Original Article

Trends of the fast game in men's EHF European handball championships

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ABSTRACT

The aim of this study was to measure the effect of fast play on a handball team's performance by assessing ranking in three European Men's Championships (Euro 2018, 2020, 2022) as a dependent variable. The independent variables indicating fast play were the ranking of the team in the tournament, total fast breaks (TFB) per match played, successful fast breaks (SFB) per match played, total fast throw-offs (TFTO) per match played, and successful fast throw-offs (SFTO) per match played. Analyses for each tournament included descriptive statistics, correlation analyses between team ranking and TFB, SFB, TFTO, and SFTO per match played, and hierarchical regression analyses to identify whether the independent variables could predict team ranking in a tournament. TFB and SFB per match played were statistically significant predictors of tournament placement for all three European tournaments examined. Euro 2018 scored the highest team ranking prediction for both TFB and SFB. However, TFTO and SFTO per match played were not significant predictors of tournament placement in all three tournaments. In conclusion, the TFB and SFB per match played were statistically significant predictors of tournament placement.

Keywords: Performance analysis of sport, Fast breaks, Fast throw-offs, Team ranking, High-performance level, Handball.

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INTRODUCTION

Team sports assume their current form based on trends that appear over the years (Pfeiffer & Perl, 2006). The scientific documentation of the modern form of a team sport is mainly shaped by match analysis and the determination of the prevailing trends (Meletakos et al., 2020; Hatzimanouil et al., 2017). Game analysis is a distinct field of sports performance analysis, referring to the recording and subsequent analysis of actions and behaviours during a game, by individual players, teams or both (Williams et al., 2005). The aim of game analysis is to identify reliable performance indicators to help coaches improve their players' and/or team's performance, allowing them to adjust their training accordingly (Prieto et al., 2015). McGarry and colleagues (2002) note that coaches need to know those critical performance characteristics that will change the future behaviours of the team, based on the information gathered from previous competitions.

These models should be designed in such a way that, through specific analyses, the organization of a team's game can be formalized according to the variations and regularities formed by events during the match and according to phases of play, such as attack, defence, and transition play from defence to attack and vice versa (Garganta, 2009). The model should gather indicators that are able to describe the main events of the game, considering the relations of cooperation and opposition among players and between teams. The same author mentions that a holistic game analysis, focusing on the organization of a team's play by ascertaining not only the regularity but also the random characteristics of the moves in the game, taking offensive and defensive efficiency into account, is beneficial. Therefore, the primary objective of a tactical analysis is not a specific player' actions, taken in isolation, but the order and sequence of a play that is the result of actions during the game. Thus, when there are changes and trends, these appear during the organization of the game, arising from the characteristics of the series of actions and the successive actions (tactical elements) of the teams, from the consequences leading to different results, and finally from situations where there is a difference in the attack-defence balance, whether a goal is cored or not (Garganta, 2009).

Balagué and Torrents (2005) and Lames and Hansen (2001) point out that qualitative research methods should be included in scientific research in addition to mathematical modelling, simulation and/or modern computer techniques, in order to consistently reach the correct conclusion and apply it to sports practice. As Skoufas (2019) argues, the longitudinal analysis of national teams' matches in major competitions and tournaments over a long period of time allows the evolution and development of the sport to be monitored on the world map.

Over the years, handball, like other similar team sports, has assumed a form of play that involves speed and fast play (Przednowek et al., 2019; Michalsik, 2018). Przednowek and colleagues (2019) were led to this conclusion after finding that in major national team competitions, efficiency in fast play (counterattacks and fast throw-offs) improved due to an increase in active playing time in attack and an increase in number of attacks. Ferrari et al. (2020) report that top winning teams perform better than losing teams in the fast game. Rogulj et al. (2004), Rogulj et al. (2011) and Rogulj and Srhoj (2009) also concluded that those teams whose plan was to make constant brief attacks against loose defences, and/or short-term positional attacks (under 25 seconds), were more likely to be successful. The changes in the regulations over time (fast throw-off, etc.) have also contributed to the adaptation of handball to the fast game (Michalsik, 2018).

Ferrari and colleagues (2020) report that research on handball match analysis is rare and relatively undeveloped. Moreover, it does not refer to all factors of the game but only to the frequency and effectiveness of shots, game outcome, time-outs, and analysis focused on home advantage. Hatzimanouil et al. (2019)

argue that the outcome of a game can be better understood and interpreted by focusing on a form of game analysis that reveals the relationships between the factors that ultimately result in winning.

