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Data Analytics and Football Industry on the Egyptian Premier League

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Abstract: The aim of this study is to identify the level of accuracy in penalty kicks using different techniques of performance analysis in the Egyptian Football League by making a comparison between two models of analysis techniques used, Two models were used: (Korstat XG) and (Instat XG). The researchers used the descriptive survey method for a sample of the Egyptian Football League (10) teams. The appropriate statistical method was used using the statistical analysis program Spss. The most important results of this study were the following: We note from the table that instat, which gives the penalty kick value of 0.75, is the closest to the accuracy, as its accuracy of expecrltation during five seasons reached 99.94% after it was expected that 493.5 penalty kicks were scored, while 491 penalty kicks were actually recorded. On the other hand, the KoraStat model, which gives the penalty kick a value of 0.89, has an accuracy of expectaion 83.84%, after it was expected to score 585.63 penalty kicks, while 491 penalty kicks were actually recordedWhich shows that the value of scoring a penalty kick in the Egyptian League corresponds more to the model of the company Instat, which gives for each penalty kick a value of 0.75 as an expected goal.

Keywords: Analytics, Data, Sports Industry

1. Introduction

In the past, sports training required extensive paperwork and post-practice effort from both the trainer and the athlete. While the athlete practiced, notes and video were diligently taken and then collated into charts and graphs representing that athlete's performance. After practice, trainer and athlete would work together discussing aches, pains, and thoughts about physical movements that happened much earlier. The system was grueling, but worked as far as athletes and trainers knew. That is until recent technology transformed the field of sports training [10].

Advanced technology has become smaller, more resilient, and less burdensome over recent years, paving the way for new opportunities, especially in athletics. Now athletes wear sensors that convey real-time information to a trainer's tablet, GPS accurately pinpoints motion, smartphones keep everyone current and wearable tech can prevent injuries. Compared to whiteboards and post-practice reviews, technology has substantially increased athletic potential.

Technology is revolutionizing sports training by live-tracking performances, perfecting athletic movements, enhancing communication and virtually eliminating injuries.

1.1. Tracking Performance

Using sensors placed on the body or in "smart clothing" (active wear with sensing fibers woven in), sports trainers can measure and track performance in real time. Almost anything about the athlete can be measured, from breathing and heart rate, to hydration and temperature [12].

These live metrics can help the trainer determine what aspects each athlete needs to focus on more. Athletes are unique, and real-time individual performance measurements can set a more precise and accurate baseline. During practice, trainers can read live metrics and decide when it's time to rest, stretch or train harder [11].

Lasers and GPS have been incorporated into various aspects of the sports training world. Instead of relying on times and splits, trainers can measure the exact position, distance, velocity and acceleration of athletes to better understand where they can improve. Identifying more intricate data leads to improved performance with less stress and chance for injury.

1.2. Perfecting Athletic Movements

Mounir Zok, the Director of Technology and Innovation for the U.S. Olympic Commission, has watched technology change and mold sports for the better. He claims that sports technology is so advanced that it can create a 'digital code' for winning the gold medal. What he means is: data collected and compared can ultimately translate into a gold medal performance. Technology has increased an athlete's prowess simply because it magnifies performance-related actions and events that have been previously unseen [12].

For example, cyclists can wear heads-up display (HUD) glasses that flawlessly deliver heartrate, speed, incline and other relevant cycling information. Metrics such as these can help the cyclist focus and improve because they can make adjustments mid ride [7].

Swimmers and divers participate in an extremely technical sport and have adapted sensors into their practices as well. When swimming or diving, the sensors measure more than the usual time and effort metrics. They map movements like rotational speed, dive angle, leg movement and hydrodynamics. Observing movements like this is groundbreaking, and allows trainers to help athletes perfect their movements. They may only shave milliseconds off their performance, but a millisecond in a race can be all the difference [10].

