Gergely Géczi – Zoltán Baracskai

Statistical analysis of antifragility in Hungarian ice hockey games

GERGELY GÉCZI (corresponding author)
PhD Candidate
Széchenyi István University,
Hungary
Email: geczi.gergely@sze.hu

ZOLTÁN BARACSKAI
Professor
Széchenyi István University,
Hungary
Email: baracskai.zoltan@sze.hu

Professional ice hockey provides a great environment for studying the antifragile behaviour of teams because of publicly available results and statistics. This study examines three-goal events in which a team gave up a goal but responded by scoring two goals. Thirty-four ice hockey games are studied from the last ten seasons of the Hungarian first league to identify the events' characteristics and to determine whether antifragile behaviour emerged in these events. The results indicate that if the opponent scores first and has a one- or two-goal lead, the team that responds with two goals after strengthening the line exhibits a convex and, therefore, an antifragile behaviour. Antifragility has been found in 22 cases, lending support to the assumption that antifragile behaviour emerges from high-level cooperation.

KEYWORDS: antifragility, convexity, nonparametric tests

Ice hockey teams are great examples of complex systems (*Davids et al.* [2013]) that might produce unexpected behaviours when different elements (in the case of an ice-hockey team, team members) interact with each other and teams interact with each other in games. The teams' characteristics are measured with a broad range of statistics in professional sports (*Mosteller* [1997]), although the teams' behaviours are measured through certain game situations, such as power play usage (opposing team has a player in the penalty box and fewer players on ice) and penalty killing (the team has a player in the penalty box and fewer players on ice). However, the ability to immediately respond with two goals to one goal against can turn games in favour of the team in focus.

A team's antifragile behaviour (*Taleb* [2012a]) in an ice hockey game is defined in this study as the immediate response with two goals to one goal against during equal-player situations. As every professional coach aims to win as many games as possible in their quest for championships, a team's antifragile behaviour as an emergent characteristic could give the team a competitive edge over opponents (*Kennon–Schutte–Lutters* [2015]). Data on antifragile behaviour can be obtained through practices and games, although games are the only source for public information. Accordingly, this study uses data from Hungary's first ice hockey league (currently known as Erste League).

We aim to identify the characteristics of three-goal events in professional ice hockey games and whether these events show antifragile behaviours. The study begins with an overview of antifragility in ice hockey games and a short review of statistical analysis in sports. The statistical methods used in this study are descriptive statistics, parametric or nonparametric tests depending on the sample variables' normality, correlation, and cluster analysis.

Understanding these events can help academics and practitioners build antifragile teams, an issue of interest to all participants in professional sports.

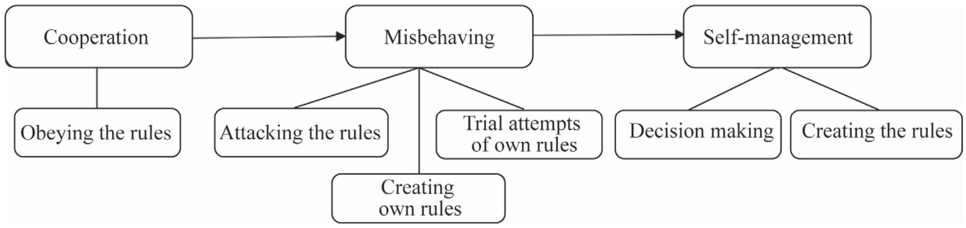
1. Literature review

Planning and executing process as per the plan can help achieve certain team behaviours, although spontaneous processes might also produce the desired behaviours (*Yu et al.* [2018]). A one-fits-all approach does not exist, as each team has different participants and structures. However, successful teams share common characteristics, especially regarding self-management (*Levi–Slem* [1995]). Self-management is an endogenous activity that can occur either as a planned or spontaneous process (*Bertolotti–Macrì–Tagliaventi* [2005]). Spontaneous conversations contain a higher number of turns than planned ones do (*Taboada* [2006]). By contrast, planned conversations offer more development through more diverse interactions (*Linley–Joseph* [2004]). The team's performance is also related to diversity, as more diverse teams perform better (*Parshakov–Coates–Zavertiaeva* [2018]).

As sports leagues aim to maximise competition in games (*Rosner–Shropshire* [2004]), they group teams that play at similar levels, which constrains the teams' development. However, facing as many teams as possible to have diverse interactions has geographical, fiscal, or physiological limits. Moreover, playing teams that are at the same level can make a team robust in progressing toward antifragility (*Johnson–Gheorghe* [2013]). In the development process, cooperation might increase the chances of a system's (team's) survival and success

(*Leitao-Valckenaers–Adam* [2009]), although it is not considered vital in the evolution of networks (*Perc* [2009]). Cooperation acts as a starting point for a system to evolve, as shown in Figure 1.

Figure 1. The evolution of a self-managing team



Learning is inevitable in the evolution process, where the components of a system eventually become systems with their own components. Cooperation serves as a strong factor in sports teams' cohesion (*Garcia-Mas et al.* [2009]). Sports teams are internally cooperative, but are externally competitive, with many stressors affecting the performance of athletes (*Mellalieu et al.* [2009]). Eustress and distress have separate effects on athletes' performance (*Brandao et al*. [2021]), although whether both should just be called 'stress' and considered phenomena triggering adaptation mechanisms, remains an open question (*Bienertova-Vasku–Lenart–Scheringer* [2020]). Stressors can improve people's arousal level (*Noteboom–Barnholt–Enoka* [2001]), and achieving the optimal level of arousal is key for performance (*Kerr* [2007]). Managing the team's arousal level is a learned method based on the evolution model. Initially, the athlete cooperates with the coach to learn the rules. Afterwards, the athlete misbehaves and creates own rules for self-management. Lastly, this method becomes part of self-management, which is performed without external impact. Antifragility is important when dealing with complex systems (*Russo–Ciancarini* [2017]). Collaboration is a key strategy to achieve common goals with antifragilistic attributes: convexity through decreased probability of failure and increased probability of success (*Ramezani–Camarinha-Matos* [2020]). In addition, cooperation is identified as a facet of collaboration (*Gulati–Wohlgezogen–Zhelyazkov* [2012]). Therefore, a higher cooperation level leads to more antifragile attributes in a system.