The intention of the International Handball Federation (IHF) and the European Handball Federation (EHF) is to create faster playing conditions, with the aim of making handball a more attractive, exciting sport. This led to a change in the rules from July 1st, 2022. More specifically, the throw-off is not executed from the centre line but inside the specific centre circle. During the throw-off, the player cannot bounce or jump but is allowed an unlimited number of steps within the centre circle. The opposing team must stay outside the throw-off circle and can only intercept the ball when it has crossed the circle line. The defenders are only allowed to enter the circle after the first complete pass (International Handball Federation, [IX Rules of the Game a) Indoor Handball], 2022).

The work of the coach and the performance of the team can be greatly affected by changes in the rules. Some changes may be advantageous for some teams, but others are not. The tasks of the coach and/or the team must be adapted to the new rules with the aim of reducing the negative impact or taking advantage of the changes (Marczinka & Gál, 2018). Under the new IHF rules, the fast throw-off becomes faster, and therefore so does the whole game.

The aim of the present study is to analyse the trend of the fast game in the final tournaments of the EHF European Men's Handball Championships (Euro 2018, 2020, and 2022). The specific aim was to evaluate the fast play of high-level teams and to discover which of the measured independent variables, consisting of fast play tactics (fast breaks and fast throw-offs), could predict the final ranking of a team in these tournaments. The results of the present study will also create fast game data for comparison with data from future tournaments under the new rules.

MATERIAL AND METHODS

Participants and Measures

Statistical data were collected on the teams participating in the final tournament of the EHF Men's Euro 2022 which took place from 13 to 30 January 2022 in Hungary and Slovakia, the final tournament of the EHF Men's Euro 2020 which took place from 9 to 26 January 2020 in Austria, Norway, and Sweden, and the final tournament of the EHF Men's Euro 2018 which took place from 12 to 28 January 2018 in Croatia. Free access to these statistical data is provided on the official EHF site.

Procedures

To measure the effect of fast play on a handball team's performance, the present study utilized position placement in three tournaments (Euro 2018, 2020, 2022) as a dependent variable indicating team performance, and fast breaks as well as fast throw-offs (in the same tournaments) as independent variables indicating fast play. For all the independent variables the researchers studied the effect of total efforts (whether successful or unsuccessful) and of strictly successful efforts separately, in order to determine whether it was the overall play style or its success which was better able to predict the final placement of a team in a tournament. As the number and composition of the teams participating in each tournament differed, the analysis was performed for each tournament separately. Moreover, since each team in the tournament played a different number of matches, all the variables were averaged per match played. The variables ultimately included in the analysis were the ranking of the team in the tournament, total fast breaks (TFB) per match played, successful fast breaks (SFB) per match played, total fast throw-offs (TFTO) per match played, and successful fast throw-offs (SFTO) per match played.

Analysis

The set of analyses for each tournament included calculation of descriptive statistics (mean, standard deviation, and variance) for all variables, one-sample Kolmogorov-Smirnov tests to identify whether the variable distribution conformed to the Gaussian standard, correlation analyses between team ranking and TFB, SFB, TFTO and SFTO per match played in order to identify potential relationships between variables, and finally hierarchical regression analyses to identify whether the independent variables could predict team ranking in a tournament. The stepwise method was used, in which where the model starts with zero predictors. The strongest predictor variable is then inserted in the model, followed by new predictors inserted one by one until none of the excluded predictors is thought to contribute significantly to the model. The probability of F-to-enter was .05.

RESULTS

Euro 2018

Sixteen teams participated in Euro 2018. The average for total fast breaks (TFB) per match played was 4.93 (SD: 1.54), for successful fast breaks (SFB) per match played 3.55 (SD: 1.18), for total fast throw-offs (TFTO) per match played 0.82 (SD: 0.56) and for successful fast throw-offs (SFTO) per match played 0.57 (SD: 0.46) (Table 1).

Table 1. Euro 2018. Descriptive statistics.

	Mean	Standard Deviation	Variance	One-Sample Kolmogorov-Smirnov Test Statistic	Exact Sig. (2-tailed)
Ranking of teams in the tournament	-	-	-	0.081	1.000
Total fast breaks (TFB) per match played	4.93	1.54	2.38	0.132	.911
Successful fast breaks (SFB) per match played	3.55	1.18	1.40	0.197	.501
Total fast throw-offs (TFTO) per match played	0.82	0.56	0.31	0.160	.750
Successful fast throw-offs (SFTO) per match played	0.57	0.46	0.21	0.127	.928

The distribution for all variables can be considered normal since the one-sample Kolmogorov-Smirnov test produced no statistically significant results (Table 1). Therefore, Pearson correlation analysis was selected instead of a non-parametric alternative.

