Big Data, Artificial Intelligence, and Quantum Computing in Sports

Benno Torgler

Abstract

This chapter examines the exciting possibilities promised for the sports environment by new technologies such as big data, AI, and quantum computing, discussed in turn. Together and separately, the technologies' capacity for more precise data collection and analysis can enhance sports-related decision-making and increase organization performance in many areas. Torgler also emphasizes technologies' limitations—and considerations like privacy and inefficiencies—by reflecting on the nature of sport. Finally, it explores the factors beyond technology that influence individual's deep involvement in and emotional attachment to sports and sports-related events.

How puzzling all these changes are! I'm never sure what I'm going to be, from one minute to another.

Lewis Carroll, *Alice's Adventures in Wonderland*.

I know that it is ninety feet from first base to second base, ninety feet from second base to third base, and that a baseball batted between those points is fair. I know that approximately 20 out of every 100 balls batted fair during the season are 'safe hits.' I know that of 1,284 ground balls batted during the season of 1909 in the American and National leagues (1,284 chosen at random) 138 got past the infielders. I know that infielders of the National League (pitchers not included) fielded 9,382 ground balls errorlessly during the season of 1909. But how many millionths of a watt constitutes the chances of a hit being safe I cannot figure out. The average speed of fifty ground balls hit in three games during which three of us

B. Torgler (✉)
Centre for Behavioural Economics, Society and Technology (BEST), Queensland University of Technology, Brisbane, Australia
e-mail: benno.torgler@qut.edu.au

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held twentieth-of-a-second watches we calculated to be 100 feet in one and three twentieth seconds. We know that the third baseman plays ordinarily about 96 feet from the home plate, that the short stop playing 'middling deep' is about 130 feet from the batter, that the second baseman is about two feet closer, and the first baseman 90 feet when a runner is on first base and 102 when no one is on bases. Given the speed and direction of the ball and the speed of the player, it is possible to figure to a millionth of a watt where his hands will meet the ball; but just as you start to write Q. E. U. the ball will take a bad bound. Given the average speed of the infielders, it would be possible to calculate beforehand approximately the number of base hits each team will make in a season—if the players were automatons.

Fullerton (1910), *American Magazine*, p. 3.

Turning to quantum mechanics, we know immediately that here we get only the ability, apparently, to predict probabilities. Might I say immediately, so that you know where I really intend to go, that we always have had (secret, secret, close the doors!) we always have had a great deal of difficulty in understanding the world view that quantum mechanics represents. At least I do, because I'm an old enough man that I haven't got to the point that this stuff is obvious to me. Okay, I still get nervous with it. And therefore, some of the younger students … you know how it always is, every new idea, it takes a generation or two until it becomes obvious that there's no real problem.

Richard Feynman (1982), p. 471.

1 Introduction

Competitive sports and athletic games have evoked deep emotional involvement from old and young, rich and poor in both modern and ancient societies, with superior performances greeted by visceral reactions of excitement and awe. The 2018 FIFA World Cup, for example, attracted a combined individual viewership of 3.5 billion, equivalent to half the global population aged four and above,[1] and rarely do people enter disputes or embrace their loyalties in quite the way (or to the degree) as when sports is the topic of conversation (Weiss, 1969). It is not surprising, then, that the sports environments have recently been penetrated by the new technologies of big data, artificial intelligence, and quantum computing, whose capacity for more precise data collection and analysis can enhance sports-related decision-making and increase organizational performance in many areas (Brynjolfsson et al., 2011). Just as political campaigns, governments, and businesses use big data from social media, census, and voter lists, and active outreach to get ahead of the curve and learn as much as possible about their constituents or customers (Weber et al., 2014), decision-makers in competitive environments like professional sports are naturally incentivized to use decision-enhancing tools and instruments that exploit the potential of advanced technologies.

[1] https://www.fifa.com/worldcup/news/more-than-half-the-world-watched-record-breaking-2018-world-cup.

As a result, the *analytical* way of winning outlined in Michael Lewis's 2003 *Moneyball* drew major attention, culminating in a film adaptation with Brad Pitt as Billy Beane, general manager of the Oakland Athletics baseball team, and Jonah Hill as Peter Brand, the young Yale economics graduate assistant full of new ideas about how to assess player value. In this inspiring David and Goliath story, rigorous statistical analysis replaced a slingshot as the secret weapon, one whose deadly precision allowed the underdog to compete successfully with far better-funded rivals in major league baseball (MLB). Armed with this highly accurate instrument, the Oakland A's stayed ahead of the curve and reached the playoffs for four straight seasons in the early 2000s despite substantially smaller budgets than league "big boys" like the New York Yankees. In fact, during the 2002 season, the Oakland A's tied with the Tampa Bay Devil Rays for the lowest payroll in the league (about 40 million USD), while the New York Yankees benefited from a payroll more than three times that amount (140 million USD). Yet the A's won more games across the 2001 and 2002 seasons than the Yankees (205–198) despite being unlucky in the playoffs.

