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A COMPARISON OF PERFORMANCE INDICATORS IN FOOTBALL ACROSS THE TOP FIVE EUROPEAN LEAGUES

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***Abstract**. The appetite for European football has been in continuous increase over the last decade with resulting debates about league supremacy. The purpose of this investigation was to compare the top five European football leagues using aggregated seasonal match data from the Premier League, Bundesliga, La Liga, Serie A and Ligue 1, over nine complete seasons from 2009-2010 to 2017-2018. Multivariate analysis of variance and profile analysis with subsequent univariate tests and post-hoc multiple comparison procedures were carried out on 15 football match performance indicators. It was observed that the Bundesliga had significantly higher averages than Ligue 1 in offensive, defensive and physical profiles. The Premier League averaged more aerial duels than Ligue 1, La Liga, and Serie A but a lower number of tackles and fouls committed. The Premier League had the highest average shots per game and was outperformed only by the Bundesliga in the other offensive metrics. Overall, the study yielded results that may find utility in further comparative football research to understand the differences in attribute profiles across leagues and serve as a basis for insights into the contrasting performances of teams from the respective leagues in European club competitions.*

***Keywords**: ANOVA; Aggregated data; European football; Key performance indicators; Profiles.*

1. INTRODUCTION

Association football is the most popular sport in the world, but empirical studies centred around performance analysis in football have been limited to exploration of specific aspects of on-field performance, including influences on match outcomes, factors affecting team performance and physiological estimates of individual player characteristics (Hughes and Franks, 2005; Kubayi, et al., 2017;

Taylor, et al., 2008). However, it has been suggested that emphasis should be placed on the development and the use of key performance indicators (Carling, et al., 2008; M. D. Hughes and Bartlett, 2002), which has been the case in football research of the last decade. Performance indicators have been outlined as the selection and combination of variables that define some aspect of performance and help achieve sporting success (Hughes and Bartlett, 2002; Wright, Carling, et al., 2014). These indicators constitute a profile of ideal performance, and identification of physical and technical parameters that could influence team performances to predict the future behaviour (Fernandez-Navarro, et al., 2016; Jamil, et al., 2021; Jones, et al., 2004; O'Donoghue, 2005; Zhou, et al., 2018).

Although there have been attempts to construct individual performance profiles in team sports such as basketball, baseball, rugby, volleyball, and American football (Boulier and Stekler, 2003; Campos, et al., 2014; Csataljay, et al., 2009; Drikos and Vagenas, 2011; García, et al., 2013; Ibáñez, , 2009; Jones et al., 2004; Ortega,et al., 2009), there has been little research on the construction of these indicators and profiles and their applications in association football (Cefis and Carpita, 2024a, 2024b). Earlier studies have attempted to provide indicators of performance through wins and losses of teams (Hughes and Churchill, 2005; Hughes and Franks, 2005; Jones et al., 2004; Lago-Ballesteros and Lago-Peñas, 2010). However, these provided contradictory findings. Authors previously compared the performance of European and African teams during the 2018 FIFA World Cup matches and found that differences existed, with European teams producing better performance metrics in terms of shots, goals scored, possession, passes and corner kicks (Kubayi and Toriola, 2020). Other authors found that successful teams had longer periods of possession than unsuccessful teams during the UEFA Euro 2016 Tournament (Casal, and al., 2017), and there were homogenous distributions of ball recovery for top European and South American nations at the 2014 FIFA World Cup (Maleki, et al., 2016).

In a comparative study of the divisions of English football, Bradley et al. (2013) discovered several differences between football at the elite level and the lower levels (Bradley et al., 2013). Different styles of play not only existed among football leagues within a country, but across leagues of various countries as well. Di Salvo et al. (2012) found that physical aspects of performance, as well as technical skills varied in players across elite football leagues (Di Salvo, et al., 2013). Other studies, through traditional data analysis, determined that the

Spanish La Liga was characterized by a higher concentration of ball possession and players with high technical skills (Espitia-Escuer and Garcia-CebriAn, 2004; Espitia-Escuer and García-Cebrián, 2006), the English Premier League was characterized by direct, fast play and solid defending (Sarmento et al., 2011), the Italian Serie A became well-known for a highly tactical defence and a well-developed use of the counterattack (Vialli and Marcotti, 2007), while the Bundesliga was known for its high tempo and speed of play (Vialli and Marcotti, 2007). However, due to the limited research conducted to determine the tactical and technical characteristics of each competition, popular speculation and perceived performance characteristics have created an open debate (Wilson, 2013).

