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Original Article

Identifying playing styles of european soccer teams during the key moments of the game

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Abstract
Performance analysis considerably contributes to improving performance in sports. Therefore, researchers have increased their interest in sports analytics. In football in particular, playing styles are the subject of extensive research. Identifying and measuring different playing styles that soccer teams can adopt during a match is a very important step toward a more effective analysis of opponents, own team post-match analysis, and recruiting players. Specifically, it has been a great challenge to identify and classify playing styles in football during all phases of the game (i.e., during key moments and sub-phases of the game). Therefore, the aim of this study is to recognize and quantify distinct playing styles in European soccer leagues. In achieving this, a wide range of competitions and variables were used. Data were collected from 2999 league matches (5998 observations) in 11 different countries during the 2021–22 season. Factor analysis with principal component analysis (PCA) was used to analyze and group 88 performance indicators. Nineteen factors had eigenvalues greater than 1, accounting for 84.8% of the total variance. Most of the variance (49.35%) was explained by the first four factors, which are related to build-up and transitions. Sixteen out of the nineteen factors were associated with teams' playing styles. They were classified across all phases and sub-phases of the game, whereas the remaining three were related to matches. The findings of this study were classified in such a way as to provide a structured framework for analysts and coaches that can be used in the training process of all four key moments of the game.
Keywords: **football tactics; playing styles; match analysis; performance indicators; factor analysis**

Introduction

A game style is the characteristic playing pattern demonstrated by a team and distinguished within the key moments of play (Hewitt et al., 2016). There are four phases (i.e. key moments) in soccer: attack, defensive transition, defense, and attacking transition (da Costa et al., 2009; Delgado-Bordonau, 2012; Hewitt et al., 2016), which concern the open play (Bauer & Ingbert, 2021; Hewitt et al., 2016). Set-pieces provide a separate category, suggested as the fifth key moment of the game (Hewitt et al., 2016; Plakias, Kokkotis, et al., 2023), which could also be broken further down into offensive and defensive set-pieces (Bauer & Ingbert, 2021). Furthermore, for the offensive and defensive phases, some sub-phases have been recognized. In particular, attack is divided into the build-up phase, the progressive or creativity phase, and the finishing phase (Barreira et al., 2011; da Costa et al., 2009; Gregory et al., 2022; Sporiš et al., 2012; Tenga et al., 2015). In defense, teams may choose high-press or low-press (Fernandez-Navarro et al., 2016; Low et al., 2018). In the latter case, they can defend either in mid-block or low-block (Bauer & Ingbert, 2021; Gréhaigne et al., 2011; Power et al., 2017). Therefore, for a comprehensive analysis of a team's opponent, or the game-play of the team itself, it is necessary to identify playing styles for all phases and sub-phases of the game. This kind of analysis is expected to maximize the effectiveness of the team's training process.

Regarding game style recognition, the current relevant literature presents a variety of techniques. Big data has enabled the use of artificial intelligence in multiple areas of research. These studies have focused on the identification of formations (Narizuka & Yamazaki, 2019), player movement patterns (Beernaerts et al., 2020), or even styles of play (Bialkowski et al., 2016; Bialkowski et al., 2014) using tracking data, however they have not

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managed to identify the characteristics of each style, due to they did not perform interpretation of clustering mechanisms. The inability of identifying game-play styles is also evident in studies employing performance indicators with the t-distributed stochastic neighbor embedding (t-SNE) dimensionality reduction technique (García-Aliaga et al., 2022). Finally, other studies adopted artificial intelligence methods identified styles only during the ball possession phase (Bekkers & Dabadghao, 2019; Brooks et al., 2016; Gyarmati et al., 2014).

Inductive statistics have also been used in game-style recognition. Performance analysis literature in soccer has traditionally focused on separated variables such as performance indicators to explain teams' and players' performances (Amatria et al., 2021; Andersson et al., 2008; Basevitch et al., 2013; Fernandes et al., 2020; Tenga & Larsen, 2003). Recent research has tried to interpret the complexity of the soccer game.

For this objective, the combination of multiple performance indicators has provided a more comprehensive picture of the teams' playing style or tactical patterns, which may explain their performance in matches and competitions (Gómez et al., 2018; Lopez-Valenciano et al., 2022). There had only been few studies investigating team tactics. One reason in this regard has been the lack of available, relevant data. However, this situation has recently changed because of the development of advanced tracking technologies and semi-automatic coding systems (García-Aliaga, 2022). Therefore, the main new challenge is how to manage the great volume of available data (Rein & Memmert, 2016). Lopez-Valenciano et al. (2022) highlighted the need to use large datasets and big data to address explanatory multivariate models that account for performance interactions and relationships. As a result, factor analysis, a technique that groups several variables by reducing data sets, can be adopted to objectively identify and capture styles of play (Fernández Navarro, 2019).

The first time that factor analysis was applied to game-style recognition was before the use of semi-automated and automated techniques in performance analysis. For this reason, only 6 variables were analyzed in this study and the proposed factor analysis resulted to 3 components (Pollard & Reep, 1997). Data were collected from 74 matches played in 2 tournaments (1982 World Cup and 1984– 85 England First Division). Since then, due to recent technological innovations, there has been a particular increase in systems and devices that collect and provide data.

These innovations have been widely adopted by professional sports organizations and researchers (Goes et al., 2021). Winter and Pfeiffer (2016) used 11 tactical metrics from 27 matches of 2012 UEFA Euro and identified 4 components. In the same year, Fernandez-Navarro et al. (2016) performed an analysis on 19 performance indicators, that led them to 6 components using data from 97 matches from 2 tournaments (England & Spanish First Division). Lago-Peñas et al. (2017) with a sample of 240 games from one league (Chinese) concluded with 5 factors starting from an initial group of 20 performance indicators. Like previous studies, Gómez et al. (2018) employed data from a single league (2013-14 Greek championship). Approximately three hundred matches and 87 performance indicators were used. So, they identified 8 components. With data from another league (Spanish, 373 games) Castellano and Pic (2019) identified 2 components out of 9 variables. Finally, Zhou et al. (2021), used 28 performance indicators from 6 seasons of the same league (Chinese, 1429 games) and derived 7 components from their factor analysis.