The use of sports analytics, including sports statistics, is growing (*Mumcu* [2016]) due to the increased competition in professional sports and wider media coverage. Historically, baseball was the first sport to use formal analytics, starting with 'Percentage Baseball' (*Hooke–Cook–Garner* [1967]). '*Moneyball: The art of winning an unfair game*' became the most influential book regarding the use of sport analytics (*Lewis* [2004]). The National Football League (NFL) eventually adopted sports analytics by utilizing the methods of an analytics-focused website. In the National Basketball Association, sports analytics was introduced in 2006 by *Daryl Morey*, one of the chairs of the MIT Sloan Sports Analytics Conference series. The National Hockey League (NHL) was a late adopter of sports analytics, as the latter was only introduced in 2014 by *Kyle Dubas*. Between 1990 and 2009, sports analytics articles in scientific journals rapidly increased (*Coleman* [2012]), showing a greater focus on this area.

Ice hockey leagues have a long history of statistical data gathering. In most leagues, these statistics are available for anyone interested in gaining insights on how a player or team performs in certain situations; therefore, these data have been used in various research activities (*Stein et al.* [2017]). As technology for collecting statistical data develops, larger and higher-quality datasets have started to become available for research (*Thomas et al.* [2017]) and performance analysis (*Farrow et al.* [2018]). Professional leagues are likely to invest in the latest technologies to increase their success and profits, and these leagues have the most data (*Hutchins* [2016]). For example, the NHL shares extensive data about teams and players with fans through its website. These data have tremendous value for academics (*Dapiton–Canlas* [2020]) and sports professionals or analysts (*Fried–Mumcu* [2016]). Statistical analysis can help teams gain a competitive edge in games (*Carling et al*. [2008]). In addition, statistical methods can possibly measure the competitive balance of sports leagues (*Fűrész–Rappai* [2018]). Modelling techniques currently have multiple purposes, including game and championship predictions (*Marek–Šedivá–Ťoupal* [2014], *Duráczky–Bozsonyi* [2020]), player rating activity (*Thomas et al.* [2013]), and team performance analysis (*Schulte et al.* [2017]). The increased use of sports statistics has created new ways to connect with fans by offering a storytelling tool that uses statistical data (*Hahn–VanDyke–Cummins* [2018]). Meaningful statistical analyses often predict whether a team will win or lose a game (*Conte et al.* [2018]) or a team's level of success in a season (*Ibanez et al.* [2008]). Therefore, statistical analysis is intensively used in professional leagues, and is used in lower-level leagues if the appropriate conditions of data gathering and processing are present. Sports statisticians are becoming more important to coaching staff in professional leagues due to the increasing availability of data (*Green et al.* [2006]).

The games' results are usually used to measure team performance, although analysing certain aspects of the game might help better understand the team's performance. When games between the NHL and the 2018 Winter Olympic Games were compared, results showed that winning teams won 31% more defensive duels and that NHL matches averaged 36% more duels compared to Olympic Games matches due to smaller rink sizes (*Parnican–Tóth–Perácek* [2020]). Although the ratio of winning or losing defensive duels is important for coaches and video analysis, this information is not yet available in the NHL statistics databases.

Ice hockey games are often seen as a set of duels by coaches; hence, power play opportunities are a critical factor in the results of the games. The 2017 U18 Group A World Cup matches show a strong correlation between power play goals and game results, nonetheless no correlation can be found between power play utilisation and final rankings in the tournament (*Barilla et al* [2019]). Additionally, for a temporary team, players' shared work experience is positively related to individual and team performance, and teams with a less centralised structure outperform highly centralised teams (*Dalal–Nolan–Gannon* [2017]).

The ice hockey teams' line structure is where coaches maximise the teams' chance of winning by knowing how effective certain players are with each other. In a centralised team's line structure, the most effective players are in the first line, with less effective players in other lines. By contrast, a decentralised team contains lines where high-performing players are well-distributed, meaning line strengths are based on individual performance measures. Self-efficacy and collective efficacy are distinct notions and have different characteristics when teams work together (*Myers–Payment–Feltz* [2004]). Aggregating self-efficacy is not equal to collective efficacy, as synergies may arise when a group is interacting (*Lindsley–Brass–Thomas* [1995]). High cooperation can be caused by synergy between team members and physiological arousal (*Jackson et al.* [2018]).

In ice hockey, individual performance is difficult to distinguish from team performance, although individual statistics for an entire season would likely illustrate an individual's performance. Therefore, season-long statistical measures should be used when defining the players' strength in a game. The antifragile behaviour of a team depends on an important exogenous factor: the amount of stress caused by a stressor. A stressor causing very low arousal levels does not trigger a response; by contrast, a stressor causing very high arousal levels causes the team to freeze under pressure. Therefore, an optimal amount of stress should be presented so the team can respond antifragilely (*Hill et al.* [2020]).

2. Methods and processes

In the present study, Team A always scores two goals in response to one goal by Team B. The Erste League is focused on, and data were obtained from its official website and other international databases (http://www.eliteprospects.com). From 2011 to 2020, a total of 2,183 games were analysed using the examination criteria. Three-goal events were recorded in the dataset if an opponent's goal was immediately answered by two goals. A three-goal event is only recorded if no other goals are scored five minutes before the first goal and if the opponent does not score for five minutes after the second goal. All were equal-opportunity situations, wherein both teams were playing with equal strength, with 5+1 players. A total of 35 three-goal events were identified in 34 games. Team and individual performance metrics were available in the data sources consulted, although data on collective line strength were not available. Therefore, individual measurements were averaged to obtain the strength of a given line when the three-goal events occurred. To obtain clarity on the strength of the players in the line, players' season statistics were used. Ice hockey offers multiple individual offensive statistics, such as goals, assists, and total points. However, plus-minus statistics are the most useful as they measure the player's overall contribution to the games. Although the statistics of the three-goal events are accessible, their characteristics remain unknown and their antifragileness remains uncertain.