Strategically, selecting for undervalued baseball skills such as defensive capabilities is like opting for David's sling rather than Goliath's spear and armor. Hence, although the Oakland A's data strategy was specific, the story's appeal is universal: success in the face of overwhelming odds elicits feelings of greatness and beauty (Gladwell, 2013), inspiring wide replication. Such narratives not only represent the clash between rich and poor or between strong and weak, but also that between traditionalists and sabermetrics, between intuition or gut feeling and statistics, and between the democratization of decision-making through data and authoritarian decision-making by specific decision-makers. This modern contest is in fact playing out well beyond the stadium as managerial decisions rely less on a leader's gut feelings and instincts and more on business intelligence systems whose analytic tools enable in-depth investigation of a broad array of data (Brynjolfsson et al., 2011).

At the same time, the collection and analysis of sports data are becoming increasingly dependent on newly developed sports information systems capable of fast and automatic evaluation of sports-specific parameter values (Novatchkov & Baca, 2013a, 2013b). For example, in the lead-up to the 2018 World Cup in Russia, "many teams boasted a scientist on board to crunch the numbers to understand the strengths and weaknesses of the opposition, including how the network of each team behaves" (du Sautoy, 2019, p. 55). This chapter therefore takes a closer look at the key applications and implications of big data and AI in sports, as well as what to expect from sports application of quantum computing. It also addresses the limitations of such technologies by reflecting on the nature of sport.

2 Sports' Journey Through the Supercollider

2.1 Power of Sensoring Systems

The exponential growth in technological advances (Kurzweil, 1999, 2012)—including wearable nonintrusive and noninvasive instruments for monitoring athletes' physiological processes—has opened up new ways of understanding human nature (Torgler, 2019). The attraction of nonintrusive tools like surface electrodes is their potential to identify psychological or mental processes that are otherwise hard to measure. The rich continuous data they produce (e.g., second-by-second pictures; Pentland et al., 2009, p. 4) offer new ways of understanding human dynamics (Eagle & Pentland, 2006) and the messiness of human interactions in and outside the sports arena. These multimodal tools, appropriately dubbed "social fMRI" (Aharony et al., 2011), enable trainers to put athletes through a type of social supercollider, harnessing 24 h measurements of real-time continuous biological data linked to behavior and environmental conditions via a combination of multiple data sources. By ensuring the proper observation of, or controls for, individual environmental and situational realities (Eagle & Greene, 2014), such reality mining gives trainers access to a richer, more realistic portrait of athletes' physical and mental conditions, as well as their responses to, for example, training changes or contextual environmental factors like stress situations before, during, and after competition.

These digital footprints, now used intensively as exercise and training data in the field, can improve athletes' performance, long-term health status, and stress resistance, and even prolong their sports career (Passfield & Hopker, 2017). Real-time analysis is achieved in elite sports via several applications of wearable technology (for an overview, see Page, 2015). For example, adidas' elite *miCoach System* is an advanced physiological monitoring method used by Germany's team in preparation for its victory in the 2014 FIFA World Cup. The team also used it during training sessions in Brazil to monitor player performance, plan workouts, identify player fitness, and understand player movements in different positions.[2]

Nonetheless, although current research into biosensing focuses primarily on exercise-related physiology (see, e.g., Guan et al., 2019), new technologies can go beyond this aspect. For example, a group of MIT scholars (see Pentland, 2008, 2014) developed a sociometer designed to quantify human social behavior in the context of social networks by focusing on social signals like body language, facial expression, voice tone, and speech measures such as energy, pitch, and speaking rate (Gatica-Perez et al., 2005). In particular, they targeted social interactions such as individual turn-taking (Choudhury & Pentland, 2004) while also measuring stress via variation in prosodic emphasis (Pentland, 2008). According to

[2] https://www.sporttechie.com/how-the-adidas-micoach-system-has-helped-germany-in-the-world-cup/.

Pentland (2014), the sociometer can "accurately predict outcomes of dating situations, job interviews, and even salary negotiations" (p. xi) with sensors that extract information on both the users' behavior and their environment, including location, ambiance, and others involved in the conversation (for a discussion, see Torgler, 2019). Stopczynski et al. (2014) even constructed a "smartphone brain scanner" built on open source software that provides real-time imaging of brain activities (low-density neuroimaging), using neuroheadsets with 16 electrodes placed on the scalp to produce 3D EEG imaging. Given the need to better understand the connection between the brain and sports performance, such mobile brain scanners may hold great potential for athletes, particularly if wearing them is nonintrusive.

The use of this technology was extended by the International Football Association Board's (IFAB) March 2015 ruling that wearable technology can be worn in regular competitive soccer games,[3] thereby permitting observation of player performances in real and high-stakes decisions rather than only in training environments. Such newly generated information can feed into how tactics are chosen or how players can be trained to be more competitive and stress resistant when it counts. Instant feedback through the use of these wearable technologies could therefore transform how matches are organized in elite sports contexts (Memmert & Rein, 2018). Sensoring systems also offer new ways of quantifying performance; for example, a better estimation of speed, acceleration, and force in wheelchair sports to improve mobility performance proxies (van der Slikke et al., 2018).

