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Original Article

Analysis of playing styles in European football: insights from a visual mapping approach

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Abstract
Performance analysis is a rapidly evolving field in football and a subject of extensive international scientific research. Recognizing playing styles is now considered essential for effective performance analysis. This study aimed to create a map of 174 teams from 11 European leagues that could, through visualization, provide practical insights applicable to football teams' daily practice. The t-distributed Stochastic Neighbor Embedding (t-SNE) method was used to reduce the dimensions of 19 tactical situations derived from previous research. The resulting two coordinates were employed to generate a scatter plot, and simultaneous k-means cluster analysis (k = 11) was conducted. Greece (86%) and Scotland (83%) had the highest percentages of teams within the same cluster as their country's average, while Germany (11%) and Croatia (10%) had the lowest percentages. In terms of cluster dispersion, England ranked first with 9 clusters, followed by Spain and Germany with 7 clusters, while Greece and Scotland had the least with 2 clusters. The visualization and clustering of teams led to the following conclusions. a) There are variations in playing styles not only between teams from different countries but also within the same country, particularly when there is a disparity in quality. b) Coaches' philosophies and implemented strategies significantly influence the adoption of playing styles by teams. These findings provide valuable information for coaches, analysts, and team scouts, assisting them in their respective roles. By understanding the diverse playing styles present in European football, practitioners can tailor their approaches to optimize team performance and gain a competitive edge.
Keywords: soccer, performance analysis, game style, visualization, t-SNE, k-means cluster

Introduction

Performance analysis is one of the main subjects of study in sports sciences (Hatzimanouil et al., 2022; Kirkendall, 2020) and, at the same time, a useful tool for coaches (James, 2006; Plakias, Kokkotis, Tsaopoulos, et al., 2023). Traditionally, performance indicators have been widely used in the international football literature (Hughes & Bartlett, 2002; Stafylidis et al., 2022). Performance indicators have been utilized in numerous studies to examine differences among leagues in different countries. These studies have examined variables related to physical performance (e.g., total distance, sprint distance, number of sprints) (Clemente et al., 2019; Dellal et al., 2011), as well as technical-tactical variables (e.g., shots on target, possession percentage, recoveries, yellow/red cards) (García-Aliaga et al., 2022; Sapp et al., 2018; Yi et al., 2019). Additionally, several studies have investigated differences among teams within specific leagues, including the Greek league (Plakias et al., 2022), the Spanish league (Lago-Peñas et al., 2010), the Belgian league (Geurkink et al., 2021), the German league (Brinkjans et al., 2022), the Chinese league (Ma et al., 2023), among others. However, in recent years, there has been a shift by researchers towards studying playing styles, which can provide a better interpretation of tactical issues (Plakias, Moustakidis, et al., 2023).

In the literature on the identification of playing styles in soccer, there is a great deal of inconsistency due to the use of various methodologies. Some authors focused on a single factor to identify playing styles. For instance, Narizuka and Yamazaki (2019) examined variations in team formation during matches, while Gollan et al. (2018) utilized the "key moments of play framework" to differentiate teams based on their strongest phases of

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the game. On the other hand, Decroos et al. (2020) considered multiple performance indicators but recognized styles separately for each indicator using vectors. Additionally, several researchers (Amatria et al., 2019; Amatria et al., 2021; Bekkers & Dabadghao, 2019; Brooks et al., 2016; Castellano & Echeazarra, 2019; Drezner et al., 2020; Gyarmati et al., 2014; Kempe et al., 2014; Mitrotasios et al., 2019; Praça et al., 2019) focused solely on recognizing playing styles during the ball possession phase and neglected the defensive phase.
Furthermore, a significant portion of the literature on team playing styles has employed Factor Analysis (Castellano & Pic, 2019; Fernandez-Navarro et al., 2016; Gómez et al., 2018; Lago-Peñas et al., 2017; Lopez-Valenciano et al., 2022; Plakias, Kokkotis, Moustakidis, et al., 2023; Pollard et al., 1988; Ruan et al., 2022; Schulze et al., 2021; Sporiš et al., 2012; Zhou et al., 2021).Through this technique, researchers group performance indicators into factors that correspond to "tactical situations." Each factor (tactical situation) yields two styles of play based on the sign (positive or negative) of the factor scores. Consequently, two styles emerge for each distinct tactical situation. For instance, if a factor is labeled as "build-up" by the author, it can give rise to the possession style and the direct play style. Similarly, a factor characterized as "press" can generate two other styles (e.g., high press/low press), and so forth.