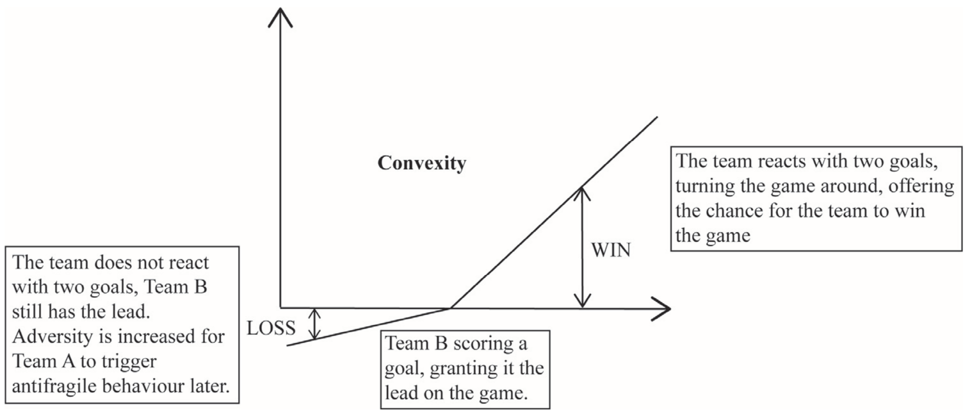
> *RQ*1: *What are the characteristics of three-goal events, and do they show antifragile behaviour?*

Identifying the characteristics of the three-goal events starts with analysing the occurrence of these events by season, team, and period number, to know whether these events are specific to the examined variable. Individual plus-minus statistics were used to identify on-ice line strengths in the three-goal events. Therefore, six variables were created for this analysis: *1*. Team A's average on-ice line strength at the first goal; *2*. Team B's average on-ice line strength at the first goal; *3*. Team A's average on-ice line strength at the time of the second goal; *4*. Team B's average on-ice line strength at the time of the second goal; *5*. Team A's average on-ice line strength at the third goal; *6*. Team B's average on-ice line strength at the third goal. Line strengths were calculated by averaging the individual end-of-season plus-minus statistics of the five players on ice when the three-goal events happened.[1] Descriptive statistics will be presented for the six variables. If significant differences are assumed, an analysis of variance (ANOVA) method will be used (*Cardinal–Aitken* [2013]) with a least significant difference post-hoc test (*Ruxton–Beauchamp* [2008]) if they are found to be normally distributed. Otherwise, the Friedman test (*Friedman* [1937]) will be performed. Pearson correlation was also used to measure the coach's line management activity. A high correlation between variables can occur in the following cases: *1*. The same line stays on ice for multiple goals; and *2*. the team has multiple equally strong lines, with one line on ice. To identify which case occurred, descriptive statistics

[1] For example, the average on-ice line strength of a team at a given goal is: player 1's plus/minus is 30, player 2's plus/minus is 40, player 3's plus/minus is 20, player 4's plus/minus is 10, and player 5's plus/minus is 5, the average strength of the line is (30+40+20+10+5)/5 = 21.

will be presented regarding the line change percentages at the three-goal events. In addition, a paired samples *t*-test will be performed to identify whether there are significant differences between the behaviours of the participant teams' coaches (*Ross–Wilson* [2017]). If the line change percentage variables are not normally distributed, the Wilcoxon signed-rank test will be performed (*Woolson* [2007]). The K-means cluster method will be used to find the hidden structure in the data, which are three-goal event scenarios. If large clusters are found in the data, the three-goal events are unique and no patterns are present. If one or only few clusters are found, the events share common characteristics and the analysis will reveal these characteristics. Antifragile behaviour is characterised as small doses of stress that prevent the occurrence of a massive stressor that may harm the system (*Johnson–Gheorghe* [2013]), and adversity is an efficient stressor (*Kiefer et al.* [2018]). The scenarios where a three-goal event might trigger antifragile behaviour are the following: *1*. Team A takes the lead with the third goal or *2*. Team A's goal, the third goal, results in a draw. Convexity (*Taleb* [2012a]) is found in Team A when Team B scored a goal. These two cases were handled separately.

Figure 2. The convex situation of Team A strengthening the lines on ice after Team B scored a goal to take the lead



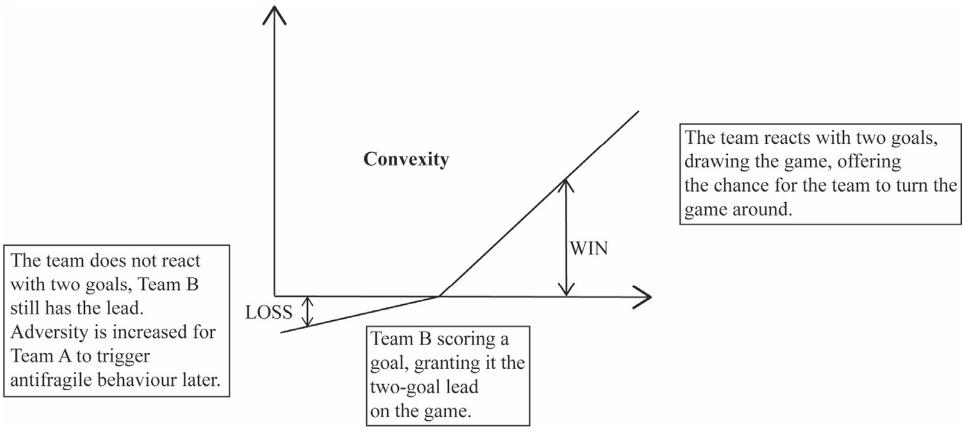
Source: Own creation based on *Taleb* [2012b].