The Union of European Football Associations (UEFA) club licensing benchmark report (UEFA, 2020) listed the top five domestic first division leagues as the Premier League (England), Bundesliga (Germany), La Liga (Spain), Serie A (Italy) and Ligue 1 (France). These rankings were based on attendance levels, stability with respect to the UEFA coefficient system, average aggregated revenue, club broadcast revenue, wage growth, and transfers (UEFA, 2020). The variety of issues associated with European football have been the source of recent research in the sport. By virtue of its popularity and sheer magnitude of resources involved in football today, together with the propagation of data mining and data analytics, significant effort into exploration of aspects of club football has taken root.

Anderson and Sally (2013) concluded that the strongest leagues in Europe, i.e., those in England, Germany, Spain, and Italy, are distinctly like each other when it comes to their key traits (Anderson and Sally, 2013). In their comparative analysis of scoring across a decade of playing, they revealed that spectators in the top European football leagues saw an average of between two and three goals per match, regardless of the four countries where the game was played. Their data also showed a similar number of shots, shots on target, corners and penalty kicks per game. They added that the number of free kicks, crosses from open play, and headed goals were also very similar. However, this convergence did not occur in the other leagues, such as the Dutch Eredivisie, Ligue 1 in France, and US Major League Soccer (Anderson and Sally, 2013). García-Aliaga et al. (2022) used machine learning to observe differences across the Premier League, Bundesliga, La Liga, and Serie A in these countries (García-Aliaga et al., 2022). They found that with the evolution of playing styles, these top European leagues appeared to be approaching a level of homogeneity in terms of technical and tactical behaviours. However, distinctions were observed in terms of fewer free kicks and long passes, more errors in ball control but greater success in dribbling in the Premier League (García-Aliaga et al., 2022).

Littlewood et al. (2011) examined trends in player acquisition at clubs belonging to the top five European football leagues between the seasons ending 2005-2009 (Littlewood, et al., 2011). They found that the numbers of home-grown players were decreasing in all leagues. However, four out of the five leagues remained indigenously dominant. The Bundesliga was the only league with most non home-grown players. The overall perception of football in some of Europe's top leagues was explored by Sarmento et al. (2013), where the differences among the English, Spanish and Italian first divisions by coaches' characterizations of the leagues' particularities were investigated (Hugo Sarmento et al., 2013). The style of play was attributed to cultural, strategic, and skill-defined factors with coaches distinguishing the styles as being physically direct, defensively tactical and aesthetically controlled, respectively. To compare quality of players in different positions in different leagues, as well as to ascertain differences in age, stature and body mass, Bloomfield et al. (2005) used non-parametric analyses of variance on data from each of England, Spain, Germany, and Italy for the 2001-2002 season (Bloomfield, et al. , 2005). There were evident differences in playing style, physical demands, as well as in physical conditioning of players from the different leagues. Further comparisons between the English Premier League and Spanish La Liga for 2006-2007 season were made using match performance variables measuring physical activity and technical abilities, including total distance covered with and without possession, heading and ground duels, passing, ball possession and ball touches (Dellal et al., 2011). Analysis was carried out using two-way analysis of variance (ANOVA) with player positions and running speeds for physical activity variables, and one-way ANOVA for technical aspects according to player position. The results indicated significant differences between variables for both leagues, concluding that cultural differences existed between them.

The relationships with elite football players and their playing positions were explored using repeated-measures ANOVA, to examine the muscle strength, anthropometric and cardiovascular profiles in a football club (Herdy et al., 2020). Sapp et al. (2017) used two-way ANOVA with leagues and seasons as independent variables to compare aggressiveness among the top five European leagues (Sapp, et al., 2018). They concluded that England boasted the most aggressive of the five leagues, while there was an overall decreasing trend in aggression over the last decade. Mitrotasios et al. (2019) compared the goal-scoring opportunities in the top four European football leagues. The results reported some differences in the four leagues: Spanish La Liga was good at the combination of offensive methods; English Premier League showed a high degree of direct play; Italian Serie A showed the shortest offensive sequences; and German Bundesliga had the greatest number of counterattacks (Mitrotasios, et al., 2019).