3 AI Techniques and Quantum Computing

3.1 AI Techniques

Artificial intelligence has come a long way since the 1840s, when Lady Ada Lovelace's prescient ideas for the analytical engine augured the future of AI (Boden, 2016). AI and quantum computing provide new ways of more efficiently using computers, applying concepts and models to better understand athletes and their competitors. The application of AI-based methodologies in sports has been discussed in fields as diverse as biomechanics, kinesiology, and the physiology subfield of adaption processes (Bartlett, 2006; Lapham & Bartlett, 1995; Mężyk & Unold, 2011; Novatchkov & Baca, 2013a, 2013b; Perl, 2001), with the first computerized analysis commercially available as early as 1971 (Lapham & Bartlett, 1995).

The artificial neural networks (ANNs) at the core of AI applications, having received substantial hype because of the success of deep learning (Boden, 2016), are attractive to the sports environment as a way to model learning (Perl, 2001).

[3] https://football-technology.fifa.com/en/media-tiles/epts-1/.

For example, parallel distributed processing (PDP) has the ability to learn patterns and associations, while not only recognizing incomplete patterns but also tolerating messy evidence via constrained satisfaction (Boden, 2016). ANNs are thus relatively well suited to sports applications given this areas' continual battle with large amounts of data, dynamics, and complex input–output relations (McCullagh & Whitfort, 2013; Perl & Weber, 2004). The applications of ANN are quite broad, ranging from identifying talents and evaluating game strategies to predicting injuries and training loads, or performance in general (McCullagh & Whitfort, 2013; Rygula, 2003). Experiments by McCullagh and Whitfort (2013), for example, indicate that because ANNs correctly predict injuries to a meaningful level (97.3% for contact and 92.2% for noncontact injuries), they could be used as an additional tool to assess injury potential. While combining such modeling with continuous monitoring of longitudinal changes can increase understanding of the multiple injury factors and dynamic nature of injury risks (Verhagen et al., 2014), employing new technologies can establish better treatment and preventive protocols, avoid overuse injuries, and better monitor injury risk factors and symptoms (Verhagen et al., 2014). The specialization of sports biostatistician is thus becoming increasingly relevant in professional sports for both the abilities outlined above and the expertise to design and improve injury surveillance systems, which has prompted some scholars to declare a desperate need to train researchers and practitioners in this field (see, e.g., Casals and Finch 2017).

According to Kahn (2003), ANNs can also be used to predict the outcomes of NFL football games, although the timing of his study toward the end of a season raises questions of efficacy in predicting earlier games. Nevertheless, because the ways in which teams win games are not likely to change over time, the author deemed it rational to assume that statistics from past seasons can be used to train the network. In fact, team sports offer a wide variety of scenarios for network exploration such as the football passes used in Peña and Tuchette's (2012) network theory-based test of the Google algorithm based on knockout stage data from the 2010 FIFA World Cup. These authors defined a team's passing network as one in which team players were the nodes with "connecting arrows between two players weighted by the successful number of passes completed between them" (p. 1). These passes were like links from one website to another and represented the trust put in that player (du Sautoy, 2019). Spain not only won the World Cup but reported the highest number of passes, clustering, and clique size, as well as high-end edge connectivity and low betweenness score, all of which reflect "total football" or a *tiki-taka* playing style with no hub (Peña & Tuchette, 2012, p. 4).

Expert systems that integrate fuzzy logic processes have also been used to identify sports talent based on knowledge of sport experts, motor skills tests, morphologic characteristic measurements, and/or functional tests (Papić et al., 2009). For example, the implementation of neural network technology to identify explanatory factors in swimming performance (Silva et al., 2007) enabled the development of highly realistic models of predicted performance with elevated prognosis precision (i.e., an error lower than 0.8% between true and estimated performance). This finding implies that neural networks are an effective avenue for dealing with such complex sports problems as performance or talent identification.

3.2 Quantum Computing

The great Richard Feynman (1982) questioned what type of computers would be capable of simulating physics, especially given that although the physical world is quantum mechanical, certain quantum mechanical effects cannot be simulated efficiently on a classical computer (Rieffel & Polak, 2000). Nonetheless, quantum computing is a newly emerging field with the potential to dramatically change the way scholars think about complexity (Rieffel & Polak, 2000). Major players such as IBM or Google are thus betting heavily on quantum computing, with the former making significant investments in large-scale adoption of quantum computing within their Q Network, a community of Fortune 500 companies, startups, academic institutions, and research labs working to advance quantum computing and explore its practical applications. More recently, IBM opened its quantum computing center, which not only expands the world's largest fleet of quantum computing systems but makes 20-qubit systems for commercial and research activity available beyond the experimental laboratory environment.[4] In a recent *Nature* article, Google scientists announced their achievement of "quantum supremacy" (Arute et al., 2019) based on their quantum computer's ability to carry out calculations that are not only beyond the capabilities of classical supercomputers but would take classical computers an estimated 10,000 years to complete. IBM scholars countered, however, that even given a worst-case scenario, an ideal simulation of the same task could be performed on a classical system in less than three days.[5]

Government agencies are also active in this space, as demonstrated by the UK government's launching of a national program to promote quantum technologies by creating a quantum community destined to become a global leader in this new market (UK National Quantum Technologies Programme, 2015).[6] This program, which has received in the first phase 385 million GBP (Knight & Walmsley, 2019)[7] from the government, represents a coordinated effort between various departments and initiatives, including the Department for Business, Innovation, and Skills; the Engineering and Physical Science Research Council; Innovate UK; the National Physical Laboratory; the Defence Science and Technology Laboratory; and the Government Communications Headquarters. According to the government, a national network of quantum technology hubs can educate a future workforce and identify the commercial opportunities that quantum technologies can bring to the

[4] https://newsroom.ibm.com/2019-09-18-IBM-Opens-Quantum-Computation-Center-in-New-York-Brings-Worlds-Largest-Fleet-of-Quantum-Computing-Systems-Online-Unveils-New-53-Qubit-Quantum-System-for-Broad-Use.