On the contrary, there are very few studies in the international literature that simultaneously integrate multiple factors to create an overall style of play for each team. More specifically, Bialkowski et al. (2014) and Bialkowski et al. (2016) utilized k-means clustering, agglomerative clustering, linear discriminant analysis, and k-nearest neighbor to develop a visualized descriptor representing the characteristic style of each team. In addition, García-Aliaga et al. (2022) employed 52 performance indicators and utilized the t-SNE and RIPPER techniques to analyze changes in playing styles among teams in the top four European leagues (based on the UEFA ranking) from season to season, as well as the disparities between English league teams and teams from the other three countries' leagues.

In the present study, instead of individual performance indicators, the playing styles of teams were assessed across 19 tactical situations. The t-SNE method was combined with k-means Cluster analysis. García-Aliaga et al. (2022), had already suggested the combination of the t-SNE method with more methods apart from RIPPER for diverse purposes. Consequently, our research aims to achieve multiple objectives, including: 1) creating a map of teams from 11 different leagues (ranked 1st to 20th in the UEFA list), 2) determining the level of homogeneity in playing styles within each league, and 3) exploring other relationships (similarities or differences) between the styles of European teams that have practical significance within the four lines of the pitch.

Material & methods
Sample: The study comprised all matches played in the 2021-2022 season in the top division of 11 European countries. However, for 8 matches, either no data or incomplete data was available through Instatscout (https://football.instatscout.com/). Previous research (Gómez et al., 2018; Kubayi & Larkin, 2020; Silva & Marcelino, 2023) has confirmed the high reliability of the indicators provided by Instatscout.. Only regular-season matches were considered, excluding any play-offs or play-outs. Table 1 presents the number of matches played and the matches included from each competition. It is important to note that separate observations were recorded for each team in every match, resulting in a total of 5992 valid observations in the sample.

Table 1. Matches played in each country, matches included in the study

COUNTRY	NUMBER OF TEAMS	MATCHES PLAYED	MATCHES INCLUDED
AUSTRIA	12	132	132
BELGIUM	18	306	303
CROATIA	10	180	178
ENGLAND	20	380	380
GERMANY	18	306	306
GREECE	14	182	182
ITALY	20	380	377
SCOTLAND	12	198	198
SPAIN	20	380	380
SWITZERLAND	10	180	180
TURKYIE	20	380	380
TOTAL	**174**	**3004**	**2996**

Variables-Procedure: The study utilized factor scores derived from Factor Analysis and Principal Components Analysis of previous research (Plakias, Kokkotis, Moustakidis, et al., 2023). These factor scores were obtained from 19 components, each representing a specific tactical situation. For each component, two playing styles were generated based on the positive or negative sign of the factor scores in each observation. The names assigned to each component are presented in Table 2. Sixteen out of the 19 latent variables pertained to the competing teams' playing styles, while the remaining three (2, 5, 13) were associated with the overall game (styles for the game). The latter were derived by considering the combined behavior of both teams participating in a match.

Table 2. The 19 components utilized as variables in the present study.

1. Elaboration of build up phase	2. Transition game	3. Attacking transition	4. Defensive transition
5. Aerial game	6. Type of attack	7. Crossing	8. Type of opponent's attack
9. Defensive blocks	10. Press	11. Individual defending actions	12. Width of creative phase
13. Effective game	14. Individual attacking actions	15. Tendency to create final attempts	16. Passing tempo
17. Defending aggressively	18. Attacking aggressively	19. Offside trap	

Statistical analysis: The mean values of the 174 teams and eleven countries on the 19 components were subjected to the t-distributed Stochastic Neighbor Embedding (t-SNE) method. T-SNE, a machine learning technique, employs a dimensionality reduction algorithm that enables the visualization of large datasets in a 2D plot (Ramírez-Arroyo et al., 2022). Additionally, k-means Cluster analysis was conducted on the resulting two coordinates from t-SNE to group teams and countries based on the 19 components. K-means Clustering serves as a tool for identifying clusters or groups of observations in multivariate data (Kodinariya & Makwana, 2013; Martínez et al., 2023). The authors performed K-means using SPSS, with a selection of K = 11 due to the presence of 11 competitions in the study. The flowchart in Figure 1 depicts the procedures we employed in the study.