Though univariate ANOVA was a useful mechanism for comparisons, multivariate approaches aimed at distinguishing multifactorial characteristics were also employed in some of the earlier literature. Reilly et al. (2000) applied multivariate analysis of variance (MANOVA) to data, split into groups, and comprised of variables measuring performance on test items designed to assess somatotype, body composition, body size, speed, endurance, technical skill, anticipation, anxiety, and task and ego orientation (Reilly, et al., 2000). The study was geared towards elite football player talent-identification and distinguished between elite and sub-elite groups on which significant multivariate effects were evident. MANOVA was also used to establish whether the footballers from the Premier League exhibited heterogeneity in anthropometric variables according to playing position but revealed that there were no differences between playing positions for overall body mass, stature, fat mass, muscle mass, skeletal mass, residual mass, or lean body mass (Hencken and White, 2006). A similar study was conducted by Chmura et al. (2022) using two seasons of German Bundesliga data (Chmura et al., 2022).

In addition, multivariate analysis of variance had utility in examining data concerning groups of players by position, across time periods and even by injury and fasting status. It allowed for the evaluation of anthropometric and functional characteristics, personality and coping factors, motivation factors as well as injury rates (Carling, et al., 2012; Chamari, et al., 2012; Ivarsson and Johnson, 2010; Mladenovic and Marjano, 2011). Kannekens, et al., (2009) were also able to discern differences between Dutch and Indonesian youth team players in terms of tactical skill variables and competitive metrics facilitated by MANOVA (Kannekens, et al., 2009). Further MANOVA analyses were used to compare game parameters between Italian and Israeli football league matches which revealed that ball movement and attacking efficiency was significantly superior in the Italian Serie A (Elyakim et al., 2020).

Many of the existing studies have not comparatively incorporated match attributes encapsulating overall footballing abilities of European clubs. If differences in the football played among professional divisions were to be identified, then one should consider all metrics related to match play. To our knowledge, there have been no big data studies with a large sample size investigating differences in key match performance indicators across the top European football leagues. There is a need for coaches and analysts to benchmark these elite European leagues to identify performance variables that defined successful team performance across the continent (Winter and Pfeiffer, 2016). Key performance indicators may differ across leagues. Therefore, the aims of this study were to assess the major match attributes by way of seasonal and league performance indicators, and examine the differences, if any, among the English, German, Spanish, Italian and French first division leagues over multiple seasons.

2. METHODOLOGY

2.1 DESIGN AND SAMPLE

A comparative study was conducted to analyze the overall match performance indicators of the top five European football leagues. Our sample included data from nine football seasons across the Premier League, Bundesliga, La Liga, Serie A, and Ligue 1, spanning from 2009/10 to 2017/18. The final metrics for each season across the leagues were recorded, resulting in a sample of 17 variables, with "League" and "Year" used as independent factors. The data was sourced from Whoscored.com (www.whoscored.com), which provides football match data collected by OPTA and made publicly available. OPTA Sports, known for having one of the largest sports databases in European football, has had its reliability tested and verified in previous studies (Liu, et al., 2016).

2.2 PERFORMANCE INDICATORS

Performance indicators were selected based on variables explored in the existing literature (Castellano and Casamichana, 2015; Elyakim et al., 2020; García-Aliaga et al., 2022; Herold,et al., 2021; Kubayi and Toriola, 2020; Velasco and Castán, 2022). These variables were divided into four profiles: offensive (Herold et al., 2021; Velasco and Castán, 2022), defensive (Ruan et al., 2022; Velasco and Castán, 2022), physical (Chmura et al., 2022; Yang, et al., 2018) and control (Casal et al., 2017; Hadji and Benosmane, 2022). Table 1 provided a summary of the variables used in this study.

Table 1: Description of selected performance indicators and independent factors

	Profile	Description
League	-	League from which data were recorded: Premier League, Bundesliga, La Liga, Serie A, Ligue 1
Year	-	Year ending the season from which data were recorded. For example, 2016 corresponds to the 2015/16 season.
Offsides	Offensive	Number of times players were caught in an offside position by match officials per game
Shots		On/off target attempts made to score a goal per match
Shots on Target		On target attempts made to score a goal per match
Goals Scored		Goals scored per game
Dribbles		Number of times players successfully dribbled past an opposition player while retaining ball possession per game
Goals Conceded	Defensive	Goals conceded per game
Shots Conceded		On/off target attempts on goal conceded per game
Shots on Target Conceded		On target attempts on goal conceded per game
Interceptions		Number of times a pass is prevented from reaching a teammate per game
Tackles	Physical	Number of tackles made per game
Fouls Committed		Number of fouls committed per game
Times Fouled		Number of fouls awarded per game
Aerial Duels Won		Number of headers won per game
Possession	Control	Time spent with the ball per game
Pass Completion		Number of passes successfully completed per game