In all the aforementioned studies, where factor analysis was used to identify playing styles in football, the sample consisted of matches from one or at most two competitions (Plakias, Moustakidis, et al., 2023). Gómez et al. (2018), Lago-Peñas et al. (2017) and Zhou et al. (2021) highlight the need of extending the research focus and analyzing playing styles in football adopted by different countries and competitions to verify whether the existing outputs are valid and applicable to them, so the results can be generalized. Additionally, another gap in the existing literature is related to the fact that playing styles have not been identified for all the phases and sub-phases of the game.

Indeed, Castellano & Pic (2019) suggested that the choice of different variables, or the incorporation of new ones, could detect new game styles and, therefore, could refine the profile description of the team performance. Therefore, aiming to address the recognized gaps in the literature, the research objectives of the present study were: (1) to identify the playing styles adopted by the European Leagues, based on analyzing data from more than two leagues; and (2) to detect playing styles for all phases and sub-phases of the game, towards the creation of a more structured framework. We hypothesized that using variables for the reported teams and their opponents, as well as measuring multiple variables in different areas of the field, could help reach the second goal.

Material & methods

*Sample***:** The sample included all matches played in the 1st league division in 11 European countries in the 2021-2022 season. Particularly, only the games from the regular season are featured (without play-offs and play-outs). The number of teams, rounds and total matches played in each competition is shown in Table 1. For each match, there were separate observations for both teams.

For 8 matches, Instatscout (https://football.instatscout.com/) had no data or the data were incomplete. Therefore, the sample included a total of 5992 valid observations.

Table 1. Number of teams, rounds and total matches played in regular season of each competition.

COUNTRY	TEAMS	ROUNDS	MATCHES
England	20	2	380
Spain	20	2	380
Italy	20	2	380
Germany	18	2	306
Belgium	18	2	306
Austria	12	2	132
Scotland	12	3	198
Turkey	20	2	380
Croatia	10	4	180
Switzerland	10	4	180
Greece	14	2	182

Procedure: 216 variables, collected by Instatscout or calculated indirectly by the authors using the data from this platform, were recorded in an excel spreadsheet (Microsoft Excel).

According to previous research, the reliability of the indicators obtained by Instatscout is very high (K values 0.90 to 0.98) (Castellano et al., 2011; Castellano & Echeazarra, 2019; Gómez et al., 2018; Plakias et al., 2022). Written informed consent was obtained from Instat Ltd allowing use of the data for this research study (08/11/2022). Ethics committee approval of the current study was gained from the University of Thessaly (12/10/2022).

Statistical analysis: A factor analysis model using PCA and Varimax rotation was run in order to pool the variables into factors - dimensions of playing styles (Zhou et al., 2021). Factor analysis is a statistical method for identifying clusters of variables.

This technique allows the reduction of data sets through the grouping of performance indicators into fewer factors that represent different styles of play (Fernandez-Navarro et al., 2016). Regarding the factor analysis, all categorical and ordinal variables were removed. The effectiveness variables (e.g., expected goals) were also excluded to avoid statistical bias (Gómez et al., 2018). Finally, 88 continuous variables were used (APPENDIX A).

Orthogonal (varimax) and oblique rotations were performed in factor analysis, and the component correlation matrix of the oblique rotation showed a negligible correlation between factors. Therefore, orthogonal rotation was used (Fernandez-Navarro et al., 2016).

The factors were extracted based on eigenvalues above 1 and considering the value of 0.60 when selecting a substantial loading of each factor (Gómez et al., 2018; Zhou et al., 2021). Each factor defined two different styles of play based on a positive or negative factor score on the continuum (Fernandez-Navarro et al., 2016).

All the analyses were performed using the statistical software IBM SPSS (version 25.0) and the statistical significance level was set at $p < 0.05$. The definitions of the variables used for factor analysis can be found in APPENDIX A and are derived from the Instatscout glossary. The glossary can be found at

http://sellers.instatfootball.tv/gad289b130fb5d6d8/%D0%93%D0%BB%D0%BE%D1%81%D1%20%81%D0%B0%D1%80%D0%B8%D0%B8%CC%86___Glossary_4.pdf.).

Results

The sampling adequacy was appropriate (Kaiser-Meyer-Olkin=0.69). Nineteen components had eigenvalues over Kaiser's criterion of 1 and, in combination, explained 84.81% of the total variance (Table 2). The percentage of variance explained by each factor decreased from factor 1 to 19 (ranging from 18.23% for the first one to approximately 1% for factor 19). The full "Total Variance Explained" table as extracted by SPSS can be found in the supplementary material 1.

The rotated component matrix for the factor loadings identified the performance indicators associated with each factor. Table 3 shows the 19 factors as well as the variables that load them.

Variables in green cells are significantly and positively related to the corresponding factors, while variables in red cells load negatively on the corresponding factors.

The full "Rotated Component Matrix" table as extracted by SPSS can be found in the supplementary material 2. The names in parentheses below each factor (1st column) are latent variables, which cannot be directly measured. The names were given to the factors based on the variables loaded each factor.

Table 2. Eigenvalues for components and total variance explained.

