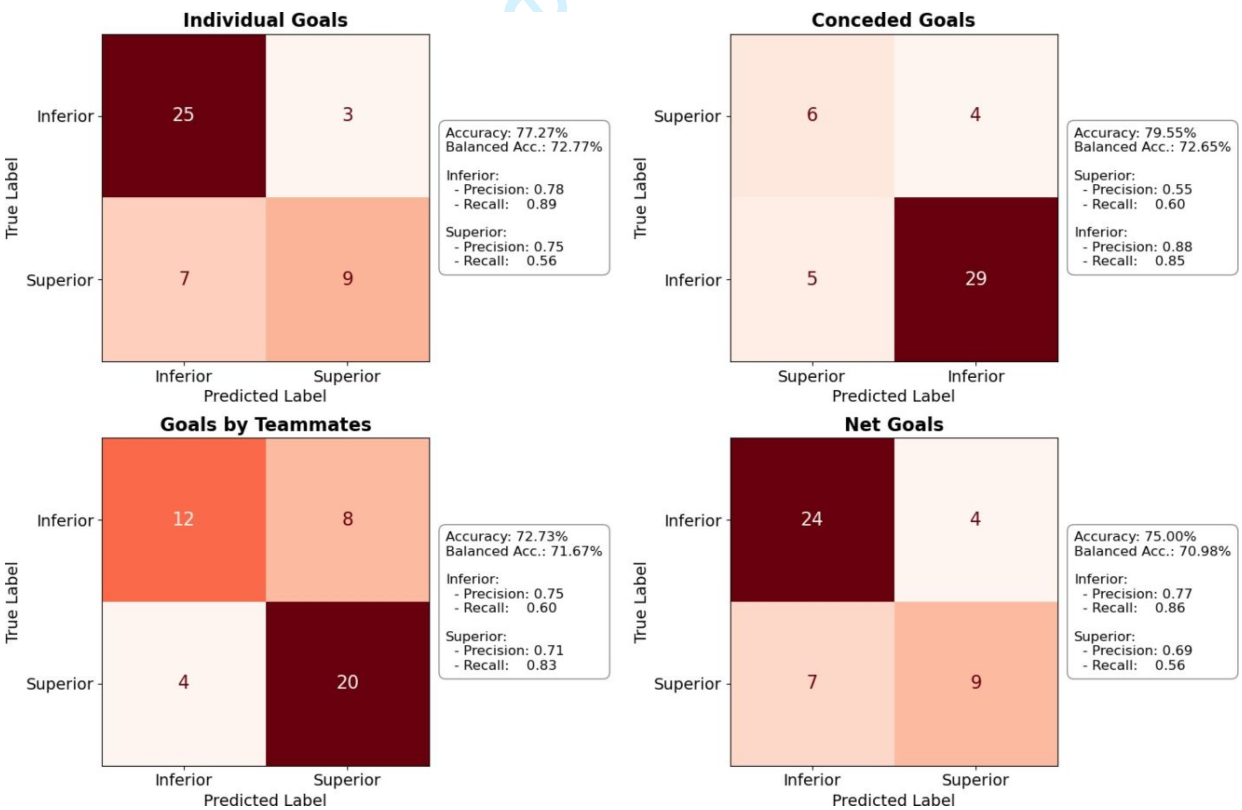


FIGURE 7 Confusion matrices and performance metrics of the best models after Leave-One-Out cross-validation.

Regarding the cognitive functions correlation with performance in small-sided games, none showed statistical significance. Perhaps with a larger sample, correlations with $p < 0.05$ could be found. However, some findings are noteworthy, such as the