In this first situation in Figure 2*,* Team A's strengthening of the lines after Team B scored a goal offers the following possible outcomes: *1*. Team A is not able to score two goals and loses the game, resulting in the team getting no points if it is a regular season game or a loss if it is a playoff game. In this outcome, strong plus-minus players could become demotivated since they failed to turn the game around and lost. *2*. Team A scores two goals and turns the game around, resulting in the team getting three points if it is a regular season game or a win if it is a playoff game.

In this outcome, the payoff of Team A strengthening the line is asymmetric. Team A does not get any points in a regular season game or gets credited with a loss in the playoffs if it does not do anything, while strengthening the lines offers it an opportunity get three points or win a playoff game. This situation is referred to as antifragile behaviour type one.

In the second situation in Figure 3*,* Team A's strengthening of the lines also offers an asymmetric payoff structure. If the move is unsuccessful, the team loses and gets zero points in the regular season or loses the playoff game. If successful, the team gets one point during the regular season. In the playoffs, this move can only extend the game and offer an opportunity to win the game. This is called antifragile behaviour type two. The data were gathered manually and organised using Microsoft Excel 2019. Statistical analyses were performed using SPSS v24.

Figure 3. The convex situation of Team A strengthening the lines on ice after Team B scored a goal that granted it a two-goal lead



Source: Own creation based on *Taleb* [2012b].

3. Results

3.1. Occurrences and line strengths mean results

The three-goal events were unequally distributed. In the ten seasons that were analysed, 32 of the 35 events happened during the 2015–20 seasons. The increased occurrence in later seasons may be attributable to the improved competition in the league. Three-goal events entice spectators; hence, it is possible that the league became more popular during the study period.

Table 1 shows that the three-goal events were unequally distributed among participants. FTC was involved in seven goal events: twice in 2020–21, once in 2019–20, twice in 2018–19, and twice in 2016–17. Csíkszereda was most often Team B in the events: one event each in seasons 2020–21, 2018–19, 2017–18, 2016–17, 2015–16, and 2013–14. UTE was in the top three in Team A and Team B, and this phenomenon requires further investigation. UTE was Team A in the following seasons: once in 2018–19, twice in 2015–16, and once in 2013–14. Additionally, UTE was Team B once in 2019–20, twice in 2017–18, once in 2016–17, and once in 2014–15. As these data are not concentrated for specific seasons, we have not seen any pattern.

Table 1

The occurrence of three-goal events by ice hockey teams

Team	Three-goal events as Team A	Team	Three-goal events as Team B
FTC	7	Csíkszereda	6
DVTK	6	UTE	5
UTE	4	Vasas SC	4
Csíkszereda	4	Brasov	4
Debrecen	3	Debrecen	3
MAC	3	MAC	3
Vasas SC	3	Dunaújváros	3
Dunaújváros	2	FTC	2
Brasov	1	Gyergyó	2
KMH	1	Titánok	1
Titánok	1	Vienna Capitals	1

Sixteen three-goal events occurred in the first period of the ice hockey games, 11 in the second period, and 8 in the third period. In every game, ice hockey teams study the opposing teams' styles throughout the periods. The first period is when these behaviours would most likely occur since it is the period for which the biggest possible gap between the teams was found.

Three-goal events occurred in 14 cases wherein Team A was the home team, and in 20 cases where Team A was the away team. Being the away team means less internal and external pressures due to fewer expectations from the management and fewer team fans.

In Table 2, the average line strengths show that Team A had stronger lines on ice for all three goals. This means that the first goal, which was from Team B, was scored by a weaker line. The second and third goals were scored by Team A, which deployed stronger lines than Team B. As a pattern was found in these data, the mean comparison was reasonable.

Table 2

Averages of six variables of the three-goal events

First goal Team A average strength	First goal Team B average strength	Second goal Team A average strength	Second goal Team B average strength	Third goal Team A average strength	Third goal Team B average strength
7.063	1.480	9.851	–0.977	12.006	–1.251

3.2. Normality and Friedman test results

The Kolmogorov–Smirnov and Shapiro–Wilk tests revealed that normality was not found in all six variables. Therefore, the Friedman test was used instead of ANOVA. The results showed that chi-square = 21.85, *df* = 5, and asymptotic significance = 0.001, meaning that the variance of the six variables differs significantly.

The results of Table 3 suggest that Team A has evidently stronger lines for the three-goal events compared to Team B. The highest significant mean rank difference was found for the third goal. Coaches strategically send strong lines on ice shortly after the team scores a goal, resulting in either another goal or higher pressure on the opponent. A mean rank difference was also found in second goals; the pattern is the same as in the case of the first goals. Coaches have offensive and defensive strategies, and matching line strengths with the opponent's line strengths is a good defensive strategy.

Table 3

Friedman test results for line strengths as variables

Variable	Mean rank
First goal Team A average strength	3.64
First goal Team B average strength	3.23
Second goal Team A average strength	3.93
Second goal Team B average strength	2.74
Third goal Team A average strength	4.50
Third goal Team B average strength	2.96

3.3. Correlation and Wilcoxon test results

The results in Table 4 indicate that there is no correlation across the teams. For example, a Team A variable is only correlated with the other two Team A variables. The same applies to Team B, where correlation is observed only among Team B variables. This implies that Team B either had the same line strength or a stronger line on ice when the second goal was scored, while Team A's line strengths were evenly distributed. When the third goal was scored, Team A's line on ice had a similar strength to the line involved during the first goal. If we consider homogeneity in the individual plus-minus statistics of teams, Team A was more likely to change line strength than Team B after the first goal, either by changing another line on the ice or restructuring the makeup of their lines. Team B showed a similar line strength during the first and second goals, while having a differing line at the third goal. By contrast, Team A had different lines when the first and second goals were scored, and the line strength at the third goal was similar to the line at the first goal. Based on the results, Team A's lines were likely to have the same strength at the first and third goals, while Team B's lines were likely to have the same strength at the first and second goals.