	Initial Eigenvalues			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	18,23	20,72	20,72	18,23	20,72	20,72	14,18	16,12	16,12
2	12,58	14,30	35,01	12,58	14,30	35,01	7,50	8,53	24,64
3	6,80	7,73	42,74	6,80	7,73	42,74	5,87	6,67	31,32
4	5,81	6,61	49,35	5,81	6,61	49,35	5,26	5,98	37,30
5	4,87	5,54	54,88	4,87	5,54	54,88	4,72	5,36	42,66
6	3,42	3,89	58,77	3,42	3,89	58,77	4,23	4,81	47,47
7	3,24	3,68	62,46	3,24	3,68	62,46	4,20	4,77	52,24
8	3,00	3,41	65,87	3,00	3,41	65,87	3,44	3,91	56,15
9	2,18	2,47	68,34	2,18	2,47	68,34	3,36	3,82	59,97
10	1,99	2,26	70,61	1,99	2,26	70,61	3,26	3,71	63,67
11	1,83	2,08	72,69	1,83	2,08	72,69	2,97	3,38	67,05
12	1,69	1,92	74,60	1,69	1,92	74,60	2,86	3,25	70,30
13	1,57	1,79	76,39	1,57	1,79	76,39	2,55	2,90	73,20
14	1,49	1,69	78,08	1,49	1,69	78,08	2,36	2,68	75,88
15	1,37	1,56	79,63	1,37	1,56	79,63	2,21	2,51	78,39
16	1,29	1,47	81,10	1,29	1,47	81,10	1,56	1,78	80,16
17	1,18	1,35	82,45	1,18	1,35	82,45	1,54	1,75	81,92
18	1,06	1,20	83,65	1,06	1,20	83,65	1,38	1,57	83,49
19	1,02	1,16	84,81	1,02	1,16	84,81	1,16	1,32	84,81
20	0,94	1,07	85,88						

Discussion

Recognizing and quantifying the different playing styles that soccer teams can adopt during a match is critical for coaches and performance analysts when gathering performance data (Fernandez-Navarro et al., 2016; Gómez et al., 2018; Lago-Peñas et al., 2017). Consequently, the purpose of this study was to identify and quantify playing styles in the European Leagues. Segmenting the game into moments of play helps to detect and quantify a combination of playing patterns, which constitute the game styles for each of the above moments (Hewitt et al., 2016). For this reason, the second aim of the study was to develop a structured framework that would categorize the identified styles of play into the phases (key moments) and sub-phases of the game (Figure 1).

Specifically, Figure 1 is divided into two parts; the top part presents the sixteen styles identified by our research and concerns a competing team (PLAYING STYLES OF TEAMS), while the bottom part shows the three styles (2, 5, 13) related to the game (STYLES FOR THE GAME). The latter results from the combination of the behavior of both teams participating in a match. The circular piece in the center of the upper part (PLAYING STYLES OF TEAMS) shows the 4 key moments (phases) from which the sub-phases arise, while in the center of the circle are the SET PIECES (DEFENSE and ATTACK). Among the 16 team styles there are some styles that do not refer to any sub-phase of the game, but are either generally offensive (14, 16, 18), or generally defensive (11, 17, 19) and are depicted in the two dark blue boxes as OTHER ATTACK and OTHER DEFENSE respectively.

Overall, the proposed exploratory factor analysis extracted 19 factors that explained 84.8% of the total variance. Based on the sign (positive or negative) of the factor, two different styles of play were defined per case (Fernandez-Navarro et al., 2016). Sixteen factors concerned the teams and three the game. Positive or negative scores for these 19 factors determine how much a team (or a game) relies on one specific style (Gómez et al., 2018). Therefore, we found 38 soccer styles (32 for the teams and 6 for the game). The 32 playing styles cover all phases and sub-phases for the teams in a game.

Table 3. Factors, variables and loadings from Rotated Component Matrix.

FACTORS (PLAYING STYLES)	VARIABLES (LOADINGS)					
FACTOR 1 (ELABORATION OF BUILD UP PHASE)	Accurate passes	Passes	Sum duration with ball possession	Average passes / ball possession	Passes / lost balls	Average duration of ball possession
	Ball possession, %	Opponent's ball possession %	Passes / wrong passes	Accurate passes, %	Long passes / passes	Building ups without pressing
	Building ups	Pass long def 3rd	Opponent's sum duration of ball possession			
FACTOR 2 (TRANSITION GAME)	Ball recoveries	Ball possessions, quantity	Lost balls	Ball recoveries in own half	Wrong passes	Lost balls in opponent's half
	Free ball pick ups					
FACTOR 3 (ATTACKING TRANSITION)	Positional attacks %	Counterattacks %	Positional att. from open play / open play att. %	Counterattacks/ open play attacks %	Counterattacks / ball recoveries	Counterattacks
FACTOR 4 (DEFENSIVE TRANSITION)	Opponent Counter-attacks %	Opponent Positional attacks %	Opponent positional att. from open play / open play att. %	Opponent counterattack / open play attack %	Opponent Counterattacks	
FACTOR 5 (AERIAL GAME)	Air_challenges	air_challenges_mid_3rd	RATIO_ground_challenges_PER_air_challenges	air_challenges_def_3rd		
FACTOR 6 (TYPE OF ATTACK)	set_pieces_attacks_percent	open_play_attacks_percent	Set_pieces_attacks			
FACTOR 7 (CROSSING)	crosses_per_attacks_percent	crosses_per_quantity_of_possession_%	Crosses			
FACTOR 8 (TYPE OF OPP. ATTACK)	Opponent_set_pieces_att. %	Opponent_open_play_att. %	Opponent_Set_pieces_att.			
FACTOR 9 (DEFENSIVE BLOCKS)	RATIO_def_challenges_mid_3rd_PER_defensive_chal.	RATIO_def_chal._def_3rd_PER_defensive_chal.	def_challenges_mid_3rd			
FACTOR 10 (PRESS)	RATIO_def_challenges_att_3rd_PER_defensive_chal.	def_challenges_att_3rd	High_pressing			
FACTOR 11 (INDIVIDUAL DEFENDING ACTIONS)	Tackles	RATIO_tackles_PER_min of opponent's ball possession	Defensive_challenges			
FACTOR 12 (WIDTH OF CREATIVE PHASE)	Wide attacks percent	attacks_center_percent	Attacks _ center			
FACTOR 13 (EFFECTIVE GAME)	Effective time (secs)					
FACTOR 14 (INDIVIDUAL ATTACKING ACTIONS)	Dribbles	RATIO_dribbles_PER_min_of_possession	Attacking_challenges			
FACTOR 15 (TENDENCY TO CREATE FINAL ATTEMPTS)	shots_per_entrances_to_final_third_percent	shots_per_quantity_of_possession_percent				
FACTOR 16 (PASSING TEMPO)	passing_rate					
FACTOR 17 (DEFENDING AGGRESSIVELY)	Yellow_cards	Fouls				
FACTOR 18 (ATTACKING AGGRESSIVELY)	Offsides					
FACTOR 19 (OFFSIDE TRAP)	Opponent_Offsides					