Applying analytics in sports is complex. Being able to confidently predict events or outcomes requires taking many variables into account, thus producing complicated statistical outcomes and probabilities. Though data and statistical methods are available to predict who wins a football game with extraordinary accuracy, the complexity of the process leaves coaches scratching their heads,. The Big "Data" Problem [4].

During next few years, there will be a change and an increase in the functions of research and analysis in the sports field Football is one of the sports that will greatly develop in the analysis of players' performance [1, 3]. This growth is due to many current coaches recognizing the value of data analytics in helping their team. Applied toward anything from potential draft picks to fourth down prediction charts, data can quantify difficult decisions into simple, thoughtful processes.

Applying analytics in sports is complex [8]. Being able to confidently predict events or outcomes requires taking many variables into account, thus producing complicated statistical outcomes and probabilities [2, 5]. Though data and statistical methods are available to predict who wins a football game with extraordinary accuracy, the complexity of the process leaves coaches scratching their heads [15].

1.3. Eliminating Injuries

Perhaps the most important byproduct of technology in sports training is that injuries have been severely reduced and now can be identified much earlier. Tracking performance, perfecting movements and enhancing communication are not only benefits; they actually help create less injury-prone environments.

Training management software can assist coaches and trainers in monitoring all aspects of training: diet, energy, sleep, etc. When coaches and trainers can define individual practice for optimum results, they are preventing fatigue and self-created injuries. Besides, outside variables that cannot be accounted for, the future may someday see injury-free athletics [12].

2. Methods

This study, the two researchers used the descriptive survey method for a sample of the Egyptian Football League (10) teams. The data was collected by following the matches and videos of these matches for the ten teams as a representative sample of the Egyptian Football League. The two proposed models were used (Corasstat XG) and (Instat XG), and the data was extracted as follows in Table 1 and Figures 1 to 3.

The appropriate statistical method was used using the statistical analysis program Spss.

3. Results and Discussion

The result of this analysis confirmed this coordinator's "hunch" that although one punter could occasionally hit a very long punt, his counterpart was much more reliable [6, 15]. As an analyst, I found that the best way to arrive at a solution is to either confirm these "hunches" that coaches have with solid data analysis or provide alternative ways of thinking to show different possible paths. The coach might feel like one person is better than the other, and to be able to provide statistical proof of confirmation could be game changing in building trust with the coaching staff and in the overall acceptance of data analytics in any football program [19, 20].

In sum, better analysis involves better communication. To grow analytics in football, there needs to be better communication patterns to help the coaches understand and apply the insights found through data analytics initiatives to the specific problems for which the coaches are seeking solutions [9, 11, 17].

Football has recently seen an expanded use of data in an attempt to develop the game, and with the diversity of companies working in football data, become for each company has its own model that analyzes the data through it [13, 16].

One of the most famous values in football data is Expected Goals xG, and the following table provides a comparison between the value of the expected goals for the penalty kick and its connection to reality by comparing the real numbers with the hypothetical numbers of two models working on the Egyptian Premier League. and they are KoraStat and Instat.

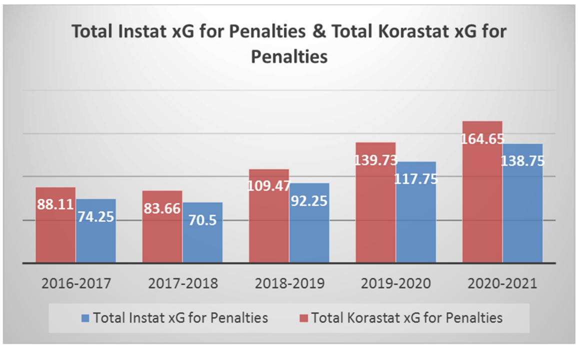

Figure 1. *Total Instat xG for Penalties & Total Korastats xG for Penalties in period 2016-2021.*