Table 4

Correlation between the six variables of three-goal events

Variable 1	Variable 2	Pearson correlation strength	Significance
First goal Team A average strength	Second goal Team A average strength	0.793	0.000
First goal Team A average strength	Third goal Team A average strength	0.877	0.000
First goal Team B average strength	Second goal Team B average strength	0.852	0.000
First goal Team B average strength	Third goal Team B average strength	0.888	0.000
Second goal Team A average strength	Third goal Team A average strength	0.837	0.000
Second goal Team B average strength	Third goal Team B average strength	0.761	0.000

Table 5 shows the teams' different lines for the three goals. The means of the line change percentages vary. Kolmogorov–Smirnov and Shapiro–Wilk tests were also performed for these variables, which further proved that they did not show normality. Therefore, Wilcoxon signed-rank tests were used to identify the differences in coach behaviours captured in line change percentages.

Table 5

Descriptive statistics of line change percentages in the three-goal events

Variable	Mean (%)	Standard deviation (%)
Team A line change % 1^{st}–2^{nd} goal	81.71	27.59
Team B line change % 1^{st}–2^{nd} goal	72.57	33.98
Team A line change % 2^{nd}–3^{rd} goal	74.29	33.10
Team B line change % 2^{nd}–3^{rd} goal	82.86	27.93
Team A line change % 1^{st}–3^{rd} goal	62.29	30.20
Team B line change % 1^{st}–3^{rd} goal	68.00	36.36

As seen in Table 6, no significant differences can be found between the participant teams' line change behaviours, meaning equality may be assumed in the coach behaviours between Teams A and B.

Table 6

Wilcoxon signed-rank test results on line change percentages as variables

Variable pair	*N*	Test statistics	Standard error	Standardized test statistics	Asymptotic significance
Team A line change % 1^{st}–2^{nd} goal – Team B line change % 1^{st}–2^{nd} goal	35	35.5	19.157	–1.696	0.090
Team A line change % 1^{st}–3^{rd} goal – Team B line change % 1^{st}–3^{rd} goal	35	224.5	41.026	0.865	0.387
Team A line change % 2^{nd}–3^{rd} goal – Team B line change % 2^{nd}–3^{rd} goal	35	142.5	28.553	0.946	0.344

3.4. Cluster analysis results

As seen in Table 7, the K-means cluster method could discern two clusters. In both clusters, Team B had weaker line strengths at every goal in the three-goal events, which meant that the first goals scored by Team B were against stronger opponents. The second and third goals were scored by Team A, which had stronger lines on ice compared to Team B. Additionally, in both clusters, Team A's line strengthened from the first goal to the third goal. This phenomenon showed antifragile characteristics, where the first goal acted as a stressor that triggered Team A to send stronger lines that allowed it to score the second and third goals. Based on the cluster centres, two main cases were identified. The first cluster showed a big difference between the line strengths of Teams A and B, while the second cluster showed almost identical line strengths.

Table 7

K-means cluster analysis and final cluster centres based on the six line strength variables

Variable	Cluster 1 (n = 15)	Cluster 2 (n = 20)
First goal Team A average strength	22.2	–4.3
First goal Team B average strength	9.1	–4.2
Second goal Team A average strength	23.4	–0.3
Second goal Team B average strength	5.7	–6.0
Third goal Team A average strength	26.1	1.4
Third goal Team B average strength	3.8	–5.1

3.5. Antifragility results

Antifragility was found in cases wherein Team B gained the lead or had a two-goal lead after the first goal of a three-goal event.

There was no antifragility in 13 games. Type one antifragility was found in 15 games, while type two antifragility was found in six games. These complex behaviours, which resulted from cooperation within the team, were found to be an emergent characteristic, as evidenced by Team A’s strengthening of the lines after a goal from Team B.

Multiple assists were made on antifragile goals: antifragile behaviour type one assists mean (n = 16): 3.31; antifragile behaviour type two assists mean (n = 6): 4. The result supports our assumption that antifragile behaviour is related to high cooperation within the team. Convexity is again supported, as the stressor goal might have caused the team to increase the level of cooperation through the unification effect to beat the opponent.

4. Discussion

The complex behaviour of ice hockey teams can easily be captured when specific performance measurements are collected. In Hungary, these data are available even for youth sports, although they are disorganised since players, parents, and coaches are the only ones interested in information about individual and team performances. The results of our cluster analysis revealed that an optimal amount of stress (*Hill et al*. [2020]) cannot be calculated using the data, as it would only be possible if one cluster could be found. However, a trend was found in which Team A strengthened its line on ice after the first goal in the three-goal events. Three-goal events mostly occurred in the last six seasons of the study period; it may be due to increased competition in the league and advanced expertise shared by players or coaches. The teams showed different involvement percentages in the three-goal events, which may be the result of high roster changes between and during the seasons. Most three-goal events occurred in the first period of the games, followed by the second period. Few events occurred in the third period. The nature of professional ice hockey supports the findings, as teams are under constant pressure to adjust between games; otherwise, the opponents start the game with a significant advantage. In addition, the first period is usually when teams try to find ways to exploit their opponents, resulting in three-goal events. Majority of the three-goal events occurred when Team A was the away team, which may be due to multiple reasons. First, they were playing at an unfamiliar ice rink, presenting increased adversity, which might trigger more antifragile behaviours (*Kiefer et al*. [2018]). Second, they faced less pressure from the management and the fans. The line strengths of Teams A and B were calculated from individual season performances. Results revealed that Team A tended to increase the line strengths on ice after allowing the first goal to Team B, and large differences were discovered between the line strengths of Teams A and B. The Friedman test discovered that the teams played on equally strong lines when the first goal occurred, but there was a bigger gap between the two lines when the second and third goals occurred. The correlation analysis indicated strong correlations between Team A's three line strengths and Team B's three line strengths separately, but no cross-correlation between the groups was found. This result was expected, as the means of the line strengths suggested that the line differences were assumable. The Wilcoxon signed-rank test revealed no significant differences between the line change tendencies of coaches in Teams A and B. The K-means cluster analysis resulted in two distinct clusters, making it impossible to identify the optimal stress load to trigger antifragility. The three-goal events were divided into three categories: *1*. no antifragile behaviour, *2*. antifragile behaviour type one, and *3*. antifragile behaviour type two. Convexity, and therefore antifragility (*Taleb* [2012a]), was identified in situations where Team B gained the lead with the first goal of the three-goal event (type one), or Team B had a two-goal lead after the first goal of the three-goal event (type two). In both cases, high cooperation was found by measuring the number of assists made on the second and third goals, which fits our assumption that antifragile behaviour is a result of high-level cooperation.