There was a strong negative Pearson correlation (r (16) = -0.738) between tournament ranking and total fast breaks (TFB) per match played; the correlation was statistically significant at the .001 level (p = .001). This correlation indicates that teams with higher TFB per match played tended to have a much higher tournament ranking than those with lower. The correlation between tournament ranking and total fast throw-offs (TFTO) per match played (r (16) = 0.100, p = .713) was not statistically significant. An additional strong negative Pearson correlation (r (16) = -0.784) was found between tournament ranking and successful fast breaks (SFB) per match played; the correlation was statistically significant at the .001 level (p < .001). This correlation indicates that teams with higher SFB per match played tended to have a much higher tournament ranking than those with lower (Table 1). The correlation between tournament ranking and successful fast throw-offs (SFTO) per match played (r (16) = 0.114, p = .673) was not statistically significant.

Hierarchical linear regression

DV: Tournament Ranking IVs: TFB, TFTO per match played

In the first hierarchical linear regression for Euro 2018, tournament ranking was the dependent variable (DV) and TFB and TFTO per match played were the potential independent variables (IV). The first predictor inserted in the model (Model A1) was TFB per match played (Beta = -2,275, p = .001). There was a statistically significant regression (F (1, 14) = 16.721, p = .001) and R^2 was .544, meaning that this predictor explained 54.4 % of the IV variance. The inclusion of TFTO did not contribute significantly to the model (Beta: 0.097, p = .608), so Model A1 is the outcome of the first hierarchical regression analysis. Beta, Standardized Beta, t, and significance for the predictor as well as the constant are presented in Table 2.

Table 2. Euro 2018. Stepwise hierarchical regression analysis.

DV Tournament Ranking with Potential IVs TFB & TFTO per match played						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
A1	(Constant)	19.707	2.864		6.881	.000
	Total fast breaks (TFB) per match played	-2.275	0.556	-0.738	-4.089	.001
DV Tournament Ranking with Potential IVs SFB & SFTO per match played						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
B1	(Constant)	19.680	2.487		7.913	.000
	Successful fast breaks (SFB) per match played	-3.150	0.667	-0.784	-4.724	.000

The Durbin-Watson statistic (d = 1.510) was within the range 1<d<3 that Field (2009) considers normal, with negative autocorrelation. The histogram of standardized residuals showed an approximately normal distribution. The Normal P-P plot of regression standardized residuals revealed a strong linear relationship between the DV and the IV, while the scatterplot of standardized residuals and regression standardized predicted values revealed no dispersion pattern. Thus, the assumptions of variance homogeneity were verified, as was the linearity of the data and the normal distribution of the residuals (Pallant, 2020).

The resulting equation for Model A1 is: Tournament Ranking = 19.707 – 2.275 * TFB. This means that the first Hierarchical Linear Regression analysis shows that total fast breaks (TFB) per match played is a statistically significant predictor of Tournament Ranking, responsible for 54.4% of the latter's variance.

DV: Tournament Ranking IVs: SFB, SFTO per match played

In the second hierarchical linear regression for Euro 2018, tournament ranking was the dependent variable and SFB and SFTO per match played were the potential independent variables. The first predictor inserted in the model (Model B1) was SFB per match played (Beta = -3.150, p < .001). There was a statistically significant regression (F (1, 14) = 22.316, p < .001) and R^2 was .614, meaning that the predictor explained 61.4 % of the IV variance. The inclusion of SFTO did not contribute significantly to the model (Beta: 0.026, p

= .883), so Model B1 is the outcome of the second hierarchical regression analysis. Beta, Standardized Beta, t, and significance for the predictor as well as the constant are presented in Table 2.

The Durbin-Watson statistic (d = 1.258) was within the range 1<d<3 that Field (2009) considers normal, with negative autocorrelation. The histogram of standardized residuals showed an approximately normal distribution. The Normal P-P plot of regression standardized residuals revealed a strong linear relationship between the DV and the IV, while the scatterplot of standardized residuals and regression standardized predicted values revealed no dispersion pattern. Thus, the assumptions of variance homogeneity were verified, as was the linearity of the data and the normal distribution of the residuals (Pallant, 2020).