2.3 STATISTICAL ANALYSIS

Multivariate analysis of variance (MANOVA) was used to determine whether there were differences across leagues for performance indicators simultaneously. Since many of the performance indicators are correlated, MANOVA tests for the differences across these variables in a single model to detect differences that might not be apparent if each dependent variable was analyzed separately. First, assumptions of the MANOVA were checked using a quantile-quantile (Q-Q) plot of the squared Mahalanobis distances against the theoretical quantiles of the appropriate chi-square distribution to assess multivariate normality; Box's M test was used to test equal variance-covariance matrices across groups; and multicollinearity was assessed based on a correlation matrix of the performance indicators. Univariate normality was assessed using Q-Q plots, while homogeneity of variances was checked using Levene's test. Multivariate normality was satisfied but departures in the homogeneity of variance assumption were observed. However, MANOVA test statistics are robust to violations of this assumption (Johnson and Field, 1993).

Following this, MANOVA using Wilks' lambda was performed for a general comparison of the 15 performance indicators across the five leagues while controlling for the season of play as a blocking factor. As our follow-up analysis, we then used two-way analysis of variance (ANOVA) with Bonferroni correction with seasons as the blocking variable to look for differences in each of the performance indicators across the leagues. Tukey's HSD procedure was applied as part of the post-hoc analysis to account for multiple comparisons. Performance indicators were standardised, and profile analysis was also conducted to analyze patterns across the five leagues. Statistical significance was set at $p < 0.05$.

The statistical program R (version 3.5.1) was used to conduct analyses in this study. The core package 'stats' provided several inbuilt functions that generated univariate plots for checking of assumptions, as well as allowing for the implementation of the MANOVA, ANOVA and Tukey's HSD tests. For multivariate normality assessment, the package 'MVN' (Korkmaz, et al., 2014) was used to construct Q-Q plots with Mahalanobis distances. The Box's M test was implemented using the 'biotools' package (da Silva and da Silva, 2017) while Levene's tests were carried out using a combination of user-defined functions and the package 'car' (Fox et al., 2012). Finally, the implementation of the package 'profileR' (Desjardins and Bulut, 2020) enabled the testing of profile hypotheses and the construction of profile plots.

3. RESULTS

3.1 ANALYSIS OF VARIANCE

Table 2 summarised the multivariate analysis of variance results. The MANOVA suggested that there was a significant difference in the performance indicators across the top five European leagues, while controlling for the season of play (Wilks' $\Lambda = 0.095$, $p < 0.001$). The blocking factor (Season) also had a significant effect (Wilks' $\Lambda = 0.076$, $p < 0.001$), indicating that performance indicators varied by season.

Table 3 summarised the analysis of variance results. In identifying which of the performance indicators were subject to these differences, the ANOVA suggested significant differences across the five leagues for each of the attributes ($p < 0.001$) were present, except for the 'Possession' attribute ($p = 0.586$).

Table 2: MANOVA summary

	Degrees of freedom	**Wilks' Λ**	**F-statistic**	**Numerator degrees of freedom**	**Denominator degrees of freedom**	**p-value**
League	4	0.095	41.661	60	3023.5	< 0.001
Season	8	0.076	20.120	120	5522.8	< 0.001

Table 3: ANOVA summary

Performance indicator	Source of variation	F-statistic	p-value
Offsides	League	29.160	< 0.001
	Season	20.34	< 0.001
Shots	League	15.793	< 0.001
	Season	3.481	< 0.001
Shots on Target	League	5.500	< 0.001
	Season	1.461	0.168
Goals Scored	League	4.614	0.001
	Season	0.461	0.884
Dribbles	League	32.260	< 0.001
	Season	16.36	< 0.001
Goals Conceded	League	7.372	< 0.001
	Season	0.741	0.655
Shots Conceded	League	11.478	< 0.001
	Season	3.031	0.002
Shots on Target Conceded	League	29.448	< 0.001
	Season	9.396	< 0.001
Interceptions	League	35.200	< 0.001
	Season	76.470	< 0.001
Tackles	League	19.030	< 0.001
	Season	41.210	< 0.001
Fouls Committed	League	188.840	< 0.001
	Season	40.780	< 0.001
Times Fouled	League	197.070	< 0.001
	Season	38.870	< 0.001
Aerial Duels Won	League	41.300	< 0.001
	Season	92.130	< 0.001
Possession	League	0.709	0.586
	Season	0.070	> 0.999
Pass Completion	League	18.459	< 0.001
	Season	6.954	< 0.001