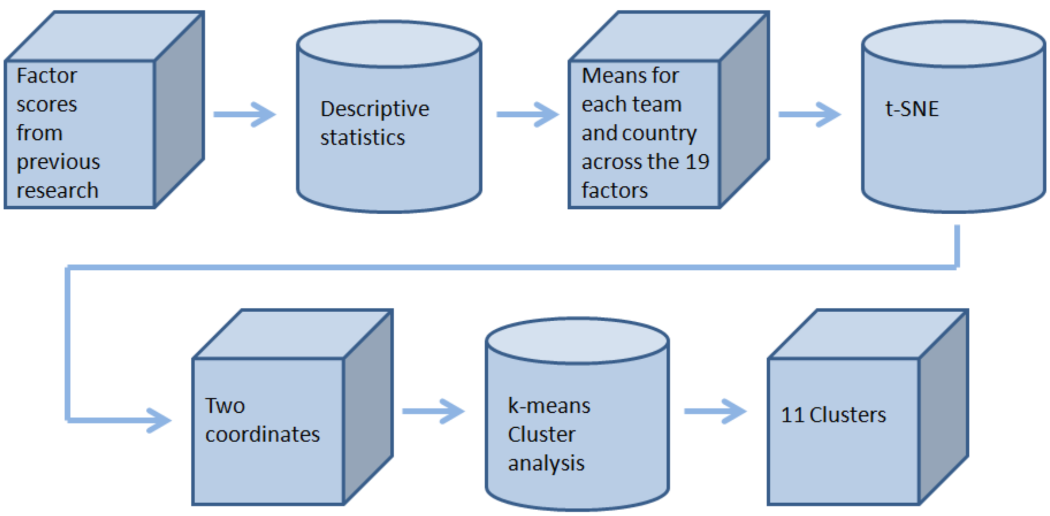

Figure 1. Flowchart illustrating the study procedures.

Results

Table 3 displays the two coordinates (X, Y) derived from the t-SNE algorithm, as well as the cluster (CL) assignments resulting from the k-means Cluster analysis, for the 174 teams and 11 countries. The scatterplot of the teams and countries based on these coordinates is visualized in Figure 2, presenting the map.

Table 3 results in Table 4, which shows the number of teams in each country, the percentage of teams in the same cluster as their country, and the number of clusters in which the teams of each country are divided. From Table 4, it can be observed that on average only 45.9% of teams from each country are within the same cluster as their country. Furthermore, teams from each country are dispersed across approximately 5 different clusters.

The countries with the highest percentages of teams within the same cluster as their country's average are Greece (86%) and Scotland (83%), while the countries with the lowest percentages are Germany (11%) and Croatia (10%). Regarding the number of clusters in which the teams of each country are dispersed, England ranks first with 9 clusters, followed by Spain and Germany with 7 clusters, while Greece and Scotland occupy the last positions with 2 clusters.

Table 3. Coordinates and clusters for teams and countries.