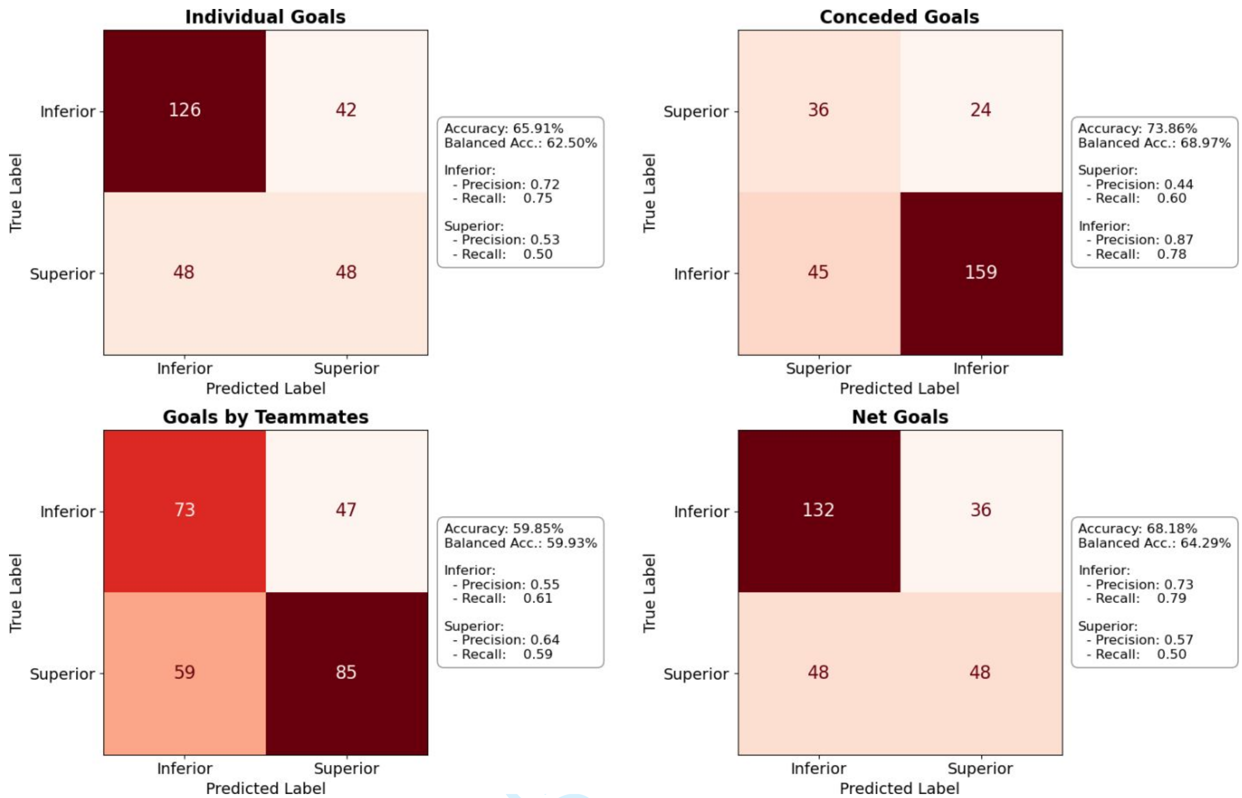


FIGURE 8 Confusion matrices and performance metrics of the best models after 6 times repeated 5-fold stratified nested cross-validation.

inversely proportional relationship of I with CG (r = –0.27), indicating a tendency for more impulsive players to concede more goals, emphasizing the importance of I control for defensive functions in soccer, as suggested by other authors (Vestberg et al., 2017). The last non-significant correlation worth highlighting is CF with IG (r = –0.21), considering that lower values in CF indicate better scores in this variable, the results describe a directly proportional association. This finding can be compared with other studies in the literature that found correlations between CF and the number of goals scored by athletes in previous (Vestberg et al., 2017) or subsequent seasons to the assessment (Vestberg et al., 2012). Another study by the same author also found no significant correlation between these variables (Vestberg et al., 2020).

In contrast to the initial hypotheses, no differences were identified in the comparison of cognitive function groups using the Mann–Whitney test. This finding shows that in players from the same competitive level, there is no difference between the cognitive functions comparing the groups of superior and inferior performance across different small-sided game demands represented by the on-field performance metrics. To the best of the authors' knowledge, this is the first study to investigate this type of analysis. A common approach is to compare cognitive functions from different competitive level athletes, most of these studies showing higher competitive level players presenting greater scores in cognitive tests (Baláková et al., 2015; Huijgen et al., 2015; Verburgh et al., 2014, 2016; Vestberg et al., 2012, 2017, 2020). However, these comparisons and correlations using traditional statistical methods may fail to capture all the relations between these variables. This is where ML algorithms can give new insights into the relation of cognitive functions and soccer performance by testing different modeling techniques and enabling the identification of non-linear patterns and interactions that traditional methods might overlook.

4.2 | Machine learning predictions

Training and evaluating ML algorithms aimed to determine which combinations of cognitive functions present higher predictive power in distinguishing athletes' performance levels across different small-sided soccer game demands such as scoring goals, defending, and creating opportunities for teammates to score. The best-performing ML models achieved ACC ranging from 59 to 79% and BACC ranging from 59 to 72% in the final evaluations. Considering that soccer performance is multifactorial (Afonso, Garganta, & Mesquita, 2012; Praça, Soares, Matias, Costa, & Greco, 2015), and only cognitive functions were considered in the predictions, these results demonstrate the potential of general cognitive functions in soccer performance prediction. They also highlight the potential of cognitive functions in moderately differentiating between athletes of superior and inferior performance within players of the same competitive level when using modeling techniques that consider the interaction between the cognitive functions. Other studies found promising results when combining cognitive functions with personality traits for competitive level predictions using artificial neural networks in a large sample of 328 participants, including 204 elite athletes (Bonetti et al., 2025).

Two other studies have previously explored the prediction of soccer performance using cognitive functions. One study classified athletes into elite and sub-elite using stepwise discriminant analysis, achieving 62.5% accuracy (Huijgen et al., 2015). Another study using logistic regression achieved 78% accuracy in classifying athletes into elite or amateur categories (Verburgh et al., 2014). To date, this study is the first to differentiate the performance levels of athletes from the same competitive tier through cognitive functions analysis and to compare multiple ML algorithms for this task. Differently from past studies, the present employed dataset partitioning for training and testing the predictive models aiming for a confident predictive power estimation of cognitive functions in soccer performance analysis.

In relation to IG, the algorithm with the best performance was MLP, which used CF, VWM and TC as predictor variables. Examining the final evaluations metrics, it was observed that the precision and recall for predicting inferior performance were higher compared to those for classifying superior-performance athletes. The literature has investigated the importance of these cognitive functions in goal scoring. Previous studies have found correlations between CF and working memory with the number of goals scored by players and game intelligence, which was subjectively assessed by coaches (Vestberg et al., 2017, 2012; Scharfen & Memmert, 2021b).

Considering CG, the model using VWM as a feature and KNN algorithm stood out. Final models evaluations demonstrated that the recall and precision were also higher for the inferior players classification. There are few studies in the literature directly investigating cognitive functions and defensive performance in soccer. The closest measure is a study comparing the cognitive functions of athletes in different positions. It showed a tendency of better SA scores among defenders compared to other positions (Schumacher, Schmidt, Wellmann, & Braumann, 2018). Other studies indirectly contribute to understanding the importance of working memory for defensive performance, finding correlation of it with ball control, overall scores in motor skill tests, tactical and technical skills, mental resilience, situational awareness, and overall performance (Glavaš, 2020; Scharfen & Memmert, 2019b).

