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ORIGINAL ARTICLE

EXERCISE PHYSIOLOGY AND BIOMECHANICS

A proposed new direct method to detect match-fixing

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ABSTRACT

BACKGROUND: This research aims to demonstrate the validity of using video analysis as a direct method of detecting the manipulation of sports competitions (*i.e.*, match-fixing).

METHODS: Using the case of an allegedly manipulated professional handball competition, the direct detection method was developed and used as evidence during expert testimony for the courts. The analysis divided the video of the alleged fixed handball competition into key points. Biomechanical analysis was conducted on each key point to identify intentional performance deficiencies (*i.e.* match-fixing) in motor behavior actions with or without a ball, performed in a favorable environment, and contrary to the interest of the team or player.

RESULTS: The video analysis method strongly limited the number of hypotheses for the explanation and thus demonstrated when aspects of the contest were fixed. This work demonstrates the high potential for a direct match-fixing detection method from video analysis not only for handball but more generally for team or individual sports.

CONCLUSIONS: This research provides important support for the use of video analysis in real time to fight against match-fixing and to protect the integrity of sport more effectively.

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KEY WORDS: Sports; Athletes; Machine learning algorithms.

Introduction

Gambling related manipulation of sports competitions (*i.e.*, match-fixing) is a recognized criminal act stated in "The Macolin Convention," which is the lone rule of international law on the manipulation of sports competitions.[1] Criminals, including organized crime networks, bribe and threaten sports competition actors (*i.e.*, athletes, players, coaches, referees) to fix the outcome or specific aspects of the contest.[2] Criminals profit financially by placing bets in the illegal or unregulated gambling markets on the guaranteed fixes where money is laundered to hide profits from their other criminal activities (*e.g.*, drug, human, or weapon trafficking).[2, 3] The United Nations estimated that each year $1.7 trillion is wagered on illicit betting markets[4] and match-fixing provides a "gateway to crime"[5]. As such, match-fixing is considered one of the greatest threats to the integrity of sport and a major concern for law enforcement agencies (*i.e.*, Europol and Interpol), international institutions (*e.g.*, Council of Europe, United Nations Office on Drugs and Crime (UNODC), and sports governing bodies (*e.g.*, International Handball Federation) where they have called for improved forensic strategies to detect match-fixing.[5-7]

Match-fixing is a covert activity that occurs in silence and has varying origins.[8] Data therefore plays a pivotal role in helping to detect match-fixing.[9] Collecting accurate data to detect such malfeasance is difficult[4] and thus provides match-fixing perpetrators motive for engaging in deceptive practices. Identifying athletes involved in match-fixing during a competition is complex because of the difficulty in distinguishing between a normal performance and a voluntary underperformance.[10] For example, some defensive errors, such as not covering an attacker closely, can be the result of low performance while a voluntary deficient position in a manipulated match is very difficult to differentiate on a single play action. Rigorous detection measures that directly identify different manipulations (*i.e.*, underperformance and poor performance) with great accuracy from scientific and numeric data are required to enhance the standard of proof in determining wrongdoing.[4]

Several types of evidence are used to establish a standard of proof for detecting match-fixing such as witness statements, wire taps, video recordings, forensic sports analytics (*e.g.*, analyzing betting odds and bets distributions), performance data and expert testimonies.[11] Forensic statistics use secondary data, such as odds variation and betting volumes, to detect corruption,[9, 12, 13] which is an indirect method that is limited in the accurate detection of manipulations.[14] Bernhardt and Heston[15] noted the "*danger of indirect methods is that, by their very nature, their identification of illegal activity hinges on subtle assumptions*" (p. 14). Indirect methods do not factor relevant game dynamics (*e.g.*, fatigue, substitution, momentum) into their predictive models and thus are imprecise as an investigative tool.[13] The Court of Arbitration for Sport, however, has increasingly used suspicious betting patterns as evidence in adjudicating match-fixing trials.[11] Such data is considered valuable legal evidence[4, 12] despite the known inexactness of indirect methods.[14, 15] Juxtaposed, direct detection of manipulation through video analysis of sports performance has the benefit of providing objective evidence to accurately distinguish unintentional errors that occur in competitions from intentional underperformances. Forrest and McHale,[12] however, suggested sport performance analysis was limited in detecting match-fixing because sport data was "inherently very noisy" and thus identifying corruption from deviations from expected performances was an imperfect endeavor" (p. 4). The key to directly detecting match-fixing through sport performance analysis lies in the production of a method capable of providing objective, quantified data based on biomechanical algorithms and article intelligence, as opposed to subjective assessments of a game situation (*e.g.*, flagging irregular betting) without performance data.[16] This paper aims to counteract Forrest and McHall's[12] questioning of the validity of using sports performance analysis for sports integrity purposes.