TEAM	X	Y	CL	TEAM	X	Y	CL	TEAM	X	Y	CL
EMPOLI	5,41	3,55	4	GENT	11,03	0,72	8	RAPID	11,84	-0,40	6
TOTTENHAM	9,03	7,20	10	GETAFE	2,66	-0,41	9	RAYO	4,94	2,77	4
ABERDEEN	1,77	-1,92	3	GIRESUNSPORT	9,54	2,98	8	SALZBURG	13,32	1,36	8
ADANA_DEM	8,04	4,61	4	GLADBAH	10,46	7,88	11	REAL	7,78	9,04	10
ADMIRA	10,43	-0,20	6	GORICA	4,07	3,23	1	R_SOCIEDAD	6,86	5,74	2
ADWERP	8,29	1,88	5	GOZTEPE	5,25	3,12	4	RHENDORF	11,68	-2,24	6
AEK	4,24	5,01	1	GRANADA	2,85	-0,50	9	RIED	7,40	-1,22	7
ALANYASPOR	8,02	6,20	2	GRASSHOPERS	8,42	1,55	5	RIJEKA	9,87	2,64	8
ALAVES	3,67	-1,87	3	GROITER	6,78	-0,56	7	ROMA	6,71	6,30	2
ALTAY	5,70	2,81	4	HARTBERG	11,41	-1,20	6	ROSS_C	2,82	-3,13	3
ANDERLECHT	10,96	4,14	8	HATAYSPORT	6,15	3,11	4	SALERNITANA	3,82	0,67	9
ANTALYASPOR	7,75	4,46	4	HEARTS	1,87	-1,92	3	SAMPDORIA	5,73	4,69	4
APOLLON	2,64	4,44	1	HERTHA	7,83	-0,69	5	SASSUOLO	7,82	7,60	2
ARIS	4,23	6,83	1	HIBERNIAN	2,12	-1,55	3	SERAIGN	9,08	2,40	5
ARMINIA	6,24	-2,93	7	HIJDUK	12,06	2,42	8	SERVETTE	10,32	1,24	8
ARSENAL	7,21	7,70	2	HOFFENHEIM	11,33	5,56	11	SEVILLA	5,47	8,52	2
ASTON_VILA	4,89	0,46	9	HRVATSK	8,26	0,33	5	SIBENIC	8,45	3,10	4
ATALANTA	11,89	6,30	11	INTER	6,78	7,73	2	SINT_TR	7,16	-3,08	7
ATL_MADRID	6,00	4,82	4	IONIKOS	2,98	4,14	1	SION	7,74	2,46	4
ATROMHTOS	3,40	5,29	1	ISTANB_BASAKS	6,84	8,90	10	SIVASSPOR	6,10	2,07	4
AUGSBURG	4,79	-1,69	3	ISTRA	5,28	5,56	2	SLAVEN	7,90	-2,98	7
AUS_KLAGERF	7,53	0,73	5	JUVE	7,61	7,47	2	SOUTHAMPTON	5,42	-0,38	9
AUS_WIEN	10,47	0,88	8	KASIMPASA	5,28	3,54	4	SPEZIA	3,59	2,13	9
BARCELONA	8,80	6,00	2	KAYSERISPOR	7,16	3,10	4	ST_GALLEN	12,62	0,04	6
BASEL	10,96	2,26	8	KOLN	9,12	-1,43	6	ST_JOHNSTON	2,82	-2,92	3
BAYERN	10,91	8,11	11	KONYASPOR	6,31	2,24	4	ST_MIRREN	2,67	-3,14	3
BEERSCHOT	7,50	0,51	5	KORTRIJK	9,75	0,60	5	ST_LIEGE	9,18	0,99	5
BESIKTAS	12,70	4,22	8	KV	10,63	-2,24	6	STURM	10,14	-3,07	6
BETIS	7,61	5,58	2	LAMIA	3,13	4,50	1	STUTTGART	9,96	3,83	8
BILBAO	5,39	4,14	4	LASK	10,53	-3,12	6	TIROL	11,71	-1,24	6
BOCHUM	6,91	-3,30	7	LAUSAN_SPORT	8,60	3,50	4	TORINO	12,81	6,94	11