The results obtained for GT indicate that the model using I and TC with the KNN algorithm presented the best predictions. Analyzing the final models evaluations, it presented a similar performance in predicting both classes. Few studies have investigated the association of cognitive functions and the capacity of creating goal opportunities for teammates in soccer.As a measure that could be compared to that evaluated in the current study, the number of assists by athletes in the two seasons following the cognitive evaluation demonstrated a correlation with the combination of I and CF, assessed by the Design Fluency test (Vestberg et al., 2012).

Finally, when analyzing the NG, a measure that aims to assess athletes' overall effectiveness in small-sided games (Wilson et al., 2021), the KNN algorithm using CF, I, and VWM as predictor variables presented the highest performance. These cognitive functions are known as the core executive functions, which are responsible for controlling and regulating thought and action, playing a crucial role in decision-making (Friedman et al., 2006). Moreover, the literature describes that the interaction of these three executive functions generates higher-order executive functions such as reasoning, problem-solving, and planning (Diamond, 2013). These results align with numerous studies highlighting the role of executive functions in superior athlete performance. This includes comparisons across different competitive levels players, with higher scores in executive function tests among elite athletes (Baláková et al., 2015; Huijgen et al., 2015; Verburgh et al., 2014, 2016; Vestberg et al., 2012, 2017, 2020), as well as correlations with superior sports performance (Glavaš, 2020; Scharfen & Memmert, 2019b, 2019a, 2021c, 2021b; Vestberg et al., 2012, 2017, 2020).

4.3 | Limitations

The findings of this study are specific to the age group of the sample used, under-17 athletes from soccer clubs. It is important to note that during adolescence, the brain is still maturing, which is reflected in cognitive functions changes (Huizinga, Dolan, & Van der Molen, 2006). The sample size, based on data from only two clubs, does not allow for generalization to all athletes in this age group. Additionally, the present study didn't consider the influence of circadian rhythms and sleep factors on the cognitive performance and physical readiness which can also limit the results generalization.

It is also worth highlighting that the athletes' performance was assessed through small-sided games. Further studies should investigate if the findings can also be identified in official matches. Finally, since this research has an exploratory character, all data were used for both training and evaluating ML models, thereby limiting the assessment of applying these trained algorithms to new, unseen datasets. The experimental design was cross-sectional, and the findings do not imply causality but association. Considering these limitations and the number of comparisons, the results should be interpreted with caution, and further studies are needed before applying general-domain cognitive function assessments to talent identification and player selection.

4.4 | Future directions

In general, the best-performing algorithm was KNN. This modeling approach classifies instances based on the distance between input features. These results suggest that grouping athletes with similar cognitive characteristics may be a promising strategy to better understand the relationship between cognitive functions and sports performance. With that, studies should be done to investigate if there are athletes' cognitive profiles that are related to certain behaviors inside the game. The present study demonstrated that certain cognitive functions are better predictors of different game demands. Future research should focus on investigating this relationship with more individual-specific technical, tactical, and physical variables for a more ecological approach in which intra-individual variability should be viewed as a functional feature reflecting the player's adaptive exploration of the environment's constraints.

Many questions remain open regarding the relationship between cognitive functions and performance in soccer. Future studies should verify if the findings of this research are replicated when analyzing official matches and across athletes of different age groups. Considering the influence of cognitive functions on decision-making, another interesting area of study is investigating the relationship between athletes' cognitive profiles and on-field performance, taking into account situational variables such as match status, location, and opponent quality (Aquino, Martins, Vieira, & Menezes, 2017). The use of ML to test the relevance of existing theories and to discover new causal mechanisms (Shmueli, 2010) appears as a promising area in the study of cognitive functions in soccer. Future research could explore different algorithms, ensembles, and techniques for hyperparameter optimization and model evaluation. It could also compare the predictive power of isolated and combined performance variables, such as physical, technical, and tactical measures, to better understand the actual contribution of each metric. Considering that machine learning models applied to static inputs cannot capture the fluidity of soccer behavior, future research should consider testing models that incorporate time-series data such as spatiotemporal tracking.

5 | CONCLUSION

The soccer players' cognitive functions from the groups of superior and inferior performance across different small-sided game demands didn't present differences. Also, no correlations were found between the cognitive functions and on-field performance. The best supervised machine learning models presented accuracies ranging from 59 to 79% and balanced accuracies from 59% to 72% in predicting the performance level of under-17 youth soccer players in different demands of small-sided games through general cognitive function analysis. Considering the small sample size, these results highlight that general cognitive functions have the potential to provide moderate predictive power for differentiating performance among athletes of the same competitive level in small-sided games.

The standout algorithms were K-nearest neighbors and Multilayer Perceptron. For predicting individual goals scored, cognitive flexibility and tracking capacity stood out. Visuospatial working memory presented better results in predicting conceded goals. Regarding goals by teammates, impulsivity and tracking capacity provided better predictions. Lastly, the combination of cognitive flexibility, impulsivity, and visuospatial working memory, precisely the executive functions, presented superior results in predicting net goals, a measure reflecting athletes' overall effectiveness. The results suggest that the interaction between cognitive functions and sport performance is not that simple as a better cognitive function results in better performance but that using modeling techniques that consider the interaction of different cognitive functions may lead to a deeper understanding of the mechanisms that associate the cognitive functions and soccer performance.

CONFLICT OF INTEREST STATEMENT
The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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DATA AVAILABILITY STATEMENT
The source code and data that support the findings of this study are available for scientific purposes on the GitHub repository[available in final version] and on Zenodo at [available in final version].