The purpose of this paper was to present a method to directly detect match-fixing using video analysis and sport performance data from a case study requested by the French courts 2012 on a handball match that was played on May 12, 2012, between Montpellier Agglomeration Handball (MAH) and Cesson Rennes Métropole Handball (CRMH). Using broadcast video, with no additional specific video capture, the central research question was how biomechanical data (*e.g.*, distances, times, speeds, angles) could be used to develop a scientific method to demonstrate or not, a possible manipulation of a match.

Materials and methods

The scientific literature on match-fixing and sport corruption encompasses a wide range of disciplines including criminology,[17] sociology[7] and law;[18] however, very few studies examine the use of video analysis to develop biomechanical data as a forensic method to detect match manipulations. This is highly paradoxical because video analysis is a powerful tool in sports performance analysis, where it is used to enhance the understanding and improvement of athletes' performances.[19, 20] Video analysis involves capturing and scrutinizing video footage of sports events or training sessions to gain insights into various aspects of performance.[21] The main contribution of this research is threefold: 1) to provide the basis for a new method of detecting match-fixing that uses a direct method based on video analysis. Previous research has relied on indirect methods which are not as accurate as direct methods; 2) performance analysis offers an objective, replicable ad adaptive measure of a form of corruption;[22] and 3) a direct method of detecting match-fixing allows investigators to generate a new form of evidence on players involved in the manipulation of sports competitions as well as clearing athletes who were accused of fixing yet innocent.

The literature generally distinguishes between match-fixing related to betting and match-fixing non related to betting.[3] Non-betting match-fixing is carried out for sporting results purposes such as avoiding relegation, preventing degradation, or deliberately losing a competition to avoid a better opponent in tournaments.[23, 24] Betting match-fixing involves manipulating aspects of a performance indicator (*i.e.*, spot fixing) (*e.g.*, first penalty of a competition) and/or the outcome of a competition for financial gain from betting markets.[3, 13] Hill[2] explained every player on a team, or an individual player can fix a match or aspect of a competition by using different tactics (*e.g.*, performing with less effort, deliberately making mistakes, intentionally deviating from a game strategy). Despite the type and reason for match-fixing, both types of fixes mostly involve underperformance by sporting participants and thus detection requires providing reliable data that supports player underperformance in a competition.[12]

Match-fixing's threat to the integrity of sport is a critical concern across many sports worldwide thus it is imperative that accurate detection methods are developed to curb this type of corruption.

Forensic statistics (*e.g.*, monitoring, predictive modeling) is an evolving field that uses economic models to detect match-fixing.[23] Forensic statistics "identify[sic] hidden behavior by testing data against a null hypothesis" that is based on economic theory.[25] One method used in predicting match-fixing is constructing two measures that capture the same economic activity but are affected differently by hidden behavior. The null hypothesis is the hidden behavior and is the main or only reason the two measures should differ. The concern for alternative explanations focuses on potential additional reasons for difference.[25] Economic models are used to predict match outcomes or detect possible match-fixing drawing from a combination of betting data or sports information (*e.g.*, strength of schedule, latest competition outcomes).[26, 27] Economics and business literature maintain that betting companies' release of betting odds provide high forecasting accuracy and are thus considered valid sources of data.[28] However, betting odds cannot consider many factors that can influence athletic performance on any given day, for instance game flow, momentum and substitutions.[29] Predictive models are based on mathematical calculations for probabilistic forecasting of game results as they identify when betting odds are operating abnormally based on a generated algorithm of benchmarked odds.[12, 27]