3.2 MULTIPLE COMPARISONS

For performance indicators having significant differences across leagues, post-hoc multiple comparison tests were observed to identify which pairs of leagues presented these differences. Table 4 summarised the results of the Tukey's HSD multiple comparisons of leagues. Tukey's HSD test was chosen since it is a more balanced and conservative approach compared to other post-hoc tests. Tukey's test provides a better balance between controlling Type I errors and maintaining the power to detect significant differences. Pairwise league comparisons for the 15 performance indicators were categorised into 'mild' for up to 5 significant differences, 'moderate' for 6-9 significant differences, and 'severe' for 10 or more significant differences. Table 5 summarised the pairwise comparisons of the leagues based on these categories.

Ligue 1 vs Bundesliga displayed differences for 12 of the 15 performance indicators in this study, highlighting contrasts for offensive, defensive and physical profiles. This was followed by Ligue 1 vs Premier League and La Liga vs Premier League with differences in 10 of the performance indicators. Distinctions in offensive, defensive and physical profiles were prominent between Ligue 1 vs Premier League, while these variations were present in offensive and physical profiles for La Liga vs Premier League. La Liga vs Bundesliga presented the least number of differences with 4 out of 15 performance indicators, primarily exhibiting contrasts in physical profiles. Serie A vs Bundesliga also displayed contrasts in physical profiles, while Ligue 1 vs La Liga had variations in defensive profiles. Both comparisons were significantly different for 5 performance indicators.

3.3 PROFILE ANALYSIS

Analysis revealed that profiles across the five leagues were not parallel (Wilks' $\Lambda = 0.175$, $p < 0.001$). Profile plots have been presented in Figures 1-4. It was observed that the Bundesliga had significantly higher averages than Ligue 1 in offensive, defensive and physical profiles. The Premier League averaged more aerial duels than Ligue 1, La Liga, and Serie A but a lower number of tackles and fouls committed. The Premier League led with average shots per game, with only the Bundesliga having better offensive attributes.

The profile plots and post-hoc pairwise comparisons were suggestive of overall trends among the five leagues. The Bundesliga appeared to be leading in terms of average dribbles completed per game, shots on target, goals scored, and offsides, thus displaying the highest offensive profile. In contrast, Ligue 1 averaged the least shots, shots on target, goals scored; and the second fewest offsides and dribbles completed per game.

For the defensive indicators, the Bundesliga conceded significantly more goals per game on average than the Serie A and League 1, and averaged the second highest number of shots on target conceded per game, with Ligue 1 conceding the fewest. The Premier League conceded the highest number of shots and shots on target on average but ranked with significantly lower interceptions than La Liga, the Bundesliga and Ligue 1.

The Bundesliga profile plot of 'physical' indicators was above other leagues with significantly higher averages than three of the remaining four leagues for all such variables. The Premier League averaged lower in every attribute apart from aerial duels won per game. Ligue 1 and La Liga shared similar characteristics in their physical profiles.

There were no significant differences among leagues regarding ball possession. Furthermore, it was the Serie A that boasted the highest average for successful passes per game, followed by the Premier League, Ligue 1, Bundesliga, and La Liga, respectively.