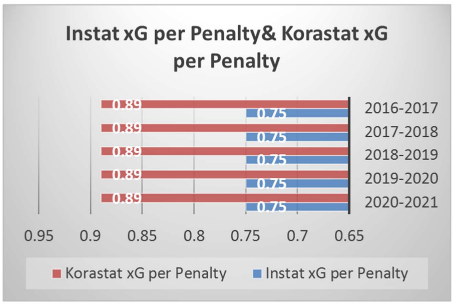

Figure 2. *Instat xG per Penalty& Korastat xG per Penalty in period 2016-2021.*

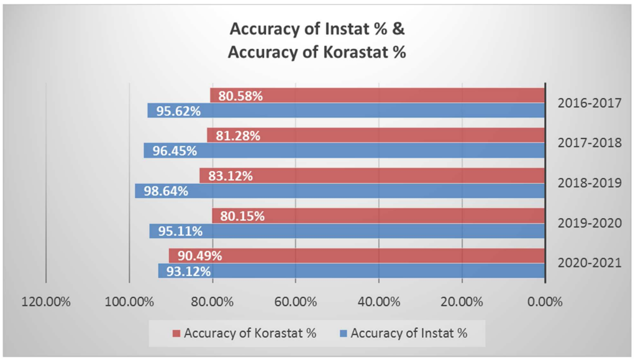

Figure 3. *Accuracy of Instat % & Accuracy of Korastat in period 2016-2021.*

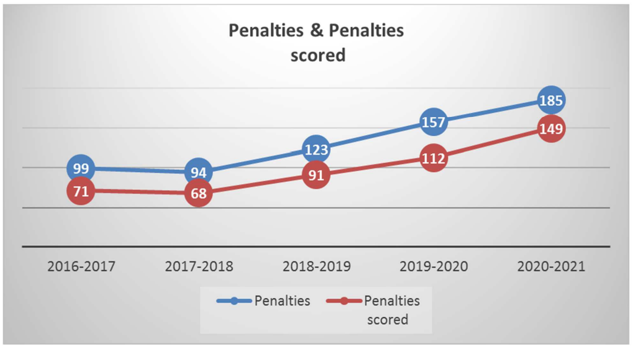

Figure 4. *Penalties & Penalties scored in period 2016-2021.*

Table 1. *The statistic was conducted for five years from the 2016-2017 season until the 2020-2021 season and monitored the penalties kick which played during five seasons individually, the total values for the five seasons together, the number of penalties scored and the percentage of penalties scored.*

Season	Penalties	Penalties scored	Penalties scored %	Instat xG per Penalty	Total Instat xG for Penalties	Accuracy of Instat %	Korastat xG per Penalty	Total Korastat xG for Penalties	Accuracy of Korastat %
2020-2021	185	149	80.54%	0.75	138.75	93.12%	0.89	164.65	90.49%
2019-2020	157	112	71.33%	0.75	117.75	95.11%	0.89	139.73	80.15%
2018-2019	123	91	73.98%	0.75	92.25	98.64%	0.89	109.47	83.12%
2017-2018	94	68	72.34%	0.75	70.5	96.45%	0.89	83.66	81.28%
2016-2017	99	71	71.71%	0.75	74.25	95.62%	0.89	88.11	80.58%
Total	658	491	74.62%		493.5	99.49%		585.62	83.84%

The table 1 and figures 1 to 4 shows the value given by each company's model, the number of penalty kicks that are supposed to be scored according to the model, and the accuracy rate of each model in predicting each season individually and for the total of the five seasons compared to the realistic numbers.

We note from the table that instat, which gives the penalty kick value of 0.75, is the closest to the accuracy, as its accuracy of expecrltation during five seasons reached 99.94% after it was expected that 493.5 penalty kicks were scored, while 491 penalty kicks were actually recorded.

On the other hand, the KoraStat model, which gives the penalty kick a value of 0.89, has an accuracy of expectaion 83.84%, after it was expected to score 585.63 penalty kicks, while 491 penalty kicks were actually recorded.