5. Conclusion

Although convexity, and therefore antifragility, can be proven in 22 out of 35 cases, these behaviours are extremely rare as the total games studied were 2,183. Teams have access to many tools to beat an opponent. This includes antifragile behaviour, as convexity can be created in ice hockey games. Antifragility was found in cases when Team B had one- or two-goal leads after scoring the first goal of the three-goal events. When Team A strengthened the line after the first goal, the situation became convex and therefore antifragile. Coaches and players should be educated on how to create these situations to increase the number of antifragile behaviours, as such modern phenomena are welcomed by all professional and youth ice hockey stakeholders.

References

BARILLA, P. – TÓTH, I. – PERACEK, P. – BABIC, M. [2019]: Impact of power plays' efficiency on ice hockey match results and team standings. *Journal of Physical Education and Sport*. Vol. 19. No. 2. pp. 1053–1059.

BERTOLOTTI, F. – MACRÌ, D. M. – TAGLIAVENTI, M. R. [2005]: Spontaneous self-managing practices in groups: Evidence from the field. *Journal of Management Inquiry*. Vol. 14. No. 4. pp. 366–384. https://doi.org/10.1177/1056492605280224

BIENERTOVA-VASKU, J. – LENART, P. – SCHERINGER, M. [2020]: Eustress and distress: Neither good nor bad, but rather the same? *BioEssays*. Vol. 42. No. 7. Article No. 1900238. https://doi.org/10.1002/bies.201900238

BRANDAO, M. R. F. – POLITO, L. F. – HERNANDES, V. – CORREA, M. – MASTOCOLA, A. P. – OLIVEIRA, D. – OLIVEIRA, A. – MOURA, L. – VILLAS BOAS JUNIOR, M. – ANGELO, D. [2021]: Stressors in indoor and field Brazilian soccer: Are they perceived as a distress or eustress? *Frontiers in Psychology*. Vol. 12. May. https://doi.org/10.3389/fpsyg.2021.623719

CARDINAL, R. N. – AITKEN, M. R. [2013]: *ANOVA for the Behavioral Sciences Researcher.* Psychology Press. New York. https://doi.org/10.4324/9780203763933

CARLING, C. – BLOOMFIELD, J. – NELSEN, L. – REILLY, T. [2008]: The role of motion analysis in elite soccer. *Sports Medicine*. Vol. 38. No. 10. pp. 839–862. https://doi.org/10.2165/00007256-200838100-00004

COLEMAN, B. J. [2012]: Identifying the 'players' in sports analytics research. *Interfaces*. Vol. 42. No. 2. pp. 109–118. https://doi.org/10.1287/inte.1110.0606

CONTE, D. – TESSITORE, A. – GJULLIN, A. – MACKINNON, D. – LUPO, C. – FAVERO, T. [2018]: Investigating the games-related statistics and tactical profile in NCAA Division I men's basketball games. *Biology of Sport.* Vol. 35. No. 2. pp. 137–143. https://doi.org/10.5114/biolsport.2018.71602

DALAL, D. K. – NOLAN, K. P. – GANNON, L. E. [2017]: Are pre-assembly shared work experiences useful for temporary-team assembly decisions? A study of Olympic ice hockey team composition. *Journal of Business and Psychology*. Vol. 32. No. 5. pp. 561–574. https://doi.org/10.1007/s10869-016-9481-6

DAPITON, E. P. – CANLAS, R. B. [2020]: Value creation of big data utilization: The next frontier for productive scholarship among Filipino academics. *European Journal of Educational Research*. Vol. 9. No. 1. pp. 423–431. https://doi.org/10.12973/eu-jer.9.1.423

DAVIDS, K. – HRISTOVSKI, R. – ARAUJO, D. – SERRE, N. B. – BUTTON, C. – PASSOS, P. [2013]: *Complex Systems in Sport*. Routledge. London. https://doi.org/10.4324/9780203134610

DURÁCZKY, B. – BOZSONYI, K. [2020]: „Nem sokaság, hanem lélek…" – A nyári olimpiai játékok nemzetek közötti éremmegoszlásának statisztikai modellje. *Statisztikai Szemle.* Vol. 98. No. 2. pp. 133–148. https://doi.org/10.20311/stat2020.2.hu0133

FARROW, D. – REID, M. – BUSZARD, T. – KOVALCHIK, S. [2018]: Charting the development of sport expertise: Challenges and opportunities. *International Review of Sport and Exercise Psychology*. Vol. 11. No. 1. pp. 238–257. https://doi.org/10.1080/1750984x.2017.1290817

FRIED, G. – MUMCU, C. (eds.) [2016]: *Sport Analytics: A Data-Driven Approach to Sport Business and Management*. Taylor & Francis. Abingdon. https://doi.org/10.4324/9781315619088

FRIEDMAN, M. [1937]: The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the American Statistical Association.* Vol. 32. No. 200. pp. 675–701. https://doi.org/10.2307/2279169

FŰRÉSZ, D. I. – RAPPAI, G. [2018]: Koncentrációs mérőszámok „sportos" szerepkörben. *Statisztikai Szemle.* Vol. 96. No. 10. pp. 949–972. https://doi.org/10.20311/stat2018.10.hu0949

GARCIA-MAS, A. – OLMEDILLA, A. – ORTEGA, E. – ALMEIDA, P. – LAMEIRAS, J. – SOUSA, C. – CRUZ, J. [2009]: Cooperation and cohesion in football teams in competition. *International Journal of Hispanic Psychology*. Vol. 2. No. 1. pp 29–45.