[5] https://www.ibm.com/blogs/research/2019/10/on-quantum-supremacy/.

[6] https://iopscience.iop.org/article/10.1088/2058-9565/ab4346.

[7] With a commitment of more than £1Bn over the next 10 years.

UK. Popkin (2016), in an article for *Science*, explained why quantum computing can be so powerful[8]:

> Qubits outmuscle classical computer bits thanks to two uniquely quantum effects: superposition and entanglement. Superposition allows a qubit to have a value of not just 0 or 1, but both states at the same time, enabling simultaneous computation. Entanglement enables one qubit to share its state with others separated in space, creating a sort of super-superposition, whereby processing capability doubles with every qubit. An algorithm using, say, five entangled qubits can effectively do 25, or 32, computations at once, whereas a classical computer would have to do those 32 computations in succession. As few as 300 fully entangled qubits could, theoretically, sustain more parallel computations than there are atoms in the universe.

Quantum computing and its parallel computations thus promise interesting applications for sports because by breaking the limitations of conventional information structures (Muhammad et al., 2014), quantum information systems open up valuable avenues through which to handle the rich data complexity of the sports ecosystem. For example, miniaturization of quantum technologies can promote new ways for portable sensor devices to increase their monitoring abilities, accuracy, and system integration in day-to-day usage. Likewise, by facilitating tasks that are beyond even the latest supercomputers, quantum computing will enable new ways of analyzing sports-related big data. It could thus dramatically speed up algorithms designed to simultaneously explore vast numbers of different paths (Popkin, 2016), a remarkable opportunity for tactical analysis and experimentation in team sports.

Beyond even these impressive advances, quantum technology further offers an interesting alternative to physical sports in the form of quantum games, whose most fascinating aspect is their use of a novel type of physical engine. For example, players in a ball game can evaluate not only one response possibility but a sample of plausible ball trajectories in parallel allowing them to implement more interesting play options (Pohl et al., 2012). Athletes could train on such games to learn and identify new playing strategies.

4 Winning and Fighting with the Strength of Numbers

Sports contests share certain characteristics with military engagements in that both seek victory over others and regularly employ such terms as “beat,” “attack,” “offense,” or “strategy” (Weiss, 1969). The search for a comparative advantage in this ferocious positional arms race means that secret weapons can be the difference between defeat and victory: when one team wins, some other team must necessarily lose, making sport the classical winner-take-all market. For example, a player who loses the Wimbledon final in a fifth-set 20-min tiebreaker because

[8] https://www.sciencemag.org/news/2016/12/scientists-are-close-building-quantum-computer-can-beat-conventional-one.

of a bad luck or a stupid mistake will just have missed out on 1,175,000 GBP in prize money by being the runner up rather than the winner.[9] Similarly, whereas Olympic gold medalists benefit from lucrative endorsement contracts, runners-up are often quickly forgotten, even if the performance gap between best and second-best is almost too small to measure (Frank & Cook, 1995). Hence, although many sports fans may remember Carl Lewis's four gold medals from the 1984 Summer Olympics (100, 200 m, long jump, and 4 × 100 m relay), which matched Jesse Owens' success at the 1936 Berlin Games, who can name the runners-up in those events? Given this strong incentive to gain a comparative advantage, both athletes and teams are increasingly turning for assistance to the additional technologies of big data and AI.

4.1 Sports Analytics

Nonetheless, whereas digital technologies are now increasingly employed in collecting and improving sports analytic procedures, such analytics and reporting are not new (see, e.g., Morgulev et al., 2018). Baseball, the oldest US professional sport, was one of the first to record its results when in 1854, several decades before the 1869 establishment of the first professional franchise, US newspapers began printing box scores to recap the performances and achievements of amateur baseball contests (Grow & Grow, 2017). Why baseball? Because the one-on-one match-ups between batter and pitcher are at the core of the game's action and easier to measure than interactions in other team sports like basketball and ice hockey: "If the batter successfully hits the ball and gets on base, he has 'won' the matchup; conversely, if the pitcher successfully gets the batter out, he is the victor" (Grow & Grow, 2017, p. 1572). As early as May 1910, Fullerton's article "The Inside Game," published in *American Magazine*, discussed the science and mathematics (or geometry) of baseball. Then, in 1947, the Brooklyn Dodgers were the first to hire Alan Roth, a full-times statistician previously employed by the National Hockey League, whose statistical insights helped transform the way the game was played[10]:

> "Wouldn't it help a manager," Mr. Roth asked, "if he knew, for example, that a certain batter hit .220 against right-handed pitchers and .300 against left-handers?" Mr. Rickey was intrigued, and Mr. Roth became the first full-time statistician hired by a major league, touching off a trend that has made the personal computer an essential element of clubhouse paraphernalia.