The resulting equation for Model B1 is: Tournament Ranking = 19.680 – 3.150 * SFB. This means that the second Hierarchical Linear Regression analysis shows that successful fast breaks (SFB) per match played is a statistically significant predictor of Tournament Ranking, responsible for 61.4% of the latter's variance.

Euro 2020

Twenty-four teams participated in Euro 2020. The average for total fast breaks (TFB) per match played was 3.75 (SD: 1.35), for successful fast breaks (SFB) per match played 3.00 (SD: 1.30), for total fast throw-offs (TFTO) per match played 0.39 (SD: 0.39) and for successful fast throw-offs (SFTO) per match played 0.34 (SD: 0.39) (Table 3).

Table 3. Euro 2020. Descriptive statistics.

	Mean	Standard Deviation	Variance	One-Sample Kolmogorov-Smirnov Test Statistic	Exact Sig. (2-tailed)
Ranking of teams in the tournament	-	-	-	0.091	.978
Total fast breaks (TFB) per match played	3.75	1.35	1.83	0.126	.795
Successful fast breaks (SFB) per match played	3.00	1.30	1.70	0.111	.897
Total fast throw-offs (TFTO) per match played	0.39	0.39	0.15	0.161	.515
Successful fast throw-offs (SFTO) per match played	0.34	0.39	0.15	0.190	.312

The distribution for all variables can be considered normal since the one-sample Kolmogorov-Smirnov test produced no statistically significant results (Table 3). Therefore, Pearson correlation analysis was selected instead of a non-parametric alternative. There was a medium strength negative Pearson correlation (r (24) = -0.509) between tournament ranking and total fast breaks (TFB) per match played, and the correlation was statistically significant at the .05 level (p = .011). This correlation indicates that teams with higher TFB per match played tended to rank higher in the tournament than those with lower. The correlation between tournament ranking and total fast throw-offs (TFTO) per match played (r (24) = 0.019, p = .930) was not statistically significant.

A medium strength negative Pearson correlation (r (24) = -0.559) was found between tournament ranking and successful fast breaks (SFB) per match played; the correlation was statistically significant at the .01 level (p = .004). This correlation indicates that teams with higher SFB per match played tended to have a higher tournament ranking than those with lower (Table 3). The correlation between tournament ranking and successful fast throw-offs (SFTO) per match played (r (24) = 0.015, p = .944) was not statistically significant.

Hierarchical linear regression

DV: Tournament Ranking IVs: TFB, TFTO per match played

In the first hierarchical linear regression for Euro 2020, tournament ranking was the dependent variable and TFB and TFTO per match played were the potential independent variables. The first predictor inserted in Model C1 was TFB per match played (Beta = -2,677, p = .011). There was a statistically significant regression (F (1, 22) = 7.692, p = .011) and R^2 was .259, meaning that the predictor explained 25.9 % of the IV variance. The inclusion of TFTO did not contribute significantly to the model (Beta: -0.79, p = .682), so Model C1 is the outcome of the first hierarchical regression analysis. Beta, Standardized Beta, t, and significance for the predictor as well as the constant are presented in Table 4.

Table 4. Euro 2020. Stepwise hierarchical regression analysis.

DV Tournament Ranking with Potential IVs TFB & TFTO per match played						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
C1	(Constant)	22.488	3.836		5.863	.000
	Total fast breaks (TFB) per match played	-2.677	0.965	-0.509	-2.774	.011
DV for Tournament Ranking with Potential IVs SFB & SFTO per match played						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
D1	(Constant)	21.608	3.142		6.878	.000
	Successful fast breaks (SFB) per match played	-3.054	0.965	-0.559	-3.166	.004

The Durbin-Watson statistic (d = 2.385) was within the range $1<d<3$ that Field (2009) considers normal, with negative autocorrelation. The histogram of standardized residuals showed an approximately normal distribution. The Normal P-P plot of regression standardized residuals revealed a strong linear relationship between the DV and the IV, while the scatterplot of standardized residuals and regression standardized predicted values revealed no dispersion pattern. Thus, the assumptions of variance homogeneity were verified, as was the linearity of the data and the normal distribution of the residuals (Pallant, 2020).

The resulting equation for Model C1 is: Tournament Ranking = 22.488 – 2.677 * TFB. This means that the first Hierarchical Linear Regression analysis shows that total fast breaks (TFB) per match played is a statistically significant predictor of Tournament Ranking, responsible for 25.9% of the latter's variance.