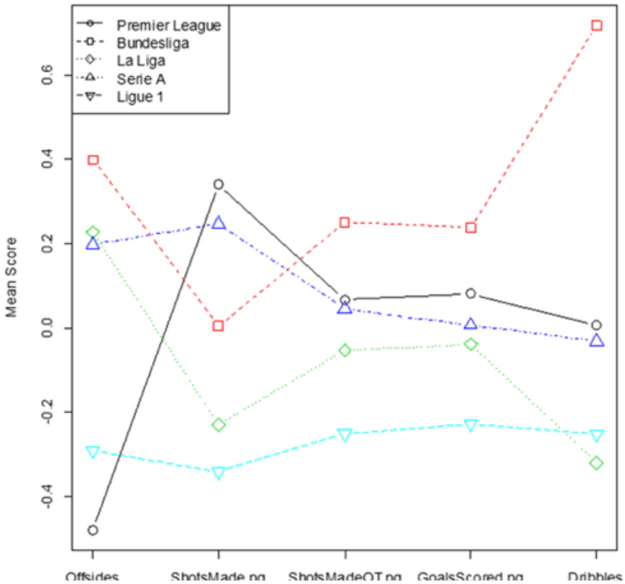

Table 4: Tukey's HSD multiple comparison summary

Profile	Performance indicators	Bundesliga - Premier League	La Liga - Premier League	Serie A - Premier League	Ligue 1 - Premier League	La Liga - Bundesliga	Serie A - Bundesliga	Ligue 1 - Bundesliga	Serie A - La Liga	Ligue 1 - La Liga	Ligue 1 - Serie A
Offensive	Offsides	*	*	*				*		*	*
	Shots	*	*		*			*	*		*
	Shots on Target				*			*			*
	Goals Scored				*			*			
	Dribbles	*	*			*		*	*		
Defensive	Goals Conceded				*		*	*		*	
	Shots Conceded				*			*	*		*
	Shots on Target Conceded	*	*	*	*			*		*	
	Interceptions	*	*		*		*		*	*	
Physical	Tackles	*	*	*			*	*		*	
	Fouls Committed	*	*	*	*	*		*	*		*
	Times Fouled	*	*	*	*	*		*	*		*
	Aerial Duels Won		*	*	*	*	*	*	*		*
Control	Possession		*	*			*		*		*
	Pass Completion										
# Significant pairwise comparisons		**8**	**10**	**7**	**10**	**4**	**5**	**12**	**8**	**5**	**8**

Table 5: Differences in pairwise comparisons of leagues

Mild	Moderate	Severe
La Liga vs Bundesliga Serie A vs Bundesliga Ligue 1 vs La Liga	Bundesliga vs Premier League Serie A vs Premier League Serie A vs La Liga Ligue 1 vs Serie A	La Liga vs Premier League Ligue 1 vs Premier League Ligue 1 vs Bundesliga