AUTHOR CONTRIBUTIONS
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References

Afonso, J., Garganta, J., & Mesquita, I. (2012). Decision-making in sports: the role of attention, anticipation and memory. *Revista brasileira de cineantropometria & desempenho humano*, *14*, 592–601.

Alvarez, J. A., & Emory, E. (2006). Executive function and the frontal lobes: a meta-analytic review. *Neuropsychology review*, *16*, 17–42.

Aquino, R., Martins, G. H. M., Vieira, L. H. P., & Menezes, R. P. (2017). Influence of match location, quality of opponents, and match status on movement patterns in brazilian professional football players. *The Journal of Strength & Conditioning Research*, *31*(8), 2155–2161.

Baláková, V., Boschek, P., & Skalíková, L. (2015). Selected cognitive abilities in elite youth soccer players. *Journal of human kinetics*, *49*, 267.

Betsch, T., & Haberstroh, S. (Eds.). (2004). *The routines of decision making* (1st ed.). Psychology Press. Retrieved from https://doi.org/10.4324/9781410611826

Bezdjian, S., Baker, L. A., Lozano, D. I., & Raine, A. (2009). Assessing inattention and impulsivity in children during the go/nogo task. *British Journal of Developmental Psychology*, *27*(2), 365–383.

Bishop, C. M., & Nasrabadi, N. M. (2006). *Pattern recognition and machine learning* (Vol. 4) (4). Springer.

Bonetti, L., Vestberg, T., Jafari, R., Seghezzi, D., Ingvar, M., Kringelbach, M. L., ... & Petrovic, P. (2025). Decoding the elite soccer player's psychological profile. *Proceedings of the National Academy of Sciences*, *122*(3), e2415126122.

Claudino, J. G., Capanema, D. d. O., de Souza, T. V., Serrão, J. C., Machado Pereira, A. C., & Nassis, G. P. (2019). Current approaches to the use of artificial intelligence for injury risk assessment and performance prediction in team sports: a systematic review. *Sports medicine-open*, *5*, 1–12.

Claudino, J. G., Capanema, D. d. O., & Santiago, P. R. P. (2022). Aim in sports medicine. In *Artificial intelligence in medicine* (pp. 1819–1824). Springer.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. routledge.

Corsi, P. M. (1972). Human memory and the medial temporal region of the brain.

Diamond, A. (2013). Executive functions. *Annual review of psychology*, *64*(1), 135–168.

Faubert, J. (2013). Professional athletes have extraordinary skills for rapidly learning complex and neutral dynamic visual scenes. *Scientific reports*, *3*(1), 1154.

Faubert, J., & Sidebottom, L. (2012). Perceptual-cognitive training of athletes. *Journal of Clinical Sport Psychology*, *6*(1), 85–102.

Friedman, N. P., Miyake, A., Corley, R. P., Young, S. E., DeFries, J. C., & Hewitt, J. K. (2006). Not all executive functions are related to intelligence. *Psychological science*, *17*(2), 172–179.

Glavaš, D. (2020). Basic cognitive abilities relevant to male adolescents' soccer performance. *Perceptual and Motor skills*, *127*(6), 1079–1094.

Huijgen, B. C., Leemhuis, S., Kok, N. M., Verburgh, L., Oosterlaan, J., Elferink-Gemser, M. T., & Visscher, C. (2015). Cognitive functions in elite and sub-elite youth soccer players aged 13 to 17 years. *PloS one*, *10*(12), e0144580.

Huizinga, M., Dolan, C. V., & Van der Molen, M. W. (2006). Age-related change in executive function: Developmental trends and a latent variable analysis. *Neuropsychologia*, *44*(11), 2017–2036.

Kalén, A., Bisagno, E., Musculus, L., Raab, M., Perez-Ferreiros, A., Williams, A. M., … Ivarsson, A. (2021). The role of domain-specific and domain-general cognitive functions and skills in sports performance: A meta-analysis. *Psychological bulletin*, *147*(12), 1290.

Memmert, D., Simons, D. J., & Grimme, T. (2009). The relationship between visual attention and expertise in sports. *Psychology of Sport and Exercise*, *10*(1), 146–151.

Meyerhoff, H. S., & Papenmeier, F. (2020). Individual differences in visual attention: A short, reliable, open-source, and multilingual test of multiple object tracking in psychopy. *Behavior Research Methods*, *52*, 2556–2566.

Mueller, S. T., & Piper, B. J. (2014). The psychology experiment building language (pebl) and pebl test battery. *Journal of neuroscience methods*, *222*, 250–259.

Murdoch, W. J., Singh, C., Kumbier, K., Abbasi-Asl, R., & Yu, B. (2019). Definitions, methods, and applications in interpretable machine learning. *Proceedings of the National Academy of Sciences*, *116*(44), 22071–22080.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., … others (2011). Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, *12*, 2825–2830.

Peirce, J. W. (2007). Psychopy—psychophysics software in python. *Journal of neuroscience methods*, *162*(1-2), 8–13.

Piper, B. J., Li, V., Eiwaz, M. A., Kobel, Y. V., Benice, T. S., Chu, A. M., … Mueller, S. T. (2012). Executive function on the psychology experiment building language tests. *Behavior research methods*, *44*, 110–123.

Posner, M. I. (1980). Orienting of attention. *Quarterly journal of experimental psychology*, *32*(1), 3–25.

Praça, G. M., Soares, V. V., Matias, C. J. A. d. S., Costa, I. T. d., & Greco, P. J. (2015). Relationship between tactical and technical performance in youth soccer players. *Revista Brasileira de Cineantropometria & Desempenho Humano*, *17*, 136–144.