DV: Tournament Ranking IVs: SFB, SFTO per match played

In the second hierarchical linear regression for Euro 2020, tournament ranking was the dependent variable and SFB and SFTO per match played were the potential independent variables. The first predictor inserted in Model D1 was SFB per match played (Beta = -3.054, p = .004). There was a statistically significant regression ($F_{(1, 22)}$ = 10.021, p = .004) and R^2 was .313, meaning that the predictor explained 31.3% of the IV variance. The inclusion of SFTO did not contribute significantly to the model (Beta: -0.090, p = .629), so model D1 is the outcome of the second hierarchical regression analysis. Beta, Standardized Beta, t, and significance for the predictor as well as the constant are presented in Table 4.

The Durbin-Watson statistic (d = 2.401) was within the range 1<d<3 that Field (2009) considers normal, with negative autocorrelation. The histogram of standardized residuals showed an approximately normal distribution. The Normal P-P plot of regression standardized residuals revealed a strong linear relationship between the DV and the IV, while the scatterplot of standardized residuals and regression standardized predicted values revealed no dispersion pattern. Thus, the assumptions of variance homogeneity were verified, as was the linearity of the data and the normal distribution of the residuals (Pallant, 2020).

The resulting equation for Model D1 is: Tournament Ranking = 21.608 – 3.054 * SFB. This means that the first Hierarchical Linear Regression analysis shows that successful fast breaks (SFB) per match played is a statistically significant predictor of Tournament Ranking, responsible for 31.3% of the latter's variance.

Euro 2022

Twenty-four teams participated in Euro 2020. The average for total fast breaks (TFB) per match played was 3.80 (SD: 1.50), for successful fast breaks (SFB) per match played 2.99 (SD: 1.20), for total fast throw-offs (TFTO) per match played 0.31 (SD: 0.35) and for successful fast throw-offs (SFTO) per match played 0.24 (SD: 0.34) (Table 5).

Table 5. Euro 2022. Descriptive statistics.

	Mean	Standard Deviation	Variance	One-Sample Kolmogorov-Smirnov Test Statistic	Exact Sig. (2-tailed)
Ranking of teams in the tournament	-	-	-	0.073	.998
Total fast breaks (TFB) per match played	3.80	1.50	2.26	0.091	.979
Successful fast breaks (SFB) per match played	2.99	1.20	1.43	0.128	.780
Total fast throw-offs (TFTO) per match played	0.31	0.35	0.13	0.224	.154
Successful fast throw-offs (SFTO) per match played	0.24	0.34	0.12	0.260	.064

The distribution for all variables can be considered normal since the one-sample Kolmogorov-Smirnov test produced no statistically significant results. Thus, Pearson correlation analysis was selected instead of a non-parametric alternative.

There was a medium strength negative Pearson correlation (r (24) = -0.576) between tournament ranking and total fast breaks (TFB) per match played; the correlation was statistically significant at the .01 level (*p* = .003) (Table 5). This correlation indicates that teams with higher TFB per match played tended to have a higher tournament ranking than those with lower. The correlation between tournament ranking and total fast throw-offs (TFTO) per match played (r (24) = -0.10, *p* = .626) was not statistically significant (Table 5). A medium strength positive Pearson correlation (r (24) = -0.407) was identified between TFB per match played and TFTO per match played; the correlation was significant at the .05 level (*p* = .049) (Table 5). This correlation indicates that teams with higher TFB per match played also displayed higher TFTO per match played.

There was a medium strength negative Pearson correlation (r (24) = -0.519) between tournament ranking and successful fast breaks (SFB) per match played. This correlation was statistically significant at the .01 level (p = .009). This correlation indicates that teams with higher SFB per match played tended to have a higher tournament ranking than those with lower (Table 5). The correlation between tournament ranking and successful fast throw-offs (SFTO) per match played (r (24) = -0.081, p = .706) was not statistically significant (Table 5).

Hierarchical linear regression

DV: Tournament Ranking IVs: TFB, TFTO per match played

In the first hierarchical linear regression for Euro 2022, tournament ranking was the dependent variable and TFB and TFTO per match played were the potential independent variables. The first predictor inserted in Model E1 was TFB per match played (Beta = -2,705, p = .003). There was a statistically significant regression ($F_{(1, 22)}$ = 10.905, p = .003) and R^2 was .331, meaning that the predictor explained 33.1% of the IV variance. The inclusion of TFTO did not contribute significantly to the model (Beta: 0.155, p = .429), so Model E1 is the outcome of the first hierarchical regression analysis. Beta, Standardized Beta, t, and significance for the predictor as well as the constant are presented in Table 6.