* Variables in green cells load positively, while variables in red cells load negatively on the corresponding factors.

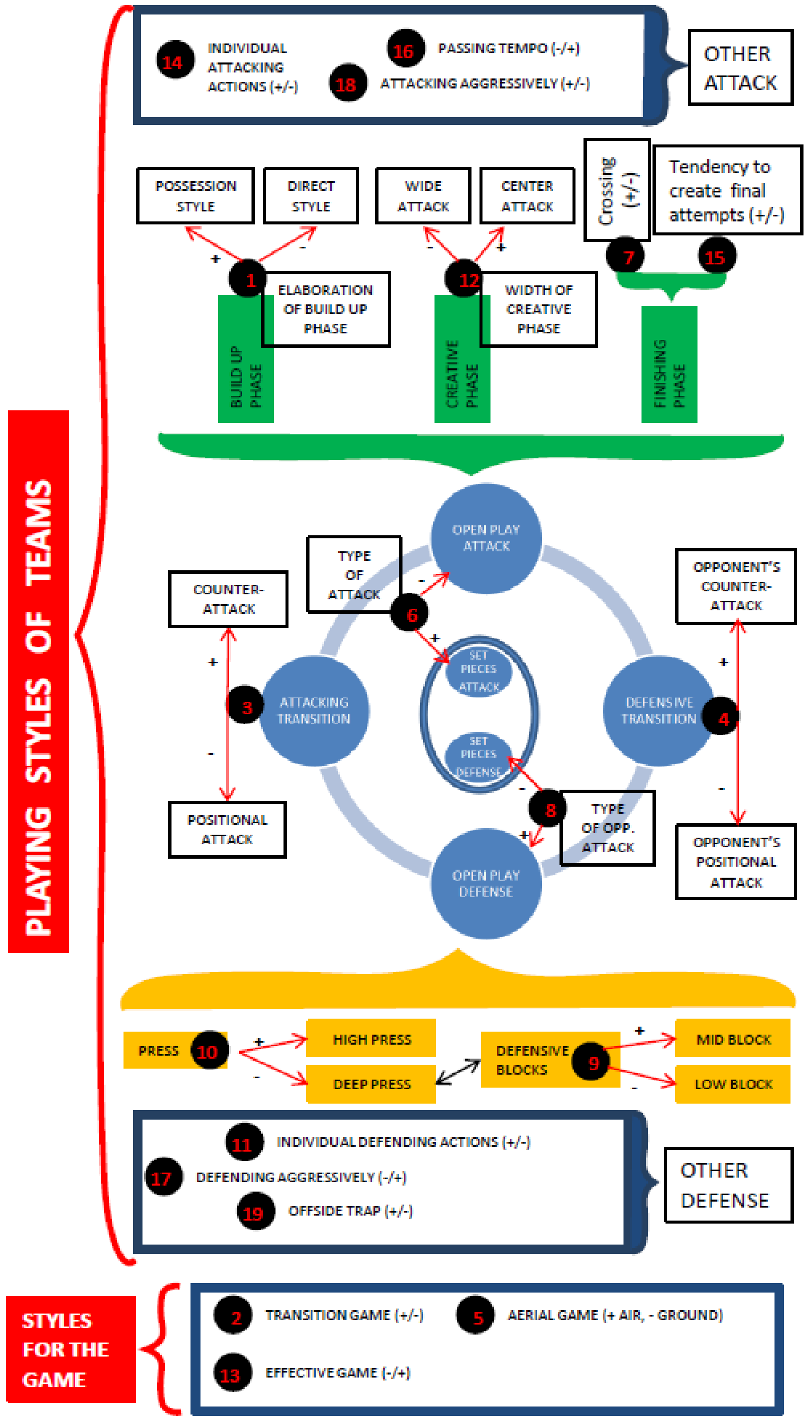

Figure 1. The identified styles of play classified in the respective phases of the game.

Starting with the **attack**, the *elaboration of the build-up phase* (factor 1) was the component that explained the highest percentage of variance and differentiated the direct and possession styles of build-up. Most of the variables loading the factor are those that in other studies constituted the “possession directness”, “possession style” or “elaborate style” (Castellano & Pic, 2019; Fernandez-Navarro et al., 2016; Gómez et al., 2018; Gonzalez-Rodenas et al., 2020; Lago-Peñas et al., 2017; Pollard & Reep, 1997; Zhou et al., 2021).