4. Conclusion

After this Analytics we found that value of scoring a penalty kick in the Egyptian League corresponds more to the model of the company Instat, which gives for each penalty kick a value of 0.75 as an expected goal.

References

[1] Lu WL, Ting JA, Little JJ, Murphy KP (2013) Learning to track and identify players from broadcast sports videos. IEEE Trans Pattern Anal Mach Intell 35 (7): 1704–1716.

[2] Lucey P, Bialkowski A, Carr P, Morgan S, Matthews I, Sheikh Y (2013) Representing and discovering adversarial team behaviors using player roles. Paper presented at the IEEE CVPR. 23–28 June 2013.

[3] Lucey P, Oliver D, Carr P, Roth J, Matthews I (2013) Assessing team strategy using spatiotemporal data. Paper presented at the 19th ACM SIGKDD, Chicago, Illinois, USA.

[4] Lynch C (2008) Big data: How do your data grow? Nature 455 (7209): 28–29.

[5] Mackenzie R, Cushion C (2013) Performance analysis in football: a critical review and implications for future research. J Sports Sci 31 (6): 639–676. doi: 10.1080/02640414.2012.746720.

[6] Marx V (2013) Biology: the big challenges of big data. Nature 498 (7453): 255–260. doi: 10.1038/498255a.

[7] McGarry T, Anderson DI, Wallace SA, Hughes M, Franks IM (2002) Sport competition as a dynamical self-organizing system. J Sports Sci 20: 771–781.

[8] Medeiros J (2014) The winning formula: data analytics has become the latest tool keeping football teams one step ahead. Wired. http://www.wired.co.uk/magazine/archive/2014/01/features/the-winning-formula.

[9] Memmert D, Perl J (2009) Analysis and simulation of creativity learning by means of artificial neural networks. Hum Mov Sci 28 (2): 263–282. doi: 10.1016/j.humov.2008.07.006.

[10] Mesirov JP (2010) Computer science. Accessible reproducible research. Science 327 (5964): 415–416. doi: 10.1126/science.1179653.

[11] Mohr M, Krustrup P, Bangsbo J (2005) Fatigue in soccer: a brief review. J Sports Sci 23 (6): 593–599. doi: 10.1080/02640410400021286.

[12] Montoliu R, Martin-Felez R, Torres-Sospedra J, Martinez-Uso A (2015) Team activity recognition in Association Football using a Bag-of-Words-based method. Hum Mov Sci 41: 165–178. doi: 10.1016/j.humov.2015.03.007.

[13] Nakanishi R, Murakami K, Naruse T (2008) Dynamic positioning method based on dominant region diagram to realize successful cooperative play. In: Visser U, Ribeiro F, Ohashi T, Dellaert F (eds) Robo cup 2007: Robot Soccer World Cup XI, Vol 5001. Springer, Berlin, pp 488–495.

[14] Noor AM, Holmberg L, Gillett C, Grigoriadis A (2015) Big data: the challenge for small research groups in the era of cancer genomics. Br J Cancer 113 (10): 1405–1412. doi: 10.1038/bjc.2015.341.

[15] Norton S (2014) Germany’s 12th man at the World Cup: Big Data. CIO Journal. http://blogs.wsj.com/cio/2014/07/10/germanys-12th-man-at-the-world-cup-big-data/

[16] Ohmann C, Canham S, Danielyan E, Robertshaw S, Legre Y, Clivio L, Demotes J (2015) ‘Cloud computing’ and clinical trials: report from an ECRIN workshop. Trials 16: 318. doi: 10.1186/s13063-015-0835-6.

[17] Olthof SB, Frencken WG, Lemmink KA (2015) The older, the wider: on-field tactical behavior of elite-standard youth soccer players in small-sided games. Hum Mov Sci 41: 92–102. doi: 10.1016/j.humov.2015.02.004.