GREEN, M. R. – PIVARNIK, J. M. – CARRIER, D. P. – WOMACK, C. J. [2006]: Relationship between physiological profiles and on-ice performance of a National Collegiate Athletic Association Division I hockey team. *Journal of Strength and Conditioning Research.* Vol. 21. No. 1. pp. 43. https://doi.org/10.1519/00124278-200602000-00007

GULATI, R. – WOHLGEZOGEN, F. – ZHELYAZKOV, P. I. [2012]: The two facets of collaboration: Cooperation and coordination in strategic alliances. *Academy of Management Annals.* Vol. 6. No. 1. pp. 531–583. https://doi.org/10.5465/19416520.2012.691646

HAHN, D. A. – VANDYKE, M. S. – CUMMINS, R. G. [2018]: It's a numbers game: Change in the frequency, type, and presentation form of statistics used in NFL broadcasts. *International*

Journal of Sport Communication. Vol. 11. No. 4. pp. 482–502. https://doi.org/10.1123/ijsc.2018-0107

HILL, Y. – KIEFER, A. W. – SILVA, P. L. – VAN YPEREN, N. W. – MEIJER, R. R. – FISCHER, N. – DEN HARTIGH, R. J. [2020]: Antifragility in climbing: Determining optimal stress loads for athletic performance training. *Frontiers in Psychology*. Vol. 11. March. pp. 272. https://doi.org/10.3389/fpsyg.2020.00272

HOOKE, R. – COOK, E. – GARNER, W. R. [1967]: Percentage baseball. *Journal of the American Statistical Association.* Vol. 62. No. 318. pp. 688. https://doi.org/10.2307/2283997

HUTCHINS, B. [2016]: Tales of the digital sublime: Tracing the relationship between big data and professional sport. *Convergence*. Vol. 22. No. 5. pp. 494–509. https://doi.org/10.1177/1354856515587163

IBANEZ, S. J. – SAMPAIO, J. – FEU, S. – LORENZO, A. – GÓMEZ, M. A. – ORTEGA, E. [2008]: Basketball game-related statistics that discriminate between teams' season-long success. *European Journal of Sport Science.* Vol. 8. No. 6. pp. 369–372. https://doi.org/10.1080/17461390802261470

JACKSON, J. C. – JONG, J. – BILKEY, D. – WHITEHOUSE, H. – ZOLLMANN, S. – MCNAUGHTON, C. – HALBERSTADT, J. [2018]: Synchrony and physiological arousal increase cohesion and cooperation in large naturalistic groups. *Scientific Reports*. Vol. 8. No. 1. pp. 1–8. https://doi.org/10.1038/s41598-017-18023-4

JOHNSON, J. – GHEORGHE, A. V. [2013]: Antifragility analysis and measurement framework for systems of systems. *International Journal of Disaster Risk Science*. Vol. 4. No. 4. pp. 159–168. https://doi.org/10.1007/s13753-013-0017-7

KENNON, D. – SCHUTTE, C. S. L. – LUTTERS, E. [2015]: An alternative view to assessing antifragility in an organization: A case study in a manufacturing SME. *CIRP Annals*. Vol. 64. No. 1. pp. 177–180. https://doi.org/10.1016/j.cirp.2015.04.024

KERR, J. H. [2007]: The experience of arousal: A new basis for studying arousal effects in sport. *Journal of Sports Sciences.* Vol. 3. No. 3. pp 169–179. https://doi.org/10.1080/02640418508729749

KIEFER, A. W. – SILVA, P. L. – HARRISON, H. S. – ARAÚJO, D. [2018]: Antifragility in sport: Leveraging adversity to enhance performance. *Sport, Exercise, and Performance Psychology.* Vol. 7. No. 4. pp. 342–350. https://doi.org/10.1037/spy0000130

LEITAO, P. – VALCKENAERS, P. – ADAM, E. [2009]: Self-adaptation for robustness and cooperation in holonic multi-agent systems. In: *Hameurlain, A. – Küng, J. – Wagner, R*. (eds.): *Transactions on Large-Scale Data- and Knowledge-Centered Systems I.* Lecture Notes in Computer Science. Springer. Berlin. Vol. 5740. pp. 267–288. https://doi.org/10.1007/978-3-642-03722-1_11

LEVI, D. – SLEM, C. [1995]: Team work in research and development organizations: The characteristics of successful teams. *International Journal of Industrial Ergonomics*. Vol. 16. No. 1. pp. 29–42. https://doi.org/10.1016/0169-8141(94)00076-f

LEWIS, M. (ED.) [2004]: *Moneyball: The Art of Winning an Unfair Game.* WW Norton & Company. New York.