Table 6. Euro 2022. Stepwise hierarchical regression analysis.

DV Tournament Ranking with Potential IVs TFB & TFTO per match played						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
E1	(Constant)	22.770	3.336		6.826	.000
	Total fast breaks (TFB) per match played	-2.705	0.819	-0.576	-3.302	.003
DV Tournament Ranking with Potential IVs SFB & SFTO per match played						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
F1	(Constant)	21.676	3.462		6.261	.000
	Successful fast breaks (SFB) per match played	-3.068	1.078	-0.519	-2.846	.009

The Durbin-Watson statistic (d = 1.619) was within the range $1<d<3$ that Field (2009) considers normal, with negative autocorrelation. The histogram of standardized residuals showed an approximately normal distribution. The Normal P-P plot of regression standardized residuals revealed a strong linear relationship between the DV and the IV, while the scatterplot of standardized residuals and regression standardized predicted values revealed no dispersion pattern. Thus, the assumptions of variance homogeneity were verified, as was the linearity of the data and the normal distribution of the residuals (Pallant, 2020).

The resulting equation for Model E1 is: Tournament Ranking = 22.770 – 2.705 * TFB. This means that the first Hierarchical Linear Regression analysis shows that total fast breaks (TFB) per match played is a statistically significant predictor of Tournament Ranking, responsible for 33.1% of the latter's variance.

DV: Tournament Ranking IVs: SFB, SFTO per match played

In the second hierarchical linear regression for Euro 2022, tournament ranking was the dependent variable and SFB and SFTO per match played were the potential independent variables. The first predictor inserted in the model (Model F1) was SFB per match played (Beta = -3.068, *p* = .009). There was a statistically significant regression ($F_{(1, 22)} = 8.101$, *p* = .009) and R^2 was .269, meaning that the predictor explained 26.9% of the IV variance. The inclusion of SFTO did not contribute significantly to the model (Beta: 0.077, *p* = .695), so Model F1 is the outcome of the second hierarchical regression analysis. Beta, Standardized Beta, t, and significance for the predictor as well as the constant are presented in Table 6.

The Durbin-Watson statistic (d = 1.756) was within the range 1<d<3 that Field (2009) considers normal, with negative autocorrelation. The histogram of standardized residuals showed an approximately normal distribution. The Normal P-P plot of regression standardized residuals revealed a strong linear relationship between the DV and the IV, while the scatterplot of standardized residuals and regression standardized predicted values revealed no dispersion pattern. Thus, the assumptions of variance homogeneity were verified, as was the linearity of the data and the normal distribution of the residuals (Pallant, 2020).

The resulting equation for Model F1 is: Tournament Ranking = 21.676 – 3.068 * SFB. This means that the first Hierarchical Linear Regression analysis shows that successful fast breaks (SFB) per match played is a statistically significant predictor of Tournament Ranking, responsible for 26.9% of the latter's variance.

DISCUSSION

The results of the present study revealed that in the Euro 2018 championship the average of total fast breaks per match played was 4.93 (SD: 1.54), while that of successful fast breaks per match played was 3.55 (SD: 1.18). In Euro 2020, the average of total fast breaks (TFB) per match played was 3.75 (SD: 1.35), while that of successful fast breaks (SFB) per match played was 3.00 (SD: 1.30). Finally, in Euro 2022 the average of total fast breaks (TFB) per match played was 3.80 (SD: 1.50), while that of successful fast breaks (SFB) per match played was 2.99 (SD: 1.20). Thus, the highest average of total and successful fast breaks was found in Euro 2018.

Results similar to ours are reported by Ferrari and colleagues (2020), who found that in high-level European teams such as those analysed at the EHF Champions League for five seasons (2012/2013 to 2016/2017) and across a total of 55 games, the winning teams had an average of 5.52 ± 2.77 total fast breaks, while the losing teams had an average of 4.81 ± 2.41 TFB. The winning teams also had an average of 4.24 ± 2.38 successful fast breaks, while the losing teams had an average of 3.45 ± 1.68 SFB. However, these authors found no statistically significant differences in TFB and SFB between winning and losing teams. Slightly higher results than those of our own study were found much earlier by Leuciuc (2012), who states that in Euro 2012 the average of total fast breaks per match played was 6.42 while the successful fast breaks average per match played was 4.19. Similar results to Leuciuc, in terms of total fast breaks per match played, were found by Michalsik (2018), who reported 6.0 ± 4.2 total fast breaks for high-level male handball players in the Danish Premier Male Team Handball League.