However, in the above studies, there were no variables for "build up". The fact that this factor is negatively loaded by long passes from the defensive third, in addition to the presence of the variables "building ups" and "building ups without press," led us to the conclusion that this factor pertains to the first sub-phase of the attack, which is the build-up phase (Bauer & Ingbert, 2021; da Costa et al., 2009; Fernández et al., 2019). Positive and negative values differentiate the two styles: elaborative (possession) style and direct style. It seems that the first sub-phase of the attack is crucial in determining the style of play in the possession phase in general.

Factors 12, 7 and 15 deal with the remaining sub-phases of the attack. Factor 12 relates to the *width in the 2nd sub-phase (progressive or creative phase) of the attack* (da Costa et al., 2009; Fernández et al., 2019). We recognize this sub-phase from Instatscout's definition of "attack" as «possession of more than 3 seconds involving at least 2 passes or a dribble in the opposition half». This matches the definition given by Fernández et al. (2019) who stated that "once the midfield is reached, the possession is considered to reach a progression phase, where the objective is to keep progressing towards the opponent's goal". Positive values in the factor show teams that prefer to attack from the sidelines, while negative values indicate teams that prefer to launch attacks from the central axis. Fernandez-Navarro et al. (2016) found a similar factor in their research (with possession of the ball from the sides or the central axis rather than launching attacks). Factor 7 and 15 relate to the 3rd sub-phase (finishing phase) of the attack (da Costa et al., 2009; Fernández et al., 2019). We named factor 15 *crossing* after considering the variables that are loaded as well as the existing literature (Fernandez-Navarro et al., 2016; Fernandez-Navarro et al., 2018; Fernández Navarro, 2019; Pollard & Reep, 1997). The higher the teams' positive factor 7 value, the more they adopt the specific style. Factor 15 (*tendency to create final attempts*) also concerns the finishing phase. A similar style (ending actions) was also found in the research of Gómez et al. (2018).

In addition to the factors related to specific sub-phases of the attack there are also some that concern the entire attack phase. We named factor 16 *passing tempo* because passing rate is the sole variable that describes it, even with a negative sign. Thus, high values of the factor indicate a low tempo, while low values indicate a high tempo. No other research has identified this style, but STATS acknowledges "Fast tempo" as one of the types. Furthermore, we designated factor 18 as *attacking aggressively*, similar to Zhou et al. (2021), because it relates to the number of offsides committed by the team. Finally, factor 14 represents the styles of the teams, whose players perform many (positive values) or few (negative values) individual attacking actions. Only Gómez et al. (2018) found a factor involving individual actions. However, this one refers to both attack and defense collectively and not separately.

The 4th factor concerns the ***defensive transition phase*** and the team's ability to avoid the opponent's counterattacks (negative values) or not (positive values). A team's ability to avoid the opponent's counterattacks can be due to either the application of counter-pressing (Bauer & Anzer, 2021; Warwick, 2019) or the fact that it manages to avoid situations of imbalance in the defense at the time of losing the ball (Gonzalez-Rodenas et al., 2020; Tenga et al., 2010).

For the **defensive phase** there are factors related to the spaces the team prefers to defend and others that are independent of the spaces. Factors 9 and 10 refer to the spaces where a team prefers to defend (high, medium, and low blocks) (Bauer & Ingbert, 2021; Power et al., 2017). Factor 10 (*press*) separates teams that prefer high press from those that choose deep defending and has been identified in many studies (Castellano & Pic, 2019; Fernandez-Navarro et al., 2016; Fernandez-Navarro et al., 2018; Pollard & Reep, 1997). However, no quantitative research has so far found the separation between medium and low blocks (factor 9- *defensive blocks* here). In contrast, experts noticed a distinction between teams who choose a medium block defensive strategy and those that prefer a low block defensive style in qualitative interviews performed by Fernández Navarro (2019).

Regardless of which areas the team prefers to defend, we identified 3 additional factors related to the defensive phase. Factor 11 (following the same logic as factor 14 of the attack) represents the styles of the teams, whose players perform many (positive values) or few (negative values) *individual defensive actions*. Secondly, we named factor 17 as *defending aggressively*, because of the variables that load him (*fouls* and *yellow cards)*. Gómez et al. (2018) interpreted fouls as fouling actions and Zhou et al. (2021) red cards as serious fouls. No other research has linked fouls and yellow cards together in the same factor, which led us to interpret the factor as aggressiveness in the defensive phase. Furthermore, factor 19 was named *offside trap*, because it relates to the detected opponents' offsides. Surprisingly, no other research has identified the offside trap playing style in the defensive phase, even though it is a very common tactical tool of coaches (Bertuzzi, 1999; Kim et al., 2011; Lekavý & Wagner, 2008; Sarkar, 2018).

Factor 3 concerns the ***attacking transition phase***. It distinguishes between two styles. One that shows a tendency for counterattacks (positive values) and one that shows a tendency for securing possession and positional attacks (negative values). In the counterattack, the team that wins the ball attempts to exploit the space left by the opponent with a high tempo (Gonzalez-Rodenas et al., 2020). The style of counterattacks was also recognized in other studies (Gómez et al., 2018; Lago-Peñas et al., 2017) without, however, being separated from the positional attacks that are made after recovering the ball. Additionally, in the survey of Gómez et al. (2018) the style of counterattacks is more about the game in general and not about one of the two teams competing. This is inferred because one of the variables that positively loads the factor is lost balls. But lost balls can't lead to a counterattack by the mentioned team.

Set pieces appear in factors 6 and 8. Factor 6 (*type of attack*) concerns the type of attacks a team attempts and distinguishes between two styles of play. Positive values indicate teams that attack more from set pieces, while negative values indicate teams that attack more often from open play. Likewise, factor 8 (*type of opponent's attacks*) shows the corresponding situations for the defensive phase (positive values for the opponent's

open play attacks, negative values for the opponent's set piece attacks). The playing style of set pieces has also been reported in previous research (Gómez et al., 2018; Lago-Peñas et al., 2017).
Finally, some playing styles that do not relate to a single team but to the game as a whole were identified. No other research so far has made this specific distinction in the recognition of playing styles. But when a factor is loaded with variables that concern both teams participating in the match, then we cannot speak about a team's style of play but rather a **style of the match**. For example, we named the factor 2 *transition game* because it was related to both recoveries and lost balls for a specific team. Similarly, we referred to factor 5 as *aerial game* and factor 13 as *effective game* based on the factors that are associated to it and pertain to both teams competing in a match.