Since the 1960s inception of detailed data recording for both American football and basketball and the 1971 founding of the Society for American Baseball

[9] https://www.wimbledon.com/pdf/Championships2019_Prize_money.pdf.

[10] https://www.nytimes.com/1992/03/05/sports/alan-roth-74-dies-baseball-statistician.html.

Research, many professional sporting teams have begun investing heavily in analytics departments (Casals & Finch, 2017). In England, such record-keeping began when Thorold Charles Reep, frustrated by the slow play and marginalized wingers in soccer, started recording notes that led to his part-time employment as an advisor to Brentford (for an analysis, see Reep & Benjamin, 1968). All such sports analytics have generally been interested in new ways of identifying skill, efficiency, and effectiveness measures as a means to deal with the complexity of the sports environment.

In recent years, sports analytics have benefited from better data streaming performance. For example, the real-time systems designed by the IBM CAS-EI analytic team help sports event organizers use big data to provide fans with a more enjoyable data-driven sporting experience via streaming of tweets, scores, schedules, player information, or continual semantic website content update (Baughman et al., 2016). Likewise, the 2016 Australian Open used IBM's Continuous Availability Services to stream social sentiment composed of hybrid clouds,[11] with ongoing fan base reactions and sentiment determined by real-time analysis of tweet streams by natural language applications. These applications are but two examples of how the increasing capacities of digital technology to collect, manage, and organize video images can be used to improve sports analytics (Barris & Button, 2008).

In fact, sports broadcasting in general has benefited substantially from innovations in computer vision, with some of its best-known current applications allowing TV presenters to explore locations or trajectories in detail (Thomas et al., 2017). Not only can AI systems assist sportswriters in their narrative interpretation of events (Allen et al., 2010), but the new technologies can even overcome the inadequate video and computational facilities in sports stadiums that have caused the long-time failure of automated tracking technology in team sports with rapid interaction (Barris & Button, 2008). The use of algorithms via modern big data methods and the increased data availability has allowed the development of new performance factors, such as space control, outplayed opponents, a pressing index based on positional data tracking (Memmert & Rein, 2018), and even a potential to quantify "dangerosity" (Link, 2018).

4.2 Strategic Elite Athlete Development

Big data and AI can also facilitate the informed development of junior talent, young individuals who may neglect "their studies, skip their violin lessons, pass up opportunities to eat well, and the like, because they desire to be successful or conspicuous in a contest or game" (Weiss, 1969, p. 61). Despite such drive, the transition from junior to senior is very challenging, with very few athletes

[11] https://www.ibm.com/blogs/cloud-archive/2016/01/australian-open-2016-streaming-social-sentiment-with-bluemix-hybrid-cloud/.

making it to the professional leagues even if trained in an elite sports academy (Schmidt et al., 2017). Yet our understanding of the way in which a successful career develops is limited, as is our knowledge of whether such careers are linked to good performance in junior competition (Passfield & Hopker, 2017). New technologies, however, are challenging traditional ways of identifying talent by going beyond the blatantly problematic result-based talent identification (Brouwers et al., 2012). Such technologies can, for example, eliminate potential human perceptual and memory errors like recency and primacy (Eagle & Pentland, 2006; Pentland et al., 2009) from the decision process.

In addition, given the greater emphasis in recent decades on adopting a strategic approach to elite athlete development (Brouwers et al., 2012), big data and AI promise new ways of developing appropriate training methods and techniques that take into account the athlete's developmental stage (Kovalchik & Reid, 2017). One interesting challenge, for example, is the scaling of sports strategies for children (Buszard et al., 2016), an underdeveloped topic despite an entire book on scaling by Geoffrey West, former President of the Santa Fe Institute (West, 2017). According to West, a major challenge for the medical and health industry is to ascertain the quantifiable baseline scale of life; for example, how to scale up new drugs to prescribe a safe and effective human dosage despite the typical experimental cohort being mice. As yet, no comprehensive theory exists of exactly how to accomplish such scaling even though "the pharmaceutical industry devotes enormous resources to addressing it when developing new drugs" (West, 2017, p. 52). In sports, scaling of the physical environment through equipment and play area modification (e.g., court size, basket height, or ball size; Buszard et al., 2016) is relatively easy to implement. Yet scaling can also have substantial psychological and emotional influences, especially in the way the environment or training is structured, such as the encouragement of play, feedback, and play intensity through smaller tennis courts with lower nets or the facilitation of skill performance (e.g., stroke-making ability) by lighter racquets (Buszard et al., 2016).

In general, rather than requiring the abandonment or rethinking of earlier decision-making methods, technological developments simply enhance them, as when powerful computerized assessments of players' professional prospects complement the insights of traditional scouts. These technologies can even identify undervalued skills via new performance indicators, such as in the Boston Celtics' use of guard rebounding to identify and pick Rajon Rondo in the 2006 NBA draft from the Phoenix Suns, who only drafted him 21st overall (Morgulev et al., 2018). Rondo has since become a four-time NBA All-Star and has three times led the league in assists per game, earning four NBA All-Defensive Team honors.