In an earlier study, Bilge (2012) included total team statistics of the top eight men's handball teams during the 2004 and 2008 Olympics, the 2005, 2007, and 2009 World Championships, and the 2004, 2006, 2008, and 2010 European Championships. He found an average of 5.71 ± 1.78 of successful fast breaks per game for all the competitions he analysed. He also found a statistically significant difference between the 2004 Olympics and the 2010 European Championship, as well as between the 2004 and 2010 European

Championships and the 2005, 2007, and 2009 World Championships. He states that the European teams had fewer fast break opportunities when competing with each other, while they had more numerous and more effective fast breaks when playing non-European teams in the Olympics and the World Championships. The same conclusion was reached by Pokrajac (2008), who found that European teams have fewer fast break opportunities when playing against each other than when competing with non-European teams. Meletakos and colleagues (2020) also identified more fast breaks in World Championships than in European teams and European players. Analysing the four best teams in eight consecutive World Championships from 2005 to 2019, these authors found an average of 7 ± 1.5 TFB and 5.5 ± 1.1. SFB. However, they did not find statistically significant differences between the World Championships in terms of TFB and SFB.

Regarding successful fast breaks, Ilić et al. (2020) report that, analysing the 12 clubs of the Serbian Super League, they found that the most effective actions in the games were individual fast breaks and penetrations. They state that a necessary condition for a team to perform fast breaks is a strong and effective defence, and that the two top teams in the league had the best defence.

Regarding fast throw-offs in Euro 2018, our study found that the average of total fast throw-offs (TFTO) was 0.82 (SD: 0.56), while that of successful fast throw-offs (SFTO) was 0.57 (SD: 0.46). In Euro 2020 the average of TFTO per match played was 0.39 (SD: 0.39), while the average of SFTO per match played was 0.34 (SD: 0.39). In Euro 2022 the average TFTO per match played was 0.31 (SD: 0.35) while the average of SFTO per match played was 0.24 (SD: 0.34). A comparison of the three European Championships shows that on average the TFTO and SFTO per match played were highest in Euro 2018 and lowest in Euro 2022. These results agree with those of Silva and colleagues (2021), who report that previous tournaments had higher values compared to more recent ones.

Moreover, the TFTO and SFTO values of Ohnjec et al. (2015) were close to those of the present study. They found a 0.6 TFTO and a 0.28 SFTO per match average in the Women's Euro 2010. A slightly higher average of 1.0 TFTO and 0.71 SFTO per game was previously found by Acsinte and Alexandru (2014), for the U18 Romanian National team participating in the final phase of U18 Euro 2012.

As reported by Ohnjec et al. (2015), the opponent's fast retreat on defence and the predetermined defensive tactical plan, based on a high level of fitness and tactics to block the opponent's fast shooting, are probably the reasons for the small number of counterattacks after a conceded goal which start with fast throw-offs. Silva and colleagues (2021) state that fast throw-off (FTO) always depends on the planning of the opposing team's transition from attack to defence, on a possible lack of specific tactical and strategic player behaviour at this stage, or on players choosing an "*aggressive behaviour system*". Acsinte and Alexandru (2014) state that FTO is a key indicator in terms of the speed of the game and is used to surprise opponents who do not retreat correctly. Silva et al. (2021) further state that FTO is risky because it takes a high level of fitness, increases the possibility of technical errors, and makes the attacking game harder to control (compared to "*organized set attack*"). They also report that losing teams use fast throw-offs more often than winning ones, ending these attack sequences in a technical foul or throw more often, or finding themselves in situations with less chance of scoring. The winning teams, on the contrary, are more judicious in their use of the fast throw-off, often electing to use the "*set system attack*" rather than shooting; when shooting, they end these attacks with throws close to the goal, making them more effective. In disadvantageous game situations, losing teams use fast throw-offs more often, but in ties the winners are those who play the fast throw-off after a goal. In conclusion, these authors report that when using fast throw-off, winning teams are much more effective than losing ones.

In the present study, when predicting the ranking of the Euro 2018 teams in relation to total fast breaks, the inductive statistics prediction model scored 54.4% accuracy. In relation to successful fast breaks, the prediction model scored 61.4% accuracy. On the contrary, total fast throw-offs and successful throw-offs did not predict or affect team ranking.