The present study, together with those of Pollard & Reep (1997), Sporiš et al. (2012), Winter & Pfeiffer (2016), Fernandez-Navarro et al. (2016), Lago-Peñas et al. (2017), Gómez et al. (2018), Castellano and Pic (2019), Gollan et al. (2020), and Zhou et al.(2021), aimed to identify and measure playing styles in professional soccer. However, our study presents several novelties in comparison to previous research. Firstly, we used 88 variables in the factor analysis. With the exception of Gómez et al. (2018) which used 87 variables, all other similar studies included no more than 30 variables. Secondly, no other research has used 11 different competitions (2 at most so far). Specifically, this study utilized data from 2999 matches, whereas if we exclude the study of Zhou et al. (2021) which had 1429 matches from 6 seasons of a single competition, the sample of the rest of the studies in the recent literature did not exceed 380 matches. Thirdly, some of the styles that were identified in this paper (e.g., offside trap, defensive aggressiveness, passing tempo, individual attacking and defending actions separately, defensive blocks, game with lots of interruptions and duels, and aerial game) had not been recognized and quantified in any other research until now. Finally, it is the only study (of those that attempted to quantify styles of play) that identified styles for all phases and sub-phases of the game and presented them in a structured context (Figure 2).

With regard to the limitations of the present study, some aspects should be highlighted. Only matches from European leagues have been used, whereas physical performance related variables were omitted from our analysis. Future research should attempt to use data from leagues of other continents. Besides, Brazilian teams seem to have a distinct style of play (Tenga et al., 2003; Basevitch et al., 2013) and thus should be further investigated. Additionally, it should be evaluated whether playing styles (derived from technical-tactical factors) have particular fitness factor requirements. Finally, it should be investigated whether there are variations in playing styles among leagues, as well as the formations, which are a strategy factor.

Conclusions

This research was able to identify playing styles for all phases and sub-phases of the game, which is an important step towards a more comprehensive performance analysis. For some of these styles there was no scientific validation until now, but they were simply mentioned in expert interviews.

The grouping of performance indicators leads to the identification of playing styles that can cover all phases and sub-phases of the game. This way makes possible the reduction of data sets, which is necessary for today's era because not only do we not have a lack of data, but on the contrary, the volume of big data creates a problem in their practical exploitation.

The current findings may allow coaches, scouters, and performance analysts to classify the teams' styles so that playing style profiles could be created for each team. This will greatly assist the training process in preparation for a match against a specific opponent. Similarly, a post-match assessment of our team's performance can be more objective by factoring in the effects of styles of play. Finally, identifying playing styles can help teams recruit players whose characteristics match the playing styles adopted by each team.

Disclosure statement. The authors report there are no competing interests to declare.

APPENDIX A

Table Appendix A. Definitions of the employed variables.

VARIABLES	DEFINITIONS
pass_long_def_3rd	All types of passes (from the defensive third) with the ball passed to a teammate with more than 40 meters distance
pass_long_mid_3rd	All types of passes (from the midfield third) with the ball passed to a teammate with more than 40 meters distance
pass_long_att_3rd	All types of passes (from the attacking third) with the ball passed to a teammate with more than 40 meters distance
Defensive_challenges	Challenges involving a player of the team that does not currently possess the ball; the number of defensive challenges of the team is always equal to the number of attacking challenges of their opponents.
def_challenges_def_3rd	Challenges (in defensive third) involving a player of the team that does not currently possess the ball
def_challenges_mid_3rd	Challenges (in midfield third) involving a player of the team that does not currently possess the ball