4.3 Training and Tactical Analysis

Tactical empirical evaluations emerged as early as the mid-1980s with the adoption of the personal computer (Nevill et al., 2008). Today, the application of big data in professional sports can significantly affect trainers' decisions, to the point that the

Washington Nationals replaced a highly experienced and successful but big data-averse manager with a younger colleague who embraced it (Caravelli & Jones, 2019). For example, new information gathering processes can offer additional insights into responses to and the effects of exercises, thereby allowing trainers to fine-tune exercise regimes while also taking into account individual characteristics. Likewise, automated player tracking systems can benefit both coaches and athletes in team sports by permitting all stakeholders to examine team interactions and group dynamics in more detail. New technologies can also generate simulations that forecast the implications of team behaviors and biomechanistic or motor control aspects based on intrapersonal coordination and game decision-making (Barris & Button, 2008). Yet despite this potential, many sports organizations still prescribe training processes based on experience and intuition (Passfield & Hopker, 2017), with core components in existing models of training quantification and its relation to performance based primarily on cardiovascular fitness, strength, skill, and psychology (Taha & Thomas, 2003).

Admittedly, however, sophisticated tactical analysis in sports is challenging; especially in team sports, which require not only data accessibility and reliability but also the ability to explore the dynamics of these data and measure them in constantly changing conditions. Yet given the limitations of human computational capacity (Simon, 1956), coaches' personal experiences may not be sufficient to develop proper team tactics on a constant basis (e.g., personalized game by game adjustments). Observation-based game analysis is also highly time-consuming (see Rein & Memmert, 2016), increasing the primacy of more quantitatively oriented approaches in elite sports like soccer (Carling et al., 2014). As quantum computing and quantum information science break the limitations of conventional information provision (Muhammad et al., 2014), they enable more efficient exploration of the complexity in various settings, testing and simulating various alternatives almost like a "knowledge accelerator." Sophisticated player tracking technologies, in particular, are highly beneficial for fast-paced team sports such as football, basketball, or ice hockey, which can use them to improve training, identify talent, and scout for future players (Thomas et al., 2017).

Another reason for the increasing use of insights from AI or big data to drive in-game strategic decisions (Caravelli & Jones, 2019) is the constant public scrutiny of coaches, whose decisions on player insertions, removals, and likelihood to tire, for example, can be greatly assisted by early *warning* diagnostics (Caravelli & Jones, 2019): "Today, when one player is substituted for another, he is assessed by how much he does or does not contribute to WAR (wins above replacement)" (p. 111). In the same way, physiological sensoring systems can indicate the effect of an individual's activities even before that individual is consciously aware of what is happening. For example, in a fascinating experiment by Bechara et al. (1997), individuals were faced with four decks of cards, two with small payoffs or losses but a guaranteed profit over time and two with higher payoffs or losses but a guaranteed loss over time. Obviously, when the players began the experiment, they did not know the properties of each deck. The intriguing result was that the players began choosing from the money-making decks before they actually knew why.

By monitoring the electrical conductivity of the participants' skin, the researchers determined that skin conductance began to spike when subjects were contemplating playing from the money-losing decks. This unconscious physiological reaction steered their choices away from the losing decks before their conscious rationality was able to figure out why they should behave that way.

5 Prometheus Bound: The Limits of Technology

5.1 What is Natural?

Because human interaction with technological innovation tends to be challenging, technological advances are always subject to resistance: as Juma (2016) put it, "[t]he quickest way to find out who your enemies are is to try doing something new" (p. 1). In the eighteenth century, for example, longbows were viewed as superior to the early flintlock muskets because arrows were discharged more rapidly than bullets and cost less. In fact, muskets were so inaccurate that soldiers were advised not to shoot until they saw the sclera of the eyes; yet archery required more extensive training than firearms (Juma, 2016, p. 15). Similarly, the mechanization of US agriculture led to conflicts and arguments against the new technology: "There were genuine concerns that the adoption of the tractor would render farmers dependent on urban supplies of expertise, spare parts, fuel, and other inputs that were previously available on the farm. Horses could reproduce themselves, whereas tractors depreciated" (p. 129).

Big data and AI technologies thus reflect an old but nontrivial discussion between the "natural" and the "unnatural" in sports, a pervasive weltanschauung perhaps "best articulated" by Joe Jacobs when "his boxer, Max Schemrling, lost to Jack Sharkey in a highly contested fight: 'We wuz robbed!'" (Greenbaum, 2018, p. 32). Yet identifying what is natural or not in the sports environment is extremely challenging given that the technologies discussed here are part of a long tradition of elite athletes using scientific and technological enhancement techniques in a highly complex interplay between genetic predisposition and environmental impact (Loland, 2018). Within this tradition, physical training tools are generally acceptable because they maintain "physiological authenticity" (Greenbaum, 2018; Loland, 2018), but expensive proprietary technology—for example, Fastskin swimsuits—can negatively impact perceived fairness (Greenbaum, 2018) and spark fierce debate. In this latter case, within two months of their February 2008 introduction, swimmers wearing Fastskins broke 35 world records. Yet some athletes were blocked from access by price, locked-in sponsorship agreements, or scarcity from overdemand (Zettler, 2009). Because data analytics is potentially another technological tool for achieving competitive advantage beyond the natural (Greenbaum, 2018), the related proprietary information is highly valued, as reflected by a 2015 FBI (Federal Bureau of Investigation) investigation into whether MLB team St. Louis Cardinals had illegally accessed the rival Houston Astros' computer network.