Raschka, S., & Mirjalili, V. (2019). *Python machine learning: Machine learning and deep learning with python, scikit-learn, and tensorflow 2*. Packt publishing ltd.

Romeas, T., Chaumillon, R., Labbé, D., & Faubert, J. (2019). Combining 3d-mot with sport decision-making for perceptual-cognitive training in virtual reality. *Perceptual and Motor Skills*, *126*(5), 922–948.

Romeas, T., Guldner, A., & Faubert, J. (2016). 3d-multiple object tracking training task improves passing decision-making accuracy in soccer players. *Psychology of Sport and Exercise*, *22*, 1–9.

Sánchez-Cubillo, I. ., Periáñez, J. A., Adrover-Roig, D., Rodríguez-Sánchez, J. M., Ríos-Lago, M., Tirapu, J., & Barceló, F. (2009). Construct validity of the trail making test: role of task-switching, working memory, inhibition/interference control, and visuomotor abilities. *Journal of the International Neuropsychological Society*, *15*(3), 438–450.

Scarpina, F., D'Agata, F., Priano, L., & Mauro, A. (2021). Difference between young and old adults' performance on the psychology experiment building language (pebl) test battery: what is the role of familiarity with technology in cognitive performance? *Assessment*, *28*(6), 1723–1734.

Scharfen, H.-E., & Memmert, D. (2019a). Measurement of cognitive functions in experts and elite athletes: A meta-analytic review. *Applied Cognitive Psychology*, *33*(5), 843–860.

Scharfen, H.-E., & Memmert, D. (2019b). The relationship between cognitive functions and sport-specific motor skills in elite youth soccer players. *Frontiers in psychology*, *10*, 817.

Scharfen, H.-E., & Memmert, D. (2021a). Cognitive training in elite soccer players: evidence of narrow, but not broad transfer to visual and executive function. *German Journal of Exercise and Sport Research*, *51*(2), 135–145.

Scharfen, H.-E., & Memmert, D. (2021b). Fundamental relationships of executive functions and physiological abilities with game intelligence, game time and injuries in elite soccer players. *Applied Cognitive Psychology*, *35*(6), 1535–1546.

Scharfen, H.-E., & Memmert, D. (2021c). Relationship of executive functions and physical abilities in elite soccer players. *German J. Exer. Sport Res*, *52*, 341–349.

Schumacher, N., Schmidt, M., Wellmann, K., & Braumann, K.-M. (2018). General perceptual-cognitive abilities: Age and position in soccer. *PloS one*, *13*(8), e0202627.

Shimi, A., Tsestou, V., Hadjiaros, M., Neokleous, K., & Avraamides, M. (2021). Attentional skills in soccer: Evaluating the involvement of attention in executing a goalkeeping task in virtual reality. *Applied Sciences*, *11*(19), 9341.

Shmueli, G. (2010). To explain or to predict? *Statistical science*, 289–310.

Souaifi, M., Dhahbi, W., Jebabli, N., Ceylan, H. İ., Boujabli, M., Muntean, R. I., & Dergaa, I. (2025). Artificial Intelligence in Sports Biomechanics: A Scoping Review on Wearable Technology, Motion Analysis, and Injury Prevention. *Bioengineering*, *12*(8), 887.

Trecroci, A., Cavaggioni, L., Rossi, A., Bongiovanni, T., Invernizzi, P. L., Formenti, D., & Longo, S. (2022). Self-Regulated Learning Assessment in Young Soccer Players: Beyond Competitive Levels. The Journal of Strength & Conditioning Research, 10-1519.

Verburgh, L., Scherder, E. J., van Lange, P. A., & Oosterlaan, J. (2014). Executive functioning in highly talented soccer players. *PloS one*, *9*(3), e91254.

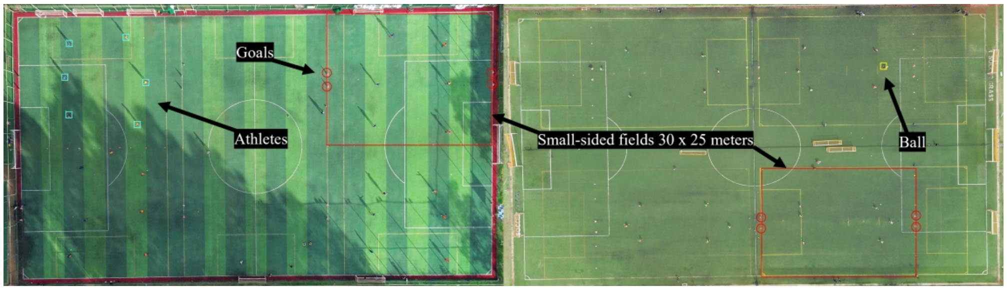
Verburgh, L., Scherder, E. J., Van Lange, P. A., & Oosterlaan, J. (2016). Do elite and amateur soccer players outperform non-athletes on neurocognitive functioning? a study among 8-12 year old children. *PloS one*, *11*(12), e0165741.

Vestberg, T., Gustafson, R., Maurex, L., Ingvar, M., & Petrovic, P. (2012). Executive functions predict the success of top-soccer players. *PloS one*, *7*(4), e34731.

Vestberg, T., Jafari, R., Almeida, R., Maurex, L., Ingvar, M., & Petrovic, P. (2020). Level of play and coach-rated game intelligence are related to performance on design fluency in elite soccer players. *Scientific reports*, *10*(1), 9852.

Vestberg, T., Reinebo, G., Maurex, L., Ingvar, M., & Petrovic, P. (2017). Core executive functions are associated with success in young elite soccer players. *PloS one*, *12*(2), e0170845.