Economic models generate predictions of competition outcomes using sports data that assumedly mirror bookmaker odds because both models are used relevant to forecast outcomes.[27] For example, Reade and Akie[27] compared bookmaker odds of 9000 international football matches over approximately a 10-year period with their economic model where they argued that in the absence of corruption the two projections should be indistinguishable. However, similar to other economic models,[12, 13] their findings were inconclusive. Stats Perform collects information on ball tracking throughout soccer matches, like shot attempts or passes, for example. While Forrest and McHale[12] state that these data collection methods can be "noisy," Footovision provides a way to sort through the enormous amount of data that is collected, recording roughly 1000 data points per soccer match but grouping linked variables to make the data analysis possible.[30] It is important to note that these detection methods currently require human analysis in the process.[30] Sportradar uses a prediction model where competitions are flagged as suspicious when drastic movement in the betting odds exists prior to the start of a competition.[12] Otting *et al.*[13] argued that match-fixing detection systems should incorporate multiple data sources such as bookmaker odds and betting volumes rather than just betting odds. Otting and colleagues maintain monitoring the volume of bets placed, alongside the monitorization of the betting odds is more dependable for detecting match-fixing because highly liquid markets are more resistant to shifting odds (*i.e.*, in betting exchanges). Results showed that analyzing a combination of odds and volume monitoring identified one more fixed match than monitoring volume alone but had a slightly higher false positive rate, whereas the combination of the two identified one less fixed match than monitoring the odds alone but had an almost 15% lower false positive rate.

Data envelopment analysis (DEA) – assessment of efficiency and productivity – is another common statistical model to monitor performance.[31] In general, performance inputs on the field are measured through different field movements and assessed in comparison to outputs representing sporting success.[32] DEA is commonly used in assessing sports efficiency research in different sports, such as baseball, basketball, cricket, football, rugby, and tennis.[33] Lin and Chen[34] used DEA to study the Chinese Professional Baseball League to create a model tracking efficiency anomaly in Chinese Professional Baseball League fielders and pitchers who were guilty of match-fixing. Offensive efficiency (at-bats *vs.* total bases) was a measure for position players and pitchers' efficiency (innings pitched *vs.* total bases allowed) was used to compare "anomalous performances." Whilst the monitoring model is an important contribution, it contains three key limitations. First, the basis for classifying abnormal matches (*i.e.*, judged matches or another criteria) or normal matches (*i.e.*, what criteria is used to operationalize 100% normal) was unclear. Second, a "suspicious match" is not a "manipulated match" (*i.e.*, false positive). Thus, we question the validity of their conclusion of a 92% detection rate with the three models, which we believe is misleading. Last, the sports data was fundamentally noisy and did not accurately account for poor performance *versus* underperformance.[12]

The use of video analysis to measure metrics during games (*i.e.*, sport performance) is an emerging method of detecting and preventing match-fixing.[30] Video analysis is particularly useful and an accepted valid and reliable method for analyzing sport motions and/or sports performance based on quantitative data.[35] Motion analysis generally "means motion detection, classification based on motion, parameter estimation, prediction and tracking of specific patterns to build trajectories. "The advent of artificial intelligence motion analysis means the detection, indication and prediction of abnormalities, incidents, and accidents."[36]

Video analysis software can extract quantitative data, such as speed, acceleration, and angles, to track an athlete's performance metrics over time[37] and above all to identify underperformance. Underperformance in sport can be defined as a situation in which an athlete or team fails to meet the expected or desired level of performance in competition.[38] It typically involves a significant deviation from the athletes' usual or potential performance capabilities. Noteworthy, underperformance is a complex issue influenced by numerous traditional factors including injuries, psychological pressure, lack of motivation, fatigue, inadequate preparation, technical errors[39, 40] but involuntary. Conversely, the complexity of detecting a manipulated match lies not so much in identifying the phases of underperformance as in demonstrating their voluntary aspect. On this last point, only a biomechanical approach with quantified data would be able to provide an answer, which would represent a key contribution to the corruption literature.

In September 2012, French authorities investigated a French handball club champions match for match-fixing. MAH 2011/2012 season champions surprisingly lost a match (31-28) against CRMH who was facing relegation.[41] Authorities were notified by the Française des Jeux (FDJ) (French national lottery) that abnormally large bets were placed in relation to the expected stakes of the competition.[42] Seventeen people were arrested (eight players and nine individuals connected to the players) for making 80,000 euros in bets earning 200,000 euros in profits.[43] A court trial was conducted in 2015 where the court judge requested match-fixing expertise to conduct video and standard performance analysis to present as evidence in the trial. The trial judge gave the first author and colleagues the match video to determine underperformance *versus* deception. The judge requested the video analysis focus on the first half of the match, *versus* the whole match. To assist the jury to easily find the video sequences in the overall video, official match timing displayed was in the form of minutes:seconds (mm:ss). Standard performance data included the results and statistics related to the game of the suspected MAH and CRMH match. Statistics related to the game are commonly used in conducting performance analysis in handball.[44] Upon appeal, fourteen defendants (including two players) were assessed fines (from 10,000 to 40,000 euros) and suspended prison sentences.[41, 42]