The constant arguments for a natural approach in the sports environment are particularly understandable in the light of public fascination with how athletes operate at the limits of their bodily capacity in such grueling challenges as the Tour de France mountain stages. Likewise, spectators watch with excitement the human drama of courage, strategy, failed nerves, and/or self-discipline playing out in penalty shoot-outs (Savage & Torgler, 2012) or are captivated by the breaking of Olympic records, with achievements compared in different places and at different times (Weiss, 1969). It was exciting, for example, to wonder year after year whether and who would beat the monumental 8.90 m long jump (at the 1968 Olympic Games in Mexico City) by Bob Beamon, who actually mis jumped two of his qualifying attempts. The record in fact remained unbroken until Mike Power's 8.95 m jump at the 1991 World Track and Field Championships in Tokyo. Similar excitement followed the feats of Sergey Bubka, a master at record-breaking performances in pole vault, who between 1984 and 1994 slowly increased the world record 17 times outdoors (from 5.85 in May 1984 to 6.14 in July 1994) and 18 times indoors (from 5.81 in January 1984 to 6.15 in February 1993). This incremental progression even prompted one sports commentator (overheard by author) to suggest Bubka's intentional underperformance in regular competition—jumping below the maximum height achieved in training sessions—to build and maintain the suspense for potential world records at major meets.

5.2 Timeless Elements of Sports

To understand the implication of new technologies it might be worth further considering some core elements of sports. For example, why are we willing to repeatedly enjoy a Shakespeare play such as Hamlet, Macbeth, or Romeo and Juliet? Why do we return to classical music concerts listening to Beethoven, Mozart, Bach, Vivaldi, Haydn, or Chopin, but we are not inclined to watch sports games once we know who won? Even hiring superstar actors like Brad Pitt, Tom Cruise, Will Smith, Keanu Reeves, and Leonardo DiCaprio to recreate epic games such as the 1966 World Cup final between England and Germany could not fill a stadium or achieve emotions similar to the actual game. One critical aspect of sporting events is the outcome uncertainty (Downward & Dawson, 2000; Pawlowski, 2013; Rottenberg, 1956; Schreyer et al., 2016, 2017, 2018a, 2018b; Schreyer & Torgler, 2018), which prompts organizations in every sport to try and eliminate inequalities where possible and compensate for them where not. Thus in ball games, teams change sides during a game; in alpine skiing, course conditions are adjusted throughout the race, and in technologically driven sports disciplines like motorsports or sailing, equipment technologies are standardized (Loland, 2018). For the same reason, many sports leagues, particularly in the US, impose roster limits, pay caps, drug bans, or revenue-sharing arrangements. No matter the precautions, however, the glory days of even the most well-trained athletes are often short-lived, a problem that new technologies might mitigate by enabling athletes to prolong their careers through high fitness maintenance and injury reduction. Nonetheless, even though superstars like soccer players Ronaldo and Messi or tennis players Roger Federer, Rafael Nadal, and Novak Djokovic still dominate their fields in their 30s, it is unclear whether new technologies will allow these superstars to triumph even longer or enable younger athletes to outperform them.

5.3 Too Intrusive?

All the innovations discussed above, but particularly the sensoring instruments, expose athletes' hidden behavioral patterns and intentions, bridging the gap between what they want and what they actually do, and how they interact with others in their environment (Michael & Miller, 2013). Not only may such close monitoring be considered highly intrusive, but if not carefully guarded, this massive amount of individual data raises two major risk concerns: hijacking for unscrupulous use in gambling (Greenbaum, 2018, p. 33) and negative externalities derived through inexpert data application, which could prematurely end young athletes' careers (see also Greenbaum, 2014). Moreover, even beyond the potential biases inherent in coach evaluations and decisions about young athletes' futures (Merkel et al., 2019), overly carefully monitoring could result in meticulous algorithmic manipulation of players like chess pieces across a board. Given that training regimes, particularly under "militaristic" coaches, are already subject to substantial repetitions which provide little room for the inventiveness, daring, surprise, and creativity that delight spectators, these latter have yet to be successfully modeled in the complex interactions of a sports environment.

Nor does technology matter only on the pitch—it also affects stadiums, whose ambience is dependent on spectator attention and behavior. Hence, Mark Cuban, owner of the Dallas Mavericks (NBA), strongly objects to spectator use of smartphone, believing it distracts from the on-court action (Hutchins, 2016). For the same reason, a 2014 decision by PSV Eindhoven's club leadership to introduce free Wi-Fi its stadium elicited mixed reactions from fans, with one group so strongly opposed that it unfolded a banner reading "Fuck Wi-Fi, support the team" (Hutchins, 2016). This aversion to modern app technology may relate to its influence over how humans act and cope with opportunities and challenges, including fears of losing control over events or being faced with unanticipated outcomes (see, e.g., Gardner & Davis, 2013 for youth). Thus, the responses of sports athletes to unexpected events in their more precisely orchestrated strategic environment is an important question that may need investigation in the future.