Wilson, R. S., Hunter, A. H., Camata, T. V., Foster, C. S., Sparkes, G. R., Moura, F. A., … Smith, N. M. (2021). Simple and reliable protocol for identifying talented junior players in team sports using small-sided games. *Scandinavian journal of medicine & science in sports*, *31*(8), 1647–1656.



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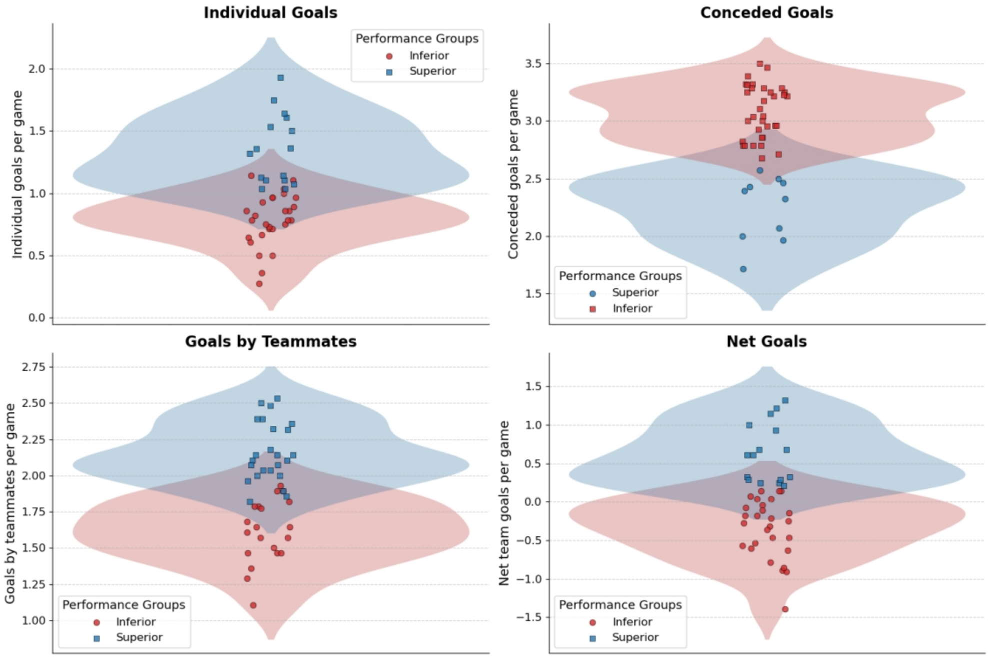

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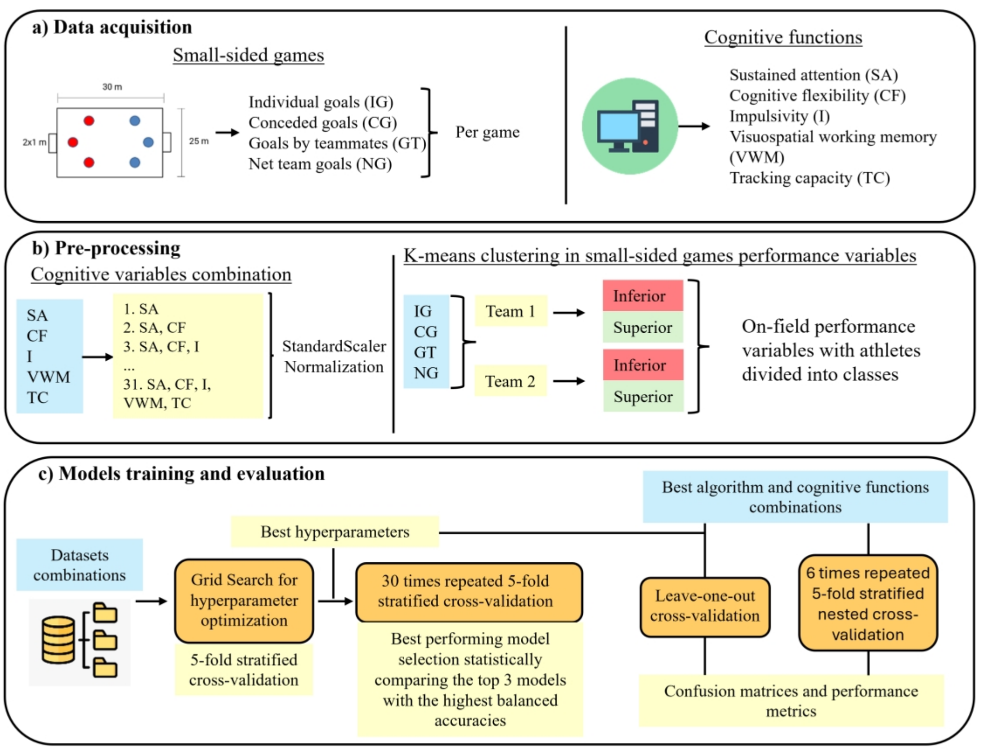