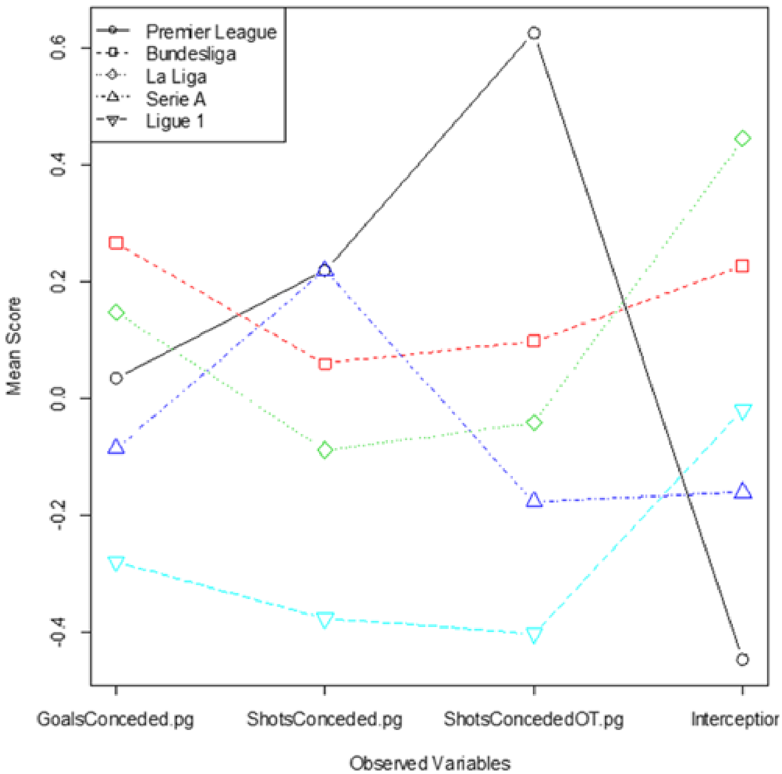

Figure 2: Profile plot of defensive performance indicators

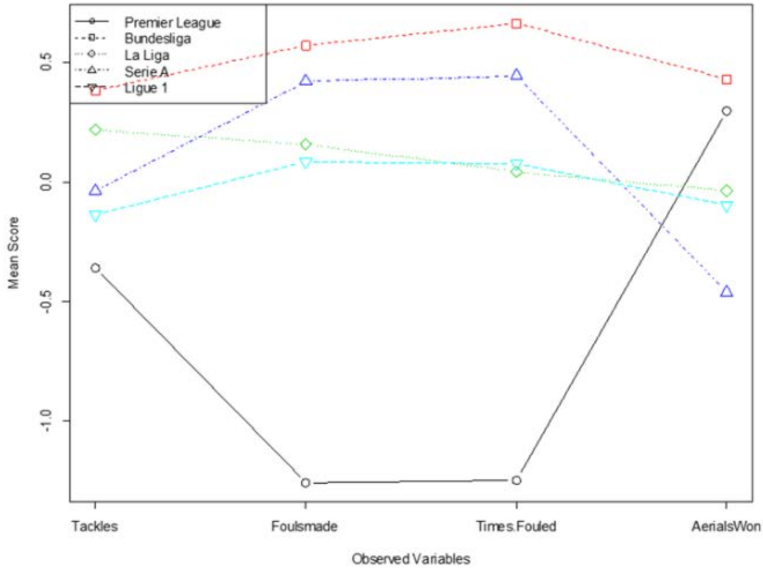

Figure 3: Profile plot of physical performance indicators

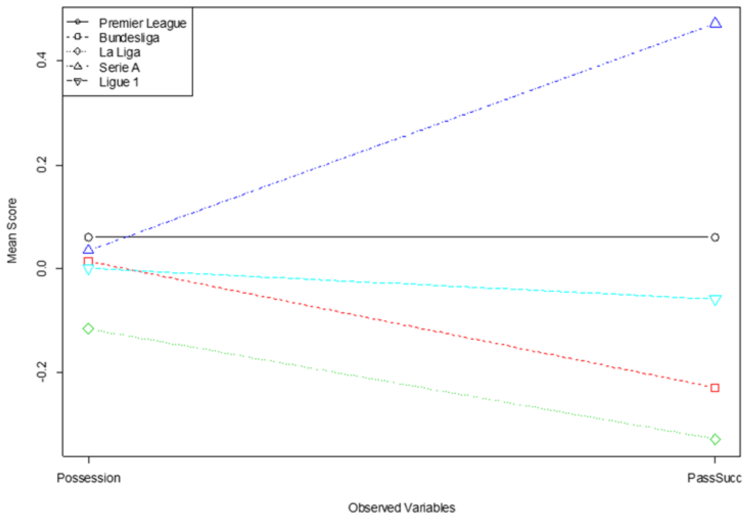

Figure 4: Profile plot of control performance indicators

4. DISCUSSION

In this research, our aim was to perform a comparative study using some of the key performance indicators across the top five European football leagues. The dataset for our analysis included 15 variables accounting for aggregated individual and team performances over nine seasons of league football which took place between 2009 and 2018. In the first step, a general comparison was performed to find attributes that differed across leagues. Much of the previous research explored similar performance indicators in isolation and only investigated leagues in a single country (Castellano and Casamichana, 2015; Chmura et al., 2022; Hadji and Benosmane, 2022; Ruan et al., 2022; Yang et al., 2018) or compared national teams and leagues from different continents (Elyakim et al., 2020; Kubayi and Toriola, 2020; Velasco and Castán, 2022). This study showed similarities but also some contrasts with prior research due to the different methods of analysis and the data sources used. Therefore, this added knowledge relevant to understanding the performance of teams from the top five European leagues.

This analysis revealed that the Bundesliga led the top five European leagues on average in the offensive profile for dribbles completed per game, shots on target, goals scored and offsides per match; and averaged higher attributes in the physical profile over three of the remaining four leagues (except for Serie A). This corroborated with the findings of Chmura et al. (2022) that the German league required high physical match demands; and Vialli, and Marcotti (2006) and Wilson (2013) who alluded to the Bundesliga having a high tempo and face-paced speed of play (Chmura et al., 2022; Vialli and Marcotti, 2007; Wilson, 2013).

Our study contrasted the findings of Vales-Vázquez et al. (2017) who observed La Liga as having the best overall competitive profile (Vales-Vázquez, et al., 2017). Our performance metrics saw La Liga's position fluctuate in each of the four attribute profiles. Other authors reported that La Liga and the Premier League performed comparable match actions, having no considerable differences across the observed performance variables (Velasco and Castán, 2022). Our findings contradicted this notion since La Liga and the Premier league displayed significant differences in 10 of the 15 performance indicators recorded. This represented contrasts in offensive and physical profiles between the two leagues;

with La Liga having higher averages in physical attributes but the Premier League displayed higher offensive metrics. Although both studies used aggregated data for each of the selected performance indicators, we collected data across nine years of league football and conducted analyses which controlled for the variations due to different seasons of play, while Velasco and Castán (2022) used only one season of match data.