Performance data was provided by the National Handball League (LNH) following an official request by the legal expert validated beforehand by the judge. In this study, official LNH player and team level game statistics were collected: match outcome (winning and losing teams) and game related statistics: shots (percentage of converted shots relative to the number of shots made); 6 m shots (percentage of converted shots at 6 m relative to the number of shots made, noting that the area is from a zone outside the 45°angle from the left and right); 7 m shots (percentage of penalties – 7 m – converted relative to the number of penalties taken; 9 m shots (percentage of converted shots at 9 m relative to the number of shots made, noting that the area from a backcourt player either 1) over or through the defense, and 2) after a breakthrough but with another defense player in front); wing shots (percentage of converted shots at wing area relative to the number of shots made, noting that the area is from within an angle of 45° left and right without a defense player in front); fast break shots (percentage of shots converted in a situation of fast break – rapid switch from defense to attack without the defense organized – relative to the number of shots made in this situation); breakthroughs shots (percentage of shots converted in a situation of breakthroughs 1) from the backcourt players after breakthrough in the 9 m zone without a defense player in front; 2) of the pivot after 1:1 situation; and 3) from the left or right back).

The average reference value (*i.e.*, average value for a single match) of each team was calculated based on each player's number of matches played in the same season (*i.e.*, 2011-2012) during the championship, and does not include international competitions. The analysis of the standard performance data was carried out using IBM SPSS software version 21. Descriptive statistics on players' technical performances (*i.e.*, number of shots, shots on target) were expressed as means plus or minus standard deviation (SD). Anova and Fisher's *post hoc* test was used to study differences among playing positions and groups. Significance was set at the $P<0.05$ level.

The video analysis was carried out using the KINOVEA[45] software version 0.8.15. KINOVEA video (n.d) is a sport analysis annotation tool that provides various utilities to "capture, slow motion, comparison, annotation and measurement of motion in video" (par. 1). KINOVEA software is an accepted valid and reliable video analysis used to assess handball player performance.[46] Video analysis first consisted of identifying and sequencing the competition into key performance points. In this case, the handball competition was separated into two specific phases of game play: goals scored and goal situations.

For each given key point the video sequence is taken from the master video file and coded as the specific key point, the time of the start of the timing, and the end time. Player performances within each of the two performance points were then analyzed to detect potential anomalies (*i.e.*, deficiencies) based on quantifiable observed biomechanical and physiological performance data (*i.e.*, distances, times, speeds, angles, trajectories, and force vectors).

A deficiency differs from a simple error in play in that it is always based on repetitive elements that can be measured according to a precise reading grid, which includes the start and finish conditions of a phase of play. The deficiency METRICS=data values (4 types=distance in meters + time in mmss + velocity in km/h + angulation in degrees) related to physical behaviors (*e.g.*, low run) or to game play attitudes (*e.g.*, no marking) that are contrary to the team's interest. The deficiencies were further divided based on the nature of the deficiency (*i.e.*, minor deficiency and major deficiency) and its consequences (*e.g.*, turnover, goal). All possible player deficiencies were identified for each key point. A deficiency differs from a simple error in play in that it is always based on repetitive elements that can be measured according to a precise reading grid (confidential=industrial properties), which includes the start and finish conditions of each phase of play. Based on the metrics player performance were then classified into either a "normal deficiency," which are an involuntary error or a non-intentional action that occur in a handball match; or "abnormal deficiency" that is an intentional underperformance depicted by one or several deliberate actions of a player or players. The key points are then classified into a three-level scale, normal sports performance, potentially abnormal sports performance, and abnormal sports performance. In the event of an abnormal sports performance, each player involved was identified.

Results

The average reference value of the number of ball losses in the first half was equal to 4.75±2.30 for the MAH team and was not significantly different (P=0.601>0.05) from the value of the assessed match equal to five (Table I).