BOLOGNA	6,41	5,47	2	LAZIO	8,55	8,32	10	TRABZONSPORT	7,92	6,98	2
BREDFORD	6,22	-1,38	7	LEEDS	9,68	-0,40	6	TRIPOLI	1,91	4,68	1
BRIGHTON	6,18	0,27	9	LEICESTER	9,86	6,67	11	UDINEZE	2,44	2,15	1
BRYGGE	11,53	5,41	11	LEIPZIG	10,00	8,05	10	UNION_BELG	11,77	0,86	8
BURNLEY	4,09	-2,11	3	LEVANTE	4,99	4,12	1	UN_BERLIN	5,27	-2,39	7
CADIZ	5,25	1,75	9	LEVERKUSEN	9,66	4,76	11	VALENCIA	1,90	3,60	1
CAGLIARI	3,09	-0,53	9	LIVERPOOL	9,94	8,64	10	VENECIA	3,50	2,15	9
CAYCUR	7,22	3,44	4	LIVINGSTON	3,02	-3,83	3	VERONA	12,40	6,53	11
CELTA	9,51	0,03	5	LOKOMOTIVA	8,38	-3,14	7	VILLAREAL	8,68	5,77	2
CELTIC	8,36	10,49	10	LUGANO	9,52	1,49	5	VOLOS	4,31	4,48	1
CERCLE	9,78	-3,45	6	LUZERN	11,12	1,71	8	WATFORD	4,65	-0,39	9
CHARLEROI	10,25	2,85	8	MAINZ	8,14	-1,80	7	WEST_HAM	5,46	0,07	9
CHELSEA	8,88	8,25	10	MALLORCA	2,44	0,89	9	WOLFSBERGER	11,10	-0,93	6
CRYSTAL_PAL	9,03	4,25	4	MAN_CITY	7,11	9,27	10	WOLFSBURG	8,25	-0,89	5
DIN_ZAG	11,55	3,37	8	MAN_UTD	6,25	1,11	9	WOLVES	9,43	4,53	8
DORTMUND	10,48	7,93	11	MECHELEN	9,09	-1,26	6	YENI	7,81	3,48	4
DUND_UTD	2,45	-2,64	3	MILAN	6,93	6,80	2	YOUNG_BOYS	11,91	2,17	8
DUNDEE	2,91	-3,34	3	MOTHERWELL	2,99	-3,49	3	ZULTE	7,52	1,36	5
EINDRACHT	8,83	-2,11	7	NAPOLI	8,33	8,16	10	ZYRICH	12,07	1,34	8
ELCHE	6,70	3,82	4	NEWCASTLE	4,32	-0,29	9	**AUSTRIA**	11,03	-0,80	6
ESPANIOL	7,10	4,03	4	NORWICH	5,24	0,37	9	**BELGIUM**	9,58	1,36	5
EUPEN	9,40	2,24	8	OFI	3,80	5,59	1	**CROATIA**	9,06	1,65	5
EVERTON	4,54	-0,43	9	0H	9,95	2,11	8	**ENGLAND**	5,89	0,38	9
FATIH	8,94	5,60	2	OSASUNA	3,54	-1,86	3	**GERMANY**	8,05	-0,63	5
FENER	12,47	4,36	8	OSFP	5,74	6,86	2	**GREECE**	3,83	4,71	1
FIORENTINA	6,11	7,48	2	OSIJEC	7,32	-3,14	7	**ITALY**	6,83	5,69	2
FREIMBURG	6,09	-1,45	7	PANAITOLIKOS	3,41	4,01	1	**SCOTLAND**	2,49	-2,28	3
GALATA	7,14	6,27	2	PAO	4,25	6,89	1	**SPAIN**	6,15	3,73	4
GAZIANTEP	7,12	1,86	4	PAOK	5,71	6,83	2	**SWITZERLAND**	10,46	1,71	8
GENK	10,88	3,29	8	PAS	2,96	3,44	1	**TURKYIE**	7,21	3,81	4
GENOA	4,46	1,94	9	RANGERS	8,31	10,40	10				