def_challenges_att_3rd	Challenges (in attacking third) involving a player of the team that does not currently possess the ball
air_challenges_def_3rd	In defensive third of the mentioned team, two players of the opposing teams challenging for the ball in the air, at least above shoulder height. The rivals play or try to play with their heads.
air_challenges_mid_3rd	In midfield third of the mentioned team, two players of the opposing teams challenging for the ball in the air, at least above shoulder height. The rivals play or try to play with their heads.
air_challenges_att_3rd	In attacking third of the mentioned team, two players of the opposing teams challenging for the ball in the air, at least above shoulder height. The rivals play or try to play with their heads.
RATIO_long_passes_PER_passes	The quotient of division of long passes by total passes
Air_challenges	Two players of the opposing teams challenging for the ball in the air, at least above shoulder height. The rivals play or try to play with their heads.
RATIO_def_challenges_def_3rd_PER_defensive_challenges	The quotient of division of defensive challenges in defensive third by total defensive challenges.
RATIO_def_challenges_mid_3rd_PER_defensive_challenges	The quotient of division of defensive challenges in midfield third by total defensive challenges.
RATIO_def_challenges_att_3rd_PER_defensive_challenges	The quotient of division of defensive challenges in attacking third by total defensive challenges.
DIFFERENCE_air_ch_att_3rd_MINUS_air_ch_def_3rd	The difference air challenges attacking third minus air challenges defensive third.
Fouls	Action that impedes the progress and success of the opposing team and obtaining an advantage by breaking the rules of the game. A foul is committed after a challenge against an opponent, and the one who commits the foul loses the challenge. This parameter is registered in accordance with referee actions based on game footage and match report.
Yellow_cards (YC)	A cautionary directive illustrated by a yellow card from the referee for a moderate to serious foul or penalty.
Red_cards (RC)	An expulsion from the field for the most serious of fouls such as violent contact, blatant breaking of rules to avoid an opponent goal or a second yellow card.
Passes	An attempt to transfer a ball from one teammate to another with the purpose of attack build-up or keeping the possession.
Accurate_passes,_percent	Percentage share of accurate passes in the total number of passes. This parameter is generated automatically.
accurate_passes	Successful attempt to pass a ball from one teammate to another, when a teammate touches a ball; if a challenge was registered after a pass, this pass is still considered as an “accurate pass”.
wrong_passes	Passes minus accurate passes.
RATIO_passes_PER_wrong_passes	The quotient of division of passes by wrong passes.
Key_passes	A pass to a partner who is in a goal scoring position (one-on-one situation, empty net etc.) or a pass to a partner that “cuts off” the whole defensive line of the opponent's team (3 and more players) in the attacking phase. Usually a key pass is a vertical pass, rarely - a horizontal one. Key pass intercepted by an opponent is also registered, but not as an accurate one.
Crosses	A pass into the box from the flanks in the opponent's half of the field; strong and directed pass. It can be performed both in the air and on the ground, and it cannot be an action performed from a set piece.
Lost_balls	Additional characteristic to the last action in a team's Ball Possession before the possession transition. If the possession finishes with a goal, own goal, a shot or a foul from the team out of possession, the loss isn’t registered. It is registered when a player loses the ball by a poor trapping of the ball, errant pass, unsuccessful attempt to shoot or an unsuccessful dribble. Lost ball is registered at the moment of possession end and depends on the exact location where it occurred. This parameter is generated automatically.
RATIO_passes_PER_lost_balls	The quotient of division of passes by lost balls.
Lost_balls_in_own_half	Lost balls occurred in team’s own half of the pitch.
lost_balls_in_opponent's_half	Lost balls occurred in opponent’s half of the pitch.
Ball_recoveries	Additional characteristic to the first player’s action in a team’s Ball Possession after the team started possessing the ball, except for the cases when Ball Possession starts from a set piece (including a throw-in). Ball recovery is registered at the moment of possession end and depends on the exact location where it occurred. This parameter is generated automatically.
Ball_recoveries_in_opponent's_half	Ball recoveries occurred in team’s opponent’s half of the pitch.
Ball_recoveries_in_own_half	Ball recoveries occurred in team’s own half of the pitch.
RATIO_Entrances_to_the_final_third_PER_10_min_of_ball_possession	Entrances to the final third for a time of 10 minutes that the team had the ball in its possession. Entrances on final third is the number of team possessions during which at least one entrance into the opponent’s final third was made. Entrance is counted in as a result of one of the following actions: pass, challenge, tackle, dribble, ball recovery, ball loss, foul, YC, RC, all kinds of shots, interception, free ball pick up, GK interception, cross. This parameter is generated automatically.
RATIO_Entrance_to_the_penalty_box_PER_10_min_of_ball_possession	Entrances to the penalty box for a time of 10 minutes that the team had the ball in its possession.
Attacking_challenges	Challenges involving a player of the team that currently possesses

	the ball; the number of attacking challenges of the team is always equal to the number of defensive challenges of their opponents.
RATIO_ground_challenges_PER_air_challenges	The quotient of division of ground challenges by air challenges.
RATIO_dribbles_PER_min_of_possession	The number of dribbles per minute of team possession. Dribbles is an active action performed by a player in order to get through an opponent; can be performed as a trick or fake movement, as a ball poked at speed, no-touch ball etc.; can be performed without progression towards the opponent's goal. If after dribbling the player loses control of the ball and engages in a challenge with another opponent, then the dribble's type (successful or unsuccessful) will depend on the challenge. If the player wins the challenge, the previous dribble would be considered successful, if the player loses, then it would be unsuccessful.
Ball_interceptions	Player's active, targeted and successful action to either prevent a potentially accurate pass or to change the ball trajectory.
Free_ball_pick_ups	Recovering a neutral ball after an opponent lost it.
Opponent's_passes_per_defensive_action	Total number of passes made by opponent divided by the total number of defensive challenges. This parameter is generated automatically.
Building_ups	Build-up is registered for a team that possesses the ball and is building an attack in its own half until the ball is lost or until the team moves into the opponent's half.
Building_ups_without_pressing	Build-up without pressing. Pressing is counted for the opponents of a team that is building its attack when players are actively trying to get the ball back. Starting and ending points of build-up and pressing are registered simultaneously. This parameter is generated automatically.
High_pressing	Pressing until 30m from the opponent's goal.
Passing_rate	Passes per minute of ball possession.
AVERAGE_passes_PER_ball_possession	The quotient of division of passes by quantity of ball possessions.
Ball_possessions,_quantity	The number of ball possessions. Ball possessions are periods of play from the start to the end of possession, even if the moment of transition was not registered.
sum_duration_with_ball_possession	Sum of all time periods between the start of possession to the moment of transition, from the moment of transition to the moment of the next transition, from the moment of transition to the end of possession, as well as from the start to the end of possession in those cases when there was no moment of transition, e.g., if a ball went out. This parameter is generated automatically.
Average_duration_of_ball_possession (sec)	The quotient of division of sum duration with ball possession by quantity of ball possessions.
Ball_possession,_percent	Percentage share of one team ball possession in the total ball-in-play time. This parameter is generated automatically.
opponent's_ball_possession_percent	100 minus ball possession, percent.
RATIO_interceptions_+_free_balls_pick_up_PER_min_of_opponents_ball_possession	The sum of interceptions plus free balls pick up, divided by minutes of opponent's ball possession.
RATIO_defensive_challenges_PER_min_of_opponent's_ball_possession	The quotient of division of defensive challenges by minutes of opponent's ball possessions.
opponent's_sum_duration_of_ball_possession (sec)	Sum duration of ball possession for the opponent team.
Attacks _ center	Attack generally, is a possession of more than 3 seconds involving at least 2 passes or a dribble in the opposition half. Attacks - center (CNA) - attacks occurred between the space of left-side and right-side attacks, or central zone; the attack is determined by the last action of an attack which isn't a shot or a goal and which didn't occur inside the penalty area; determined for positional attacks and counter-attacks only. This parameter is generated automatically.
wide_attacks_percent	Wide attacks (LFA) - attacks occurred on the width of 20 meters from the left or right sideline, whole length of the sideline is considered; the attack is determined by the last action of an attack which isn't a shot or a goal and which didn't occur inside the penalty area; determined for positional attacks and counter-attacks only. This parameter is generated automatically.
attacks_center_percent	Attacks occurred between the space of left-side and right-side attacks, or central zone; the attack is determined by the last action of an attack which isn't a shot or a goal and which didn't occur inside the penalty area; determined for positional attacks and counter-attacks only. This parameter is generated automatically.
Counterattacks	Attack from the open play that starts with winning the ball from a defensive position and then quickly transitioning to offense while the prior attacking team is caught in an offensive formation; the length of possession during the attack cannot exceed 8 seconds before the possession transition or end; alternatively the length of possession can last between 8 and 30 sec., but the speed of attack cannot be less than 2.6 m/s. A counterattack cannot begin with a pass from a goalkeeper if he controlled the ball for more than 4 seconds before the action. This parameter is generated automatically.
Positional_attacks	All attacks from the open play that do not fit into counter attacks. This parameter is generated automatically.
RATIO_counterattacks_PER_ball recoveries	The quotient of division of counterattacks by ball recoveries.
Set_pieces_attacks	Total number of free-kick attacks, corner attacks, throw-in attacks and penalties. This parameter is generated automatically.
Open_play_attacks	Positional attacks plus counterattacks.
open_play_attacks_percent	The quotient (x100) of division of open play attacks by the sum of open play plus set pieces attacks.
set_pieces_attacks_percent	The quotient (x100) of division of set pieces attacks by the sum of open play plus set pieces attacks.