Individually, two MAH players showed a significant difference between their baseline mean value of the number of ball losses in the first half and their value in the assessed game (0.59±0.73 *versus* 2 with P<0.05 for Player A [Table II] and 0.1±0.44 *versus* 2 with P<0.05 for Player B [Table III]).

The average reference value of the percentage of shots missing the target in the first half were equal to 8.14±5.91% for the MAH team which was significantly different (P<0.05) from the value of the assessed match equal to 20.83% (Table IV).

Individually, two MAH players showed a significant difference between their average reference value on the percentage of shots missing the target in the first half and their value in the assessed match (8.57%±17.84 *versus* 60% with P<0.05 for Player A [Table V] and 7.33%±12.12 *versus* 16.67% with P<0.05 for Player C [Table VI]).

The average reference value of the percentage of goalkeepers' saves in the first half was equal to 35.87±13.44%

TABLE I.—*Results between the average reference value of the number of ball losses in the first half for the MAH team and the reference value of the assessed match.*

	N.	M	SD	SE		
MAH	24	4.75	2.308	0.471		
	Test value =5					
	t	df	Significance (bilateral)	MD	95% CI	
					Lower	Higher
MAH	-0.531	23	0.601	-0.250	-1.22	0.72

TABLE II.—*Results between the average reference value of the number of ball losses in the first half for Player A and the reference value of the assessed match.*

	N.	M	SD	SE		
Player A	22	0.59	0.734	0.157		
	Test value =2					
	t	df	Significance (bilateral)	MD	95% CI	
					Lower	Higher
Player A	-9.003	21	0.000	-1.409	-1.73	-1.08

TABLE III.—*Results between the average reference value of the number of ball losses in the first half for Player B and the reference value of the assessed match.*

	N.	M	SD	SE		
Player B	20	0.1	0.447	0.100		
	Test value =2					
	t	df	Significance (bilateral)	MD	95% CI	
					Lower	Higher
Player B	-19.000	19	0.000	-1.900	-2.11	-1.69

TABLE IV.—*Results between the average reference value of the percentage of shots missing the target in the first half for the MAH team and the reference value of the assessed match.*

	N.	M	SD	SE		
MAH	24	8.1463	5.91488	1.20737		
	Test value =20.83					
	t	df	Significance (bilateral)	MD	95% CI	
					Lower	Higher
MAH	-10.505	23	0.000	-12.68375	-15.1814	-10.1861

TABLE V.—*Results between the average reference value of the percentage of shots missing the target in the first half for Player A and the reference value of the assessed match.*

	N.	M	SD	SE		
Player A	22	8.5714	17.84686	3.80496		
	Test value =60					
	t	df	Significance (bilateral)	MD	95% CI	
					Lower	Higher
Player A	-13.516	21	0.000	-51.42864	-59.3415	-43.5158

TABLE VI.—*Results between the average reference value of the percentage of shots missing the target in the first half for Player C and the reference value of the assessed match.*

	N.	M	SD	SE		
Player C	20	7.3320	12.12248	2.71067		
	Test value =16.67					
	t	df	Significance (bilateral)	MD	95% CI	
					Lower	Higher
Player C	-3.445	19	0.003	-9.33800	-15.0115	-3.6645

TABLE VII.—*Results between the average reference value of the percentage of goalkeepers' saves in the first half for the MAH team and the reference value of the assessed match.*

	N.	M	SD	SE		
MAH	24	35.8771	13.44180	2.74380		
	Test value =16.67					
	t	df	Significance (bilateral)	MD	95% CI	
					Lower	Higher
Player C	3.964	23	0.001	10.87708	5.2011	16.5531

for the MAH team and was significantly different (P<0.05) from the value in the assessed match equal to 25% (Table VII).

A total of seven phases of play (*i.e.*, key points) were identified as abnormal due to the presence of deficiencies of one or more MAH players with deleterious effect on the performance such as goals scored for the CRMH team or potential missed goals for the MAH team. Conversely, no abnormal phase of play could be identified for the CRMH team during this first half. For example, the goal conceded by MAH at 16:38 was identified as an abnormal phase of play. The start of the shot by the CRMH player (circled in pink) is identified at T0=0ms (Figure 1).

Figure 2 at T0+480ms corresponds to the release of the ball during the CRMH player's shot (circled in pink, colors in the online version).