LINDSLEY, D. H. – BRASS, D. J. – THOMAS, J. B. [1995]: Efficacy-performing spirals: A multilevel perspective. *Academy of Management Review*. Vol. 20. No. 3. pp. 645–678. https://doi.org/10.5465/amr.1995.9508080333

LINLEY, P. A. – JOSEPH, S. [2004]: Positive change following trauma and adversity: A review. *Journal of Traumatic Stress*. Vol. 17. No. 1. pp 11–21. https://doi.org/10.1023/b:jots.0000014671.27856.7e

MAREK, P. – ŠEDIVÁ, B. – ŤOUPAL, T. [2014]: Modeling and prediction of ice hockey match results. *Journal of Quantitative Analysis in Sports*. Vol. 10. No. 3. pp. 357–365. https://doi.org/10.1515/jqas-2013-0129

MELLALIEU, S. – NEIL, R. – HANTON, S. – FLETCHER, D. [2009]: Competition stress in sport performers: Stressors experienced in the competition environment. *Journal of Sports Sciences.* Vol. 27. No. 7. pp. 729–744. https://doi.org/10.1080/02640410902889834

MOSTELLER, F. [1997]: Lessons from sports statistics. *The American Statistician*. Vol. 51. No. 4. pp. 305–310. https://doi.org/10.2307/2685896

MUMCU, C. [2016]: Analytics in sport marketing. In: *Fried, G. – Mumcu, C.* (eds.): *Sport Analytics.* Routledge. London. pp. 113–136. https://doi.org/10.4324/9781315619088

NOTEBOOM, J. T. – BARNHOLT, K. R. – ENOKA, R. M. [2001]: Activation of the arousal response and impairment of performance increase with anxiety and stressor intensity. *Journal of Applied Physiology*. Vol. 91. Issue 5. pp. 2093–2101. https://doi.org/10.1152/jappl.2001.91.5.2093

PARNICAN, S. – TÓTH, I. – PERÁCEK, P. [2020]: The connection between the success of a team one-on-one battles in the defensive phase of the game and the final results of ice hockey matches in the National Hockey League and the 2018 Winter Olympic Games. *Journal of Physical Education and Sport*. Vol. 20. No. 3. pp. 1529–1537.

PARSHAKOV, P. – COATES, D. – ZAVERTIAEVA, M. [2018]: Is diversity good or bad? Evidence from eSports teams analysis. *Applied Economics*. Vol. 50. No. 47. pp. 5064–5075. https://doi.org/10.1080/00036846.2018.1470315

PERC, M. [2009]: Evolution of cooperation on scale-free networks subject to error and attack. *New Journal of Physics*. Vol. 11. No. 3. https://doi.org/10.1088/1367-2630/11/3/033027

RAMEZANI, J. – CAMARINHA-MATOS, L. M. [2020]: Approaches for resilience and antifragility in collaborative business ecosystems. *Technological Forecasting and Social Change*. Vol. 151. February. Article No. 119846. https://doi.org/10.1016/j.techfore.2019.119846

ROSNER, S. – SHROPSHIRE, K. L. [2004]: *The Business of Sports.* Jones & Bartlett Learning. Burlington.

ROSS, A. – WILLSON, V. L. [2017]: Paired samples *t*-test. *Basic and Advanced Statistical Tests*. Brill Sense. Rotterdam. pp. 17–19. https://doi.org/10.1007/978-94-6351-086-8_4

RUSSO, D. – CIANCARINI, P. [2017]: Towards antifragile software architectures. *Procedia Computer Science.* Vol. 109. pp. 929–934. https://doi.org/10.1016/j.procs.2017.05.426

RUXTON, G. D. – BEAUCHAMP, G. [2008]: Time for some a priori thinking about post hoc testing. *Behavioral Ecology.* Vol. 19. No. 3. pp. 690–693. https://doi.org/10.1093/beheco/arn020

STEIN, M. – JANETZKO, H. – SEEBACHER, D. – JÄGER, A. – NAGEL, M. – HÖLSCH, J. – GROSSNIKLAUS, M. [2017]: How to make sense of team sport data: From acquisition to data modeling and research aspects. *Data*. Vol. 2. No. 1. https://doi.org/10.3390/data2010002

SCHULTE, O. – KHADEMI, M. – GHOLAMI, S. – ZHAO, Z. – JAVAN, M. – DESAULNIERS, P. [2017]: A Markov Game model for valuing actions, locations, and team performance in ice hockey. *Data Mining and Knowledge Discovery*. Vol. 31. No. 6. pp. 1735–1757. https://doi.org/10.1007/s10618-017-0496-z

TABOADA, M. [2006]: Spontaneous and non-spontaneous turn-taking. *Pragmatics*. Vol. 16. Nos. 2–3. pp. 329–360. https://doi.org/10.1075/prag.16.2-3.04tab

TALEB, N. N. [2012a]: *Antifragile: Things That Gain from Disorder*. Random House. New York.

TALEB, N. N. [2012b]: Understanding is a poor substitute for convexity (antifragility). *Edge.* 12th December. https://www.edge.org/conversation/nassim_nicholas_taleb-understanding-is-a-poor-substitute-for-convexity-antifragility

THOMAS, A. C. – VENTURA, S. L. – JENSEN, S. T. – MA, S. [2013]: Competing process hazard function models for player ratings in ice hockey. *The Annals of Applied Statistics*. Vol. 7. No. 3. pp. 1497–1524. https://doi.org/10.1214/13-aoas646

THOMAS, G. – GADE, R. – MOESLUND, T. B. – CARR, P. – HILTON, A. [2017]: Computer vision for sports: Current applications and research topics. *Computer Vision and Image Understanding*. Vol. 159. June. pp. 3–18. https://doi.org/10.1016/j.cviu.2017.04.011

WOOLSON, R. F. [2007]: Wilcoxon signed-rank test. In: *D'Agostino, R. – Massaro, J. – Sullivan, L.* (eds.): *Wiley Encyclopedia of Clinical Trials.* John Wiley and Sons Ltd. New York. pp. 1–3. https://doi.org/10.1002/9780471462422

YU, Y. – GARCIA-DE-ALCARAZ, A. – WANG, L. – LIU, T. [2018]: Analysis of winning determinant performance indicators according to teams level in Chinese women's volleyball. *International Journal of Performance Analysis in Sport*. Vol. 18. No 5. pp. 750–863. https://doi.org/10.1080/24748668.2018.1517289