Counterattacks_percent	The quotient (x100) of division of counterattacks by the sum of open play plus set pieces attacks.
Positional_attacks_percent	The quotient (x100) of division of positional attacks by the sum of open play plus set pieces attacks.
Ratio_counterattacks_per_open_play_attacks_percent	The quotient (x100) of division of counterattacks by the open play attacks.
Ratio_posit_att_from_openplay_PER_openplay_att_percent	The quotient (x100) of division of positional attacks from open play by the open play attacks.
Offsides	A player is in an offside position if: any part of the head, body or feet is in the opponents' half (excluding the halfway line) and any part of the head, body or feet is nearer to the opponents' goal line than both the ball or the second-last opponent.
Opponent_Positional_attacks	Positional attacks for the opponent team.
Opponent_Counterattacks	Counterattacks for the opponent team.
Opponent_Set_pieces_attacks	Set pieces attacks for the opponent team.
Opponent_Open_play_attacks	Open play attacks for the opponent team.
Opponent_open_play_attacks_percent	The quotient (x100) of division of open play attacks by the sum of open play plus set pieces attacks for the opponent team.
Opponent_set_pieces_attacks_percent	The quotient (x100) of division of set pieces attacks by the sum of open play plus set pieces attacks for the opponent team.
Opponent_Counterattacks_percent	The quotient (x100) of division of counterattacks by the sum of open play plus set pieces attacks for the opponent team.
Opponent_Positional_attacks_percent	The quotient (x100) of division of positional attacks by the sum of open play plus set pieces attacks for the opponent team.
Opp_Ratio_counteratt_per_openplay_att_percent	The quotient (x100) of division of counterattacks by the open play attacks for the opponent team.
Opp_Ratio_posit_att_from_openplay_PER_openplay_att_percent	The quotient (x100) of division of positional attacks from open play by the open play attacks for the opponent team.
Opponent_Offsides	Offsides for the opponent team.
crosses_per_quantity_of_possession_percent	The quotient (x100) of division of crosses by the quantity of possessions.
crosses_per_attacks_percent	The quotient (x100) of division of crosses by the quantity of attacks.
shots_per_quantity_of_possession_percent	The quotient (x100) of division of shots by the quantity of possessions. The definition of shot includes shots on target, shots wide, blocked shots and shots on post / bar. If there are doubts whether a player intended to make a shot, our analysts ensure that a GK touched the ball before registering a shot.
shots_per_entrances_to_final_third_percent	The quotient (x100) of division of shots by the quantity of entrances to final third.
Tackles	This parameter is registered automatically for own team player in case an opponent is making a dribbling attempt; successful or unsuccessful tackle depends on the success of a dribble.
Dribbles	Is an active action performed by a player in order to get through an opponent; can be performed as a trick or fake movement, as a ball poked at speed, no-touch ball etc.; can be performed without progression towards the opponent's goal. If after dribbling the player loses control of the ball and engages in a challenge with another opponent, then the dribble's type (successful or unsuccessful) will depend on the challenge. If the player wins the challenge, the previous dribble would be considered successful, if the player loses, then it would be unsuccessful.
RATIO_tackles_PER_min of opponent's ball possession	The quotient of division of tackles by the minutes of opponent's ball possession
Effective_time (secs)	Time with possession of the ball by one or other team. In general, ball possession by a team is registered only if actions are made by one team during a period of the game and at the same time the ball is controlled for a required time during this period, or there is a necessary number of passes, or some key actions. Thus, if the ball possession quickly switches from players of one team to the other, or there are successive challenges, this will be an example of non-effective time.

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