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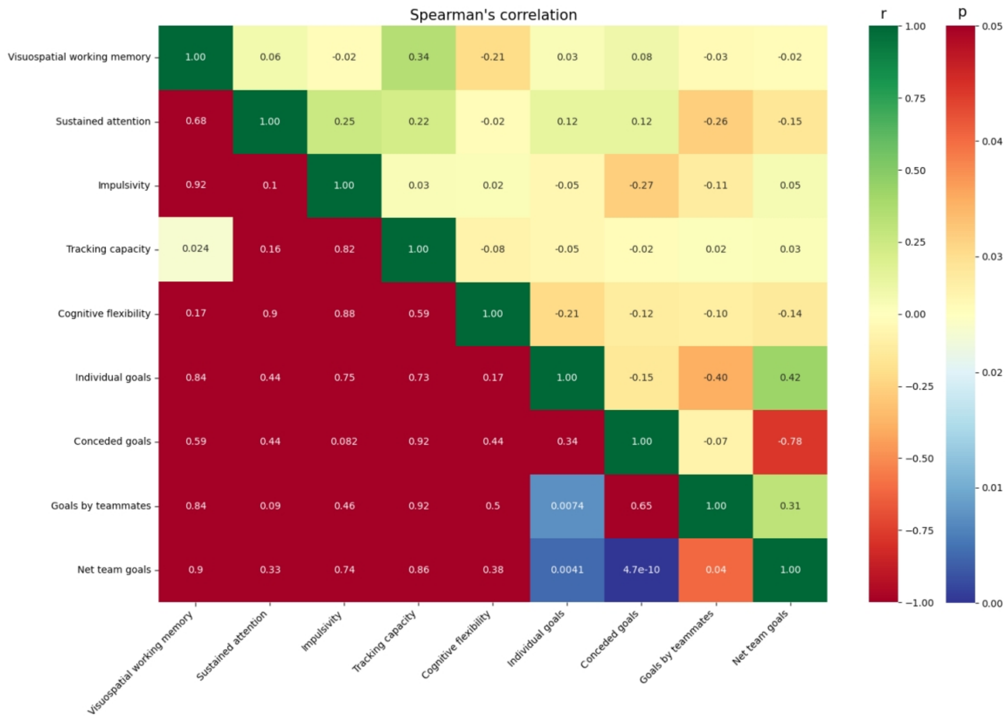

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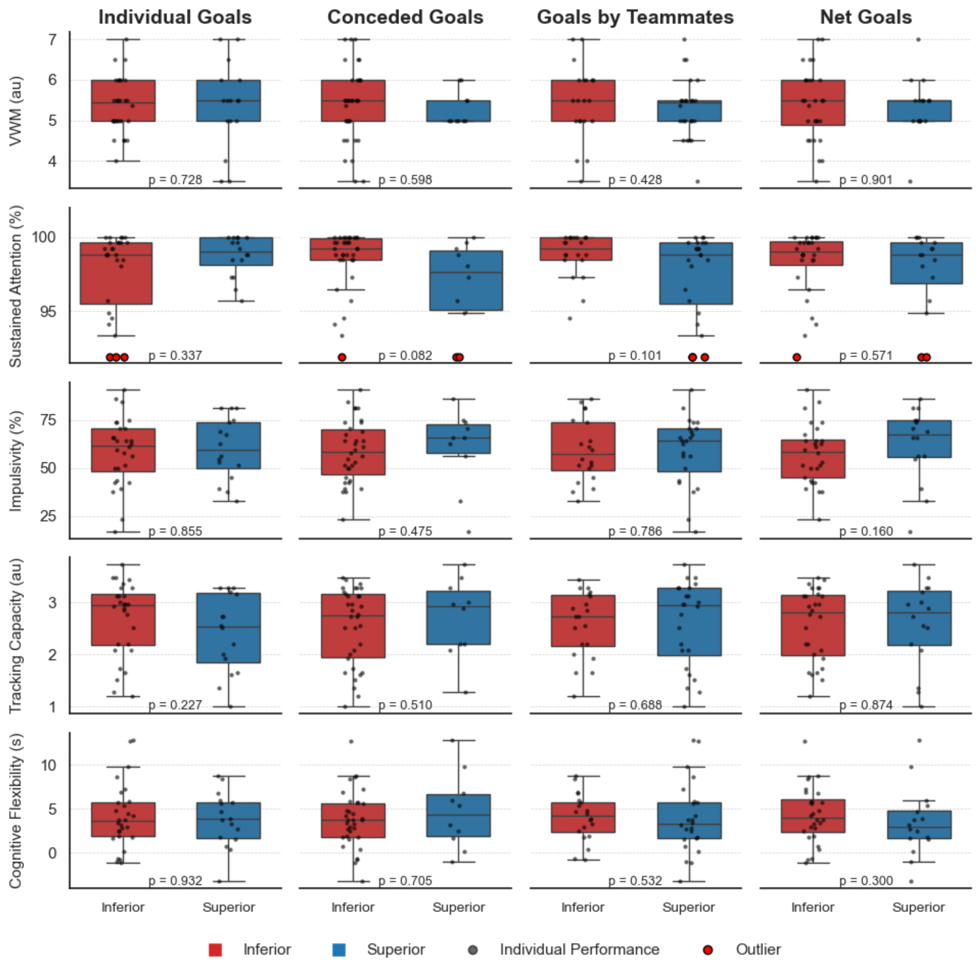