In Euro 2020, when predicting the team ranking in relation to the total fast breaks, the prediction model scored 25.9% accuracy. In relation to successful fast breaks, the prediction model scored 31.3% accuracy. On the contrary, total fast throw-offs and successful throw-offs did not predict or affect team ranking.

Finally, in Euro 2022, when predicting the ranking of the teams in relation to the total fast breaks, the prediction model scored 33.1% accuracy. In relation to successful fast breaks, the prediction model scored 26.9% accuracy. On the contrary, total fast throw-offs and successful throw-offs did not predict or affect team ranking.

Comparing the three Euros, it appears that the highest team ranking prediction accuracy for both total fast breaks and successful fast breaks occurred in Euro 2018.

The results of the present study match those of Prieto et al. (2015), who report that fast breaks are very important in modern handball. Winning teams are more effective than losing teams when implementing effective team fast breaks, usually after a mistake by the opponents. The same authors state that for a team to be effective, team tactics must be based on executing fast attacks on disorganized defences, and that fast breaks are the most successful offensive system against the opposing team's defence. Moreover, Bajgoric and colleagues (2017), analysing the differences between more and less successful teams in the Croatian league for four seasons from 2012 to 2015, showed that there are differences between successful and unsuccessful teams both in the total fast breaks and in successful fast breaks. Gümüş and Gencoglu (2020), analysing the Men's Euro 2020, report that losing teams lost more fast break goals than winning ones.

On the contrary, Ferrari and colleagues (2020), analysing quarterfinals and Final 4, report that fast breaks are not correlated with winning rather than losing teams. De Paula et al. (2020) also state that fast breaks do not help to predict victory in balanced matches but only in unbalanced matches (with over 8 goals difference) and very unbalanced matches (over 20 goals difference). However, they were comparing Women's World Championship matches from 2007–2017, which included several weak teams. Saavedra and colleagues (2017), analysing men's tournament Olympic Games from 2004 to 2016, did not find that fast breaks contributed to predicting victory.

Recently, Belcic at al. (2021) reported that the fast break is the decisive factor of success in handball teams competing in the same league; moreover, Bilge (2012) earlier found that the tactical choice of fast breaks leads to victory. Also, Celes and colleagues (2019) analysed the U19 World Handball Championship matches in 2019 and reported that successful fast breaks are the most important factor for predicting the final result. The found a 57.3%–76.4% prediction rate for successful fast breaks, as well as successful 6- and 9-meter shots, successful wing shots, successful penetrations and missed penalties. The effectiveness of fast attacks is also underlined by Ferrari et al. (2022), who state that when the duration of an offensive sequence increases by one second, the probability of success decreases by 1%. They also found that fast attack is better executed with a certain number of passes, as one more pass increases the possibility of a successful attack by 1.03, without increasing the overall time of the attacking sequence.

In our study, neither the total nor the successful fast throw-offs appeared to predict or affect the ranking of the teams in all three Euros according to the prediction model. This is probably due to the small number of fast breaks starting with fast throw-offs (Ohnjec et al., 2015). Our results show that both total fast breaks and successful fast breaks contribute to the ranking of teams at a high level (European Championships) over time. In contrast, neither the total nor the successful fast throw-offs contribute to the prediction of the ranking at this competitive level over time.

CONCLUSIONS

Total fast breaks per match played and successful fast breaks per match played were statistically significant predictors of tournament placement for all three European tournaments examined in the present study. However, total fast throw-offs and successful fast throw-offs per match played were not significant predictors of tournament placement in all three tournaments. The models with total fast breaks per match played as a sole predictor of tournament placement found an R^2 of .544 for Euro 2018, .259 for Euro 2020, and .331 for Euro 2022. Similarly, the models with successful fast breaks per match played as a sole predictor of tournament placement found an R^2 of .614 for Euro 2018, .313 for Euro 2020, and .269 for Euro 2022. We conclude from the above that a fast game is a key factor contributing to a team's final ranking, but further analysis is obviously necessary to reach more solid conclusions.

AUTHOR CONTRIBUTIONS

Dr. Hatzimanouil conceived and designed the study, Dr. Lola designed the study and analysed the data, Dr. Giatsis performed the data collection, Dr. Turpin performed the data collection, Mr. Skandalis designed the study and performed the data collection, Mrs. Kepesidou performed the data collection. All the authors wrote the paper and approve the final submission.

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