At T0+680ms, the extension of the MAH goalkeeper's arm (white arrow up) in the frontal plane positions in this segment was in opposition to the projected trajectory of the ball (circled in pink), which should have stopped the ball (Figure 3).

In spite of a possible continuous intake of information, at T0+840ms the MAH goalkeeper performed a ball avoidance movement from an extension movement (white arrow upwards) of the elbow (from 123° to 174°) in the frontal plane (Figure 4). This deficient attitude of the MAH goalkeeper results in the non-stopping of the shot and therefore a goal scored for the CRMH.

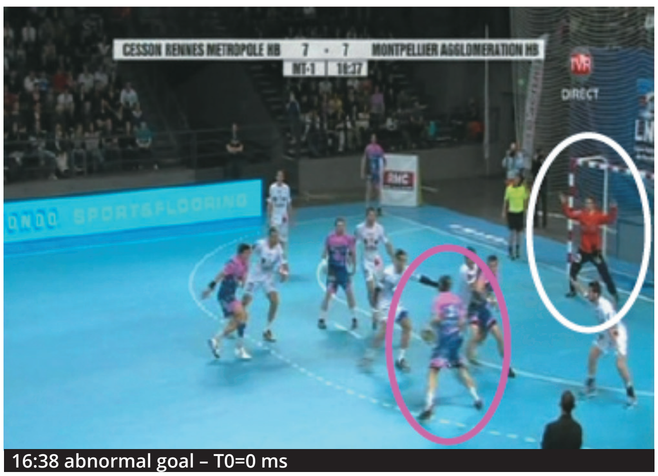

Figure 1.—Start of the shot.

Figure 3.—Goalkeeper arm in opposition on the projected trajectory of the ball.

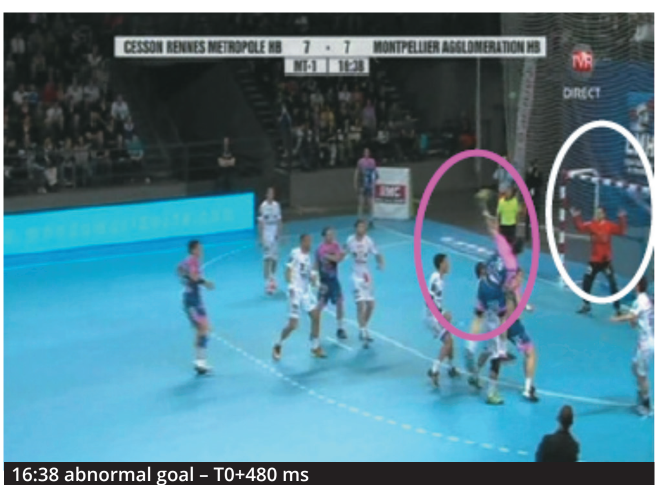

Figure 2.—Release of the ball.

Figure 4.—Avoidance movement from the goalkeeper.

Discussion

The purpose of this study was to develop a method to directly detect match-fixing using video analysis and performance data from a handball match that was suspected of match-fixing. The findings were instrumental in that they demonstrate a new method for directly detecting match-fixing through video analysis of combining sport performance and biomechanical data.

Standard performance data is typically used in team invasion sports to evaluate teams and/or players performance and are clearly part of modern training.[47] Used singularly, however, performance data is extremely limited in capacity and interest in the detection of match-fixing. In this study, significant differences in some standard performance data analysis could suggest an underperformance at first reading, as is the case, for example, for the percentage of shots that missed the target in the first half for the MAH team and for two MAH players. The comparison of these results with the other existing values, however, showed a more nuanced and contradictory result. For example, for player C, the value of 16.67% was significantly different from the reference value equal to 7.33±12.12% observed on the previous 24 days of the French First Division Handball Championship for the 2011-2012 season; the value remained far beyond the value observed of 50% on the 14th day. The performance data is, moreover, by definition integrally correlated to the total number of shots and to be expressed in terms of the nature and position of the shots taken as well as the type of defensive opposition. For the other 11 MAH players, there was also no significant difference in the percentage of shots that missed the target in the first half.