Authors have suggested that the differentiation in playing profiles across leagues could be due to a combination of cultural, historical, social, technical, tactical and physical reasons (Galeano, 2003; Mitrotasios et al., 2019; Hugo Sarmento et al., 2013). As such, Spanish football has been identifiable with possession-based play, more control of the ball and less physicality (Gonzalez-Rodenas, et al., 2015). Our findings presented no significant differences in possession across the five leagues which suggested that aspects of playing styles of leagues seem to be equalizing. This has been notably highlighted in the research presented by García-Aliaga et al. (2022).

The Premier League averaged more aerial duels won per game, as well as shots per game and dribbles but reported lower tackles and fouls per game. This supported the previous characterisation of the League as being direct and fast paced but contrasted the notion of constant and hard defending (Liu et al., 2016; Sarmento et al., 2011; Wilson, 2013). Sarmento et al. (2013) associated the Serie A with an emphasis on defensive organisation. Our study provided some support to this claim as we observed Serie A as having the second lowest average for goals conceded per game and shots on target conceded per game, with Ligue 1 having the best defensive profile.

To the best of our knowledge, this is the first study to directly compare match performance indicators across the top five football leagues in Europe. The results of this study can provide important knowledge to footballing institutions in understanding how to approach games against teams from other leagues in continental competitions, as according to Vales-Vázquez et al. (2017), this was key to achieving a competitive advantage.

4.1 LIMITATIONS

Our comparison was restricted to association league football tournaments including only first division teams in the respective domestic leagues. There exists a multi-level hierarchical pyramid of footballing divisions in each of

England, Germany, Spain, Italy and France with up to five professional divisions in some cases. The availability of reliable match data for lower league tournaments was of paramount concern and hence the study was limited to the top tier of these professional football associations only.

In addition, the analyses used data for only nine league seasons while these major European leagues have been in existence for many decades. This may give a limited comparative overall view of football in these countries and, therefore, if taken on their own, findings should only be conservatively generalized to within these leagues for a contained timeframe. It should be noted that there are stark differences in resources between clubs within a first division league and this may be translated into variation among replicates within each treatment-block ('League-Season') combination.

5. CONCLUSION

The analyses conducted in this comparative study of European football leagues found significant differences in football played across England, Germany, Spain, Italy and France based on match attributes. There were significant differences observed in attribute profiles between Ligue 1 and each of the German and English top divisions, as well as between Spain's La Liga and the Premier League. It was also notable that the average time spent in possession per match did not differ across the leagues. Overall, the methods yielded results that may find utility in further comparative football research as well as in peripheral studies which may include viewership and market demands. Understanding the differences in attribute profiles and match performance indicators across leagues may also serve as a basis for insights into the contrasting performances of teams from the different leagues in European club competitions.

5.1 SCOPE FOR FUTURE RESEARCH

Teams in lower league divisions will not necessarily share characteristics of their first division counterparts, having to employ strategic and tactical game plans that are aimed to achieve different objectives for the league season. Their attribute values may tend to reflect this and influence the offensive, defensive and physical image of the leagues in a particular country. To this end, including the comparison of the lower tiers of European association football would serve to give a more holistic view of the differences among nations subject to the availability of analogous datasets.

Furthermore, performing similar analyses on spatial and temporal match aggregates should be considered. It is possible that analyses of more informative match variables may result in the attenuation of stylistic differences among the leagues. The use of designs in the multivariate decomposition of variances to account for different or even more than one blocking factor can also be pursued. The MANOVA model can be made to account for, and reduce variability across leagues due to the disparity in clubs' resources by potentially using net revenue or expenditure by season as another blocking factor. The effect of referee bias on physical-type variables investigated can be considered in subsequent research, and non-parametric multivariate techniques such as permutation multivariate analysis of variance (Anderson, 2001, 2014) can be utilized in the future to ascertain differences among leagues. Cluster analysis and principal component analysis (PCA) can also be considered for detecting variable groups, while also creating and evaluating composite performance indicators (Oliva-Lozano, et al., 2024). This study serves as a first foray into comparatively analyzing match performance indicators in European football and provides a solid methodological framework upon which to build.

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