Figure 2. Scatterplot of the teams and countries

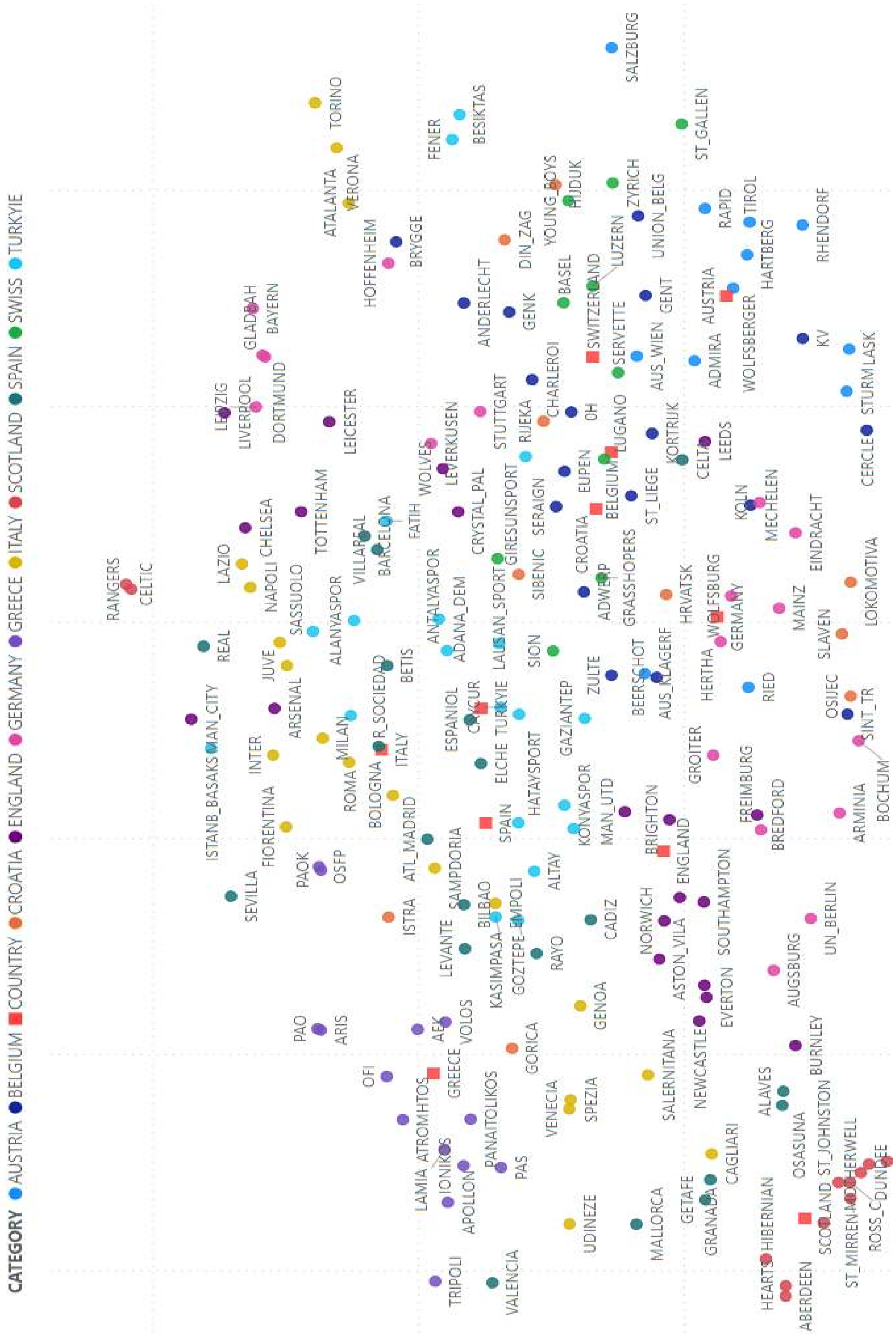

Table 4. Number of teams within the country (A), percentage of teams within the same cluster as their respective country (B), and number of clusters in which the teams of each country are divided (C).

COUNTRY	A	B	C
AUSTRIA	12	67	4
BELGIUM	18	33	5
CROATIA	10	10	6
ENGLAND	20	45	9
GERMANY	18	11	7
GREECE	14	86	2
ITALY	20	35	6
SCOTLAND	12	83	2
SPAIN	20	25	7
SWITZERLAND	10	50	4
TURKYIE	20	60	4
MEAN	**15,8**	**45,9**	**5,1**

Discussion

The aim of the present study was to create a map of the playing styles of the teams from 11 European countries, which was achieved using t-SNE. Additionally, through k-means cluster analysis, we identified the homogeneity that exists within each of the 11 domestic leagues in terms of the styles adopted by their teams.

From the visualization carried out with a scatter plot, several important conclusions with significant practical implications for coaches and team analysts emerge. For instance, in Italy, it appears that three teams (Atalanta, Verona, Torino) exhibit similar playing styles, which are distinct from the rest of the league. Juric, who coached Verona in the 2019-20 season and Torino in the 2021-22 season, favored a 1-3-4-2-1 formation. Atalanta's coach, Gasperini, also shows a preference for the same formation. In other words, team tactics, such as the formation used, seem to influence the playing style of teams, which aligns with the findings of previous research (Sarmento et al., 2013; Shaw & Glickman, 2019).