Similarly, there was no significant difference in the number of ball losses in the first half for the MAH team. The significant difference in the number of ball losses in the first half for player A was equal to two. The number of ball losses was not a unique phenomenon since it was observed a total of three times during this same season for the player concerned. The percentage of goalkeepers' saves in the first half were also identified as typical performances. The MAH team was equal to 25%, which, if it was significantly different from the reference value of 35.87±13.44%, was only the third lowest value observed compared to 23.53% during the fourth day and 11% during the twentieth day on the previous 24 days of the French First Division Handball Championship for the 2011-2012 season.

Video analysis has traditionally been used in sport as support in the identification of collective strategies[48] and/or in the assessment of individual techniques[49] but to date has not been used in the identification of match-fixing. Previous research[50] shows the ability to distinguish between actions that are deceptive and those that are not in sport. Jackson *et al.*[50] maintained that the kinematics of an actual sport performance action cannot not be carried out through deception because a motion has specific biomechanical characteristics. The video analysis method used in combination with sport performance data demonstrates a strong starting point for directly detecting match-fixing. Using sport performance analysis, we collected objective and quantifiable data based on biomechanical algorithms to differentiate between intentional underperformance and poor performance. The findings therefore countered Forrest and McHale's[12] suggestion that sports performance analysis was an invalid measure for assisting in sports integrity investigations.

While the sport of handball was used in this study, the direct match-fixing detection method is directly transferable to team and other individual sports. Contrary to the use of standard performance data, our video analysis method strongly limits the number of hypotheses for the explanation of a result given the focus on specific player deficiencies. For example, in the goal phase analyzed and described at 16:38, a goalkeeper's voluntary movement of avoidance of the arm was identified, despite its position in opposition to the projected trajectory of the ball. The findings supported the existence of a manipulation during the match between the teams of MAH and CRMH on May 12, 2012. The manipulation conclusion was also found by the court on July 10, 2015, and confirmed on appeal on February 01, 2017.[42] The practical implications of this study are that the findings led to legal convictions. The players' underperformances were corroborated with video analysis thus providing sufficient evidence to convict the players involved. As such, the developed direct detection technique could serve as a deterrent for players' considering fixing matches, which could serve as a critical contribution to curbing match-fixing.

Limitations of the study

The findings of this study should be considered in light of its limitations, which may offer future research opportunities. First, the initial findings can serve as a launching pad for developing a direct method to detect match-fixing. The technique, however, requires validation. Future research should focus on measuring the method's intrinsic validity, that is, its sensitivity and specificity. For example, using the method to detect match-fixing of a group of matches judged as manipulated by a court would measure intrinsic validity. Conversely, using a group of matches that were not fixed, which is more complex to obtain in the absence of a reference method, could also measure the method's ability to confirm that these matches were not manipulated. Second, this study reveals a new possibility for direct match-fixing detection from a specific video analysis. The analysis aims to identify the presence or not of deficiencies for one or more players that can be quantified numerically to demonstrate a voluntary underperformance. The total number of deficiencies and/or their distribution is a key point and/or the type of deficiencies are all elements capable of identifying match-fixing. However, the limits of this method are, logically, the need for a video of minimum quality for analysis, and the difficulty of demonstrating a voluntary error on a simple action, such as getting only a yellow card or a corner, for example. Future research should focus on identifying the types of deficiencies for each sport and then compare the number and distribution of these deficiencies per key point between a normal match and a manipulated match as opposed to subjective assessments of a game situation (*e.g.*, flagging irregular betting) without performance data. Gaining valid and reliable match-fixing detection techniques is critical to curbing criminal activity and protecting sports integrity.

Conclusions

Sport performance analysis tools offer a solid innovative approach to directly detect match-fixing and protect sport integrity. The findings offer encouraging support for using video analysis and biomechanical data (*e.g.*, distances, times, speeds, angles) to develop a scientific method to detect underperformance or deliberate performance deficiencies. The random distribution of the results of the standard data performances, the variable choice of the reference databases and the numerous explanatory hypotheses to be opposed, such as the tactical patterns or the fatigue for player, for example, limit the exploitation and the use of the standard data performances as evidence in sports and/or civil judicial investigation. Detection methods based on odds variations also have a low detection rate of less than 10%.[14] This is explained both by the existence of a strong unmonitored illegal gambling networks estimated at 80% of the global sports betting market[4] and the complete absence of detection possible with this method for sporting motivated form of match-fixing. Creating accurate and reliable measures to positively identify match-fixing is an important step in understanding how to objectively pinpoint corrupt acts from underperformances.

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