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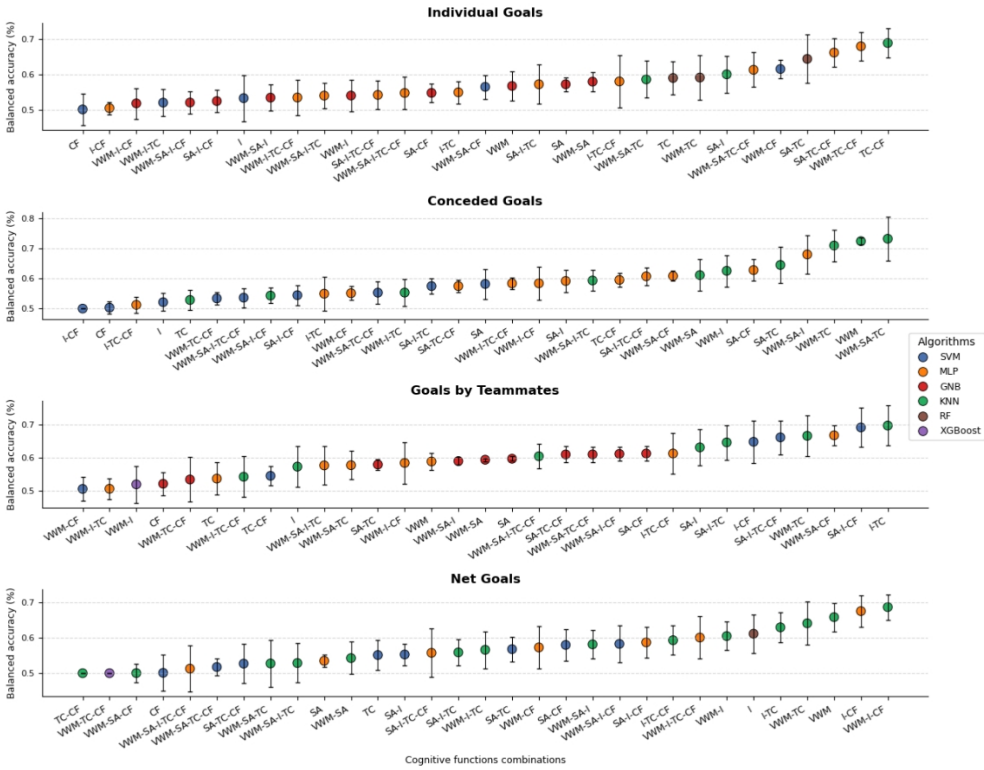

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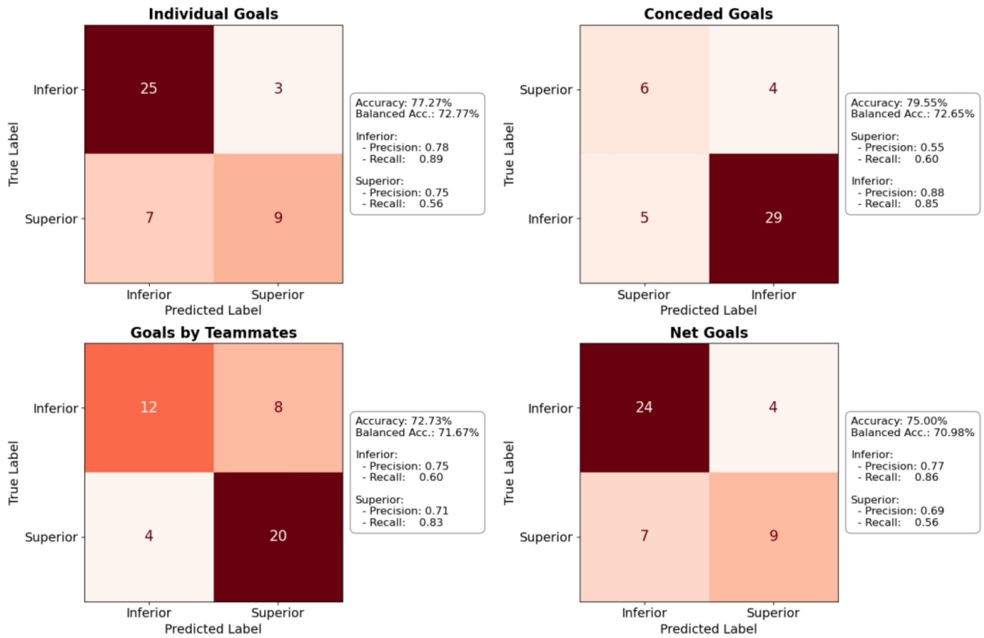

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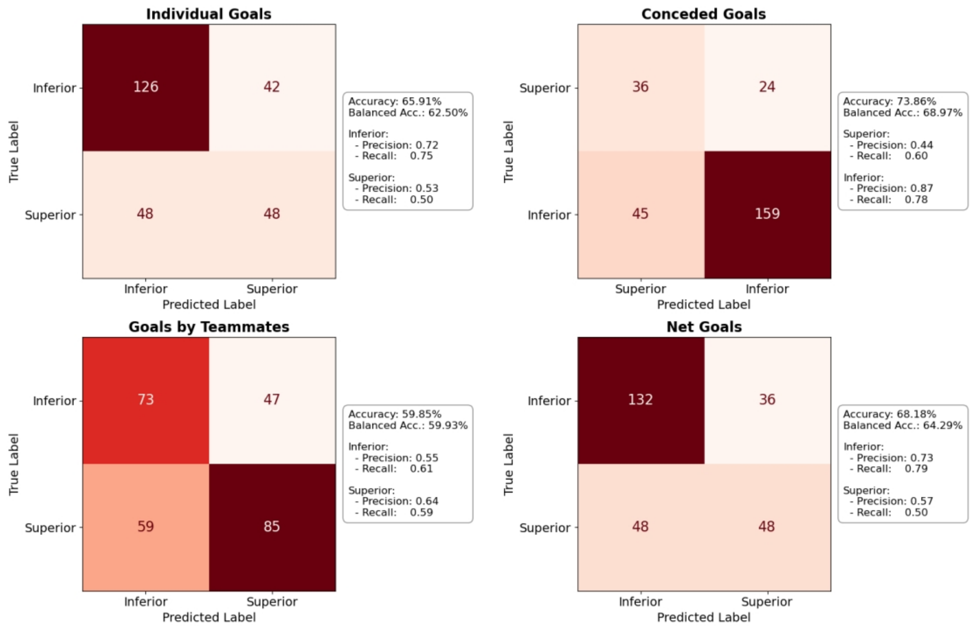

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