6 Conclusions

Because of their ability to capture spectators on a visceral level, sports attract huge amounts of financial investment, meaning that the stakes in any improvements are high. It is thus the exciting potential of new technologies like big data, AI, and quantum computing to do things "bigger, better, faster" that has driven their use so far. Even given such "exponential potential," however, grave concerns remain about privacy, inefficiency of effort/time, and hacking. Frank and Cook (1995) even argued that extreme training measures and applications are wasteful from a collective or societal perspective. Why? Because someone will win anyway, whether that person or team trains an hour or four hours per day. Yet new technologies for use in the sports environment are developed specifically for the purpose of winning the positional arms race on the battlefield of the sports arena, meaning that improved performance on both sides of the pitch will eventually be matched and evened out. In any case, humans are better at spotting relative differences than absolute difference. Hence, in two 100 m races with only one runner each, spectators are unlikely to identify a substantial difference between the first race sprinter finishing with the current world record of 9.58 s and the second race runner overshooting the ten-second barrier by a few milliseconds. Nor are they likely to analyze away the very thing that captures them about sports—the surprise, inventiveness, and skill of human effort.

Whether or not sports adopt more technology, attraction to competition as in-group favoritism versus outgroup discrimination is deeply rooted in human nature (Jordan et al., 2014). This human need to be "groupish"—which evolutionarily was conducive to survival and better defense against outgroups—even manifests in infants, who seem to distrust potential playmates with unfamiliar accents (Boyer, 2018). Likewise, in the laboratory, if individuals are allocated to meaningless groups (e.g., A vs. B) and then placed in situations of social interactions, they will reciprocate more often with their own in-group (Tajfel, 1970).

In addition, as Gigerenzer (2007) demonstrated, intuition or gut feelings are not always a bad thing: fast and frugal heuristics enable adaptive choices in real-world environments with a minimum of time, knowledge, and computation. Human minds have evolved to employ a couple of tricks that are "reasonable enough" Gigerenzer (2007), enabling the catching of a flying baseball or cricket ball in ways that even professionals do not understand. Gigerenzer (2007), for example, recounted the anecdote of a coach who suggested that his players should run as fast as they could to make last-minute corrections but found the strategy unsuccessful. The players also performed poorly when estimating where the ball would strike the ground, a failing for which Gigerenzer proposed a simple rule of thumb: "Fix your gaze on the ball, start running, and adjust your running speed so that the angle of gaze remains constant" (p. 10). This powerful gaze heuristic does not need to take into account all the different and complex parameters such as wind, air resistance, or spin.

Yet even if analytics prove able to tame the element of luck, luck will still remain important in sports as in everyday life, despite some discomfort that it alone might drive success rather than talent and effort (Frank, 2016). In fact, the role of luck is amply illustrated by the many highly talented and hardworking athletes who have failed to go professional or launch successful sports careers. One probable contributing factor is tiny initial positive or negative variations that induce positive and negative feedback loops which amplify over time (De Vany, 2004; Frank, 2016). For instance, would Al Pacino's career have evolved with another Golden Globe nomination this year at age 79 for his portrayal of Jimmy Hoffa in *The Irishman* if he had not starred in *The Godfather*? Although the answer is only speculative, not only has Pacino clearly benefited from Coppola's wish to have an unknown actor on board who looked Sicilian (Frank, 2016), but 12 other directors were offered the job of directing *The Godfather* before Coppola agreed to take it on.

In general, understanding the limits of technology requires simultaneous consideration of what sports means: why are so many individuals deeply involved in sports and why are they so caught up emotionally in sports events and athletes' lives. Answering these questions in full would require a philosophical discussion on sports (Weiss, 1969), yet philosophers—somewhat like pure mathematicians reluctant to embrace applied mathematics—have mostly failed to explore this topic in detail possibly due to disinterest. Perhaps most agree with Whitehead that the European philosophical tradition is just a series of footnotes to Plato (Weiss, 1969), meaning that as the Greeks failed to study sports, it should not be surprising that the philosophy of sports is confined to a few exceptions, such as the work of Weiss (1969). Yet philosophy is not simply concerned with the number of towering geniuses or an obsession with epistemological puzzles like Zeno's Paradox. Such a focus hinders the ability to see the discipline's great intellectual potential for explaining the important daily facets of human nature. Yes, Achilles' race against a lowly tortoise granted a head start is a fascinating problem. Yes, when Achilles covered the initial gap between himself and the tortoise, the tortoise created a new gap. However, failing to handle such problems fully is simply a reflection of human limitations in intuitively applying the tools of thought and exploration (here an understanding of space, time, and motion) in a proper manner. In addition to which the modern thinker is gifted with a wealth of empirical evidence that sports heroes can easily outrun any tortoise.

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Benno Torgler Ph.D., is a Professor of Economics at the Queensland University of Technology and the Centre for Behavioural Economics, Society and Technology and leads the program “Behavioural Economics of Non-Market Interactions” that covers the sub-programs Sportometrics, Sociometrics, Scientometrics, and Cliometrics. Besides a strong passion for doing research in the area of sportometrics, he has been carefully following the literature on AI for many years and cites AI pioneers such as Herbert Simon, Allen Newell, Marvin Minsky, and Seymour Papert as strong influences. In his free time, he loves to surf (although he is not particularly good at it) and exercise.