Additionally, prior studies (Bekkers & Dabadghao, 2019; Sarmento et al., 2014; Zainuddin et al., 2022) have demonstrated that the philosophy of the coach plays a decisive role in shaping a team's playing style. Our research confirms this with several examples. Firstly, Sarri's last four teams (Napoli, Chelsea, Juventus, and Lazio) exhibit very similar playing styles. Sarri, known for his specific principles, has contributed to the recognizable "Sarribal" style (Cintia & Pappalardo, 2021). Secondly, Arsenal's style on the map closely resembles that of Manchester City. It is highly likely that Arsenal's manager (Arteta) has been heavily influenced by his mentor (Guardiola), whom he served as an assistant at Manchester City before becoming Arsenal's head coach. Guardiola's teams are known for their distinctive style of play, characterized by "tiki-taka" and an emphasis on passing (Berri et al., 2023; Rashid, 2020). Lastly, Liverpool, under the guidance of German manager Klopp, occupies a position on the map between four German teams, one of which is Klopp's former club, Dortmund. Klopp's teams, like the German teams, are renowned for their high-intensity pressing tactics ("gegenpressing") (Abreu et al., 2022; Bauer & Anzer, 2021).

Through the Cluster Analysis, it was determined that the 11 countries could be classified into 8 distinct clusters. This indicates variations in the playing styles of teams across different countries. This finding is consistent with another study (Sarmento et al., 2013), which suggested that cultural disparities among countries could contribute to differences in playing styles among their teams. Mitrotasios et al. (2019) also identified disparities in playing styles among four leagues (English, Italian, Spanish, and German). In contrast, Gonzalez-Rodenas et al. (2021) found no differences between the English and Spanish leagues; however, this could be attributed to the focus solely on attacking styles in that research. Additionally, García-Aliaga et al. (2022) revealed differences between the teams in the English league and those from three other countries (Italian, Spanish, and German). Nonetheless, these differences were not as pronounced when examining the top teams in the English league.

The influence of team quality on playing styles is another factor examined in the international literature. In fact, three studies (Gollan et al., 2020; Gómez et al., 2018; Kong et al., 2022) have demonstrated that the quality of teams impacts their playing style. Our own research also confirms this with two notable examples. Specifically, in the Greek and Scottish leagues, the top two teams in the standings form a distinct cluster separate from the other teams in the competition. This is particularly evident in the case of Scotland, where there is a significant quality gap between the Celtic-Rangers duo and the rest of the teams, resulting in noticeable differences in playing styles among them. Considering the limitations of this particular research, several points should be noted. Firstly, our study did not examine contextual variables (such as home field advantage, opponent quality, or match status) that could potentially differentiate teams' playing styles (Fernandes et al., 2020; Fernandez-Navarro et al., 2018; Praça et al., 2019). Additionally, we focused solely on European championships and did not investigate leagues from other continents, such as Latin America, which possess unique characteristics worth exploring (Basevitch et al., 2013; Tenga & Larsen, 2003). Moreover, future research could benefit from integrating the t-SNE method with Explainable Artificial Intelligence (xAI) techniques, such as SHapley Additive explanations (SHAP), which offer enhanced interpretability of the results (Gunning et al., 2019; Moustakidis et al., 2023). This would provide a better understanding and insight into the factors driving the observed patterns.

Conclusions

Despite its inherent limitations, the current research has yielded valuable insights in the realm of identifying the playing styles exhibited by football teams. The findings have illuminated notable variations in style both among teams hailing from different countries and even within teams originating from the same country. These disparities become more pronounced when there exists a discernible discrepancy in the quality of teams. Furthermore, it has become evident that the fundamental philosophy embraced by a coach, as well as their strategic choices such as team formation, play a pivotal role in shaping the distinctive style adopted by a team. These discoveries carry significant implications for coaches, analysts, and team scouts, equipping them with crucial information to augment their roles and decision-making processes. Specifically, this information holds great practical interest for coaches and team analysts, empowering them to better prepare for forthcoming encounters with opponents. It also proves invaluable for scouts, aiding in the identification of players who align harmoniously with the prevailing style of their league and respective team. Therefore, by comprehending the diverse playing styles prevalent in European football, practitioners are afforded the opportunity to tailor their approaches, optimizing team performance and securing a competitive advantage.

Conflicts of interest: We declare that we have no conflict of interests.

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