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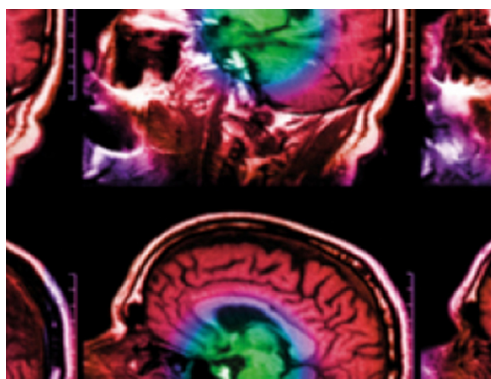
Impact and workload are dominating on-field data monitoring techniques to track health and well-being of team-sports athletes

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Impact and workload are dominating on-field data monitoring techniques to track health and well-being of team-sports athletes

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E-mail: jeroen.bergmann@eng.ox.ac.uk and runbei.cheng@eng.ox.ac.uk**Keywords:** real-world data, personal metrics, fitness, sensor, health, traumatic brain injury, physiological loading

Abstract

Objective. Participation in sports has become an essential part of healthy living in today's world. However, injuries can often occur during sports participation. With advancements in sensor technology and data analytics, many sports have turned to technology-aided, data-driven, on-field monitoring techniques to help prevent injuries and plan better player management. **Approach.** This review searched three databases, Web of Science, IEEE, and PubMed, for peer-reviewed articles on on-field data monitoring techniques that are aimed at improving the health and well-being of team-sports athletes. **Main results.** It was found that most on-field data monitoring methods can be categorized as either player workload tracking or physical impact monitoring. Many studies covered during this review attempted to establish correlations between captured physical and physiological data, as well as injury risk. In these studies, workloads are frequently tracked to optimize training and prevent overtraining in addition to overuse injuries, while impacts are most often tracked to detect and investigate traumatic injuries. **Significance.** This review found that current sports monitoring practices often suffer from a lack of standard metrics and definitions. Furthermore, existing data-analysis models are created on data that are limited in both size and diversity. These issues need to be addressed to create ecologically valid approaches in the future.

1. Introduction

Many people start engaging in sports at a young age, and there has been a clear upward trend in organized sports participation across many age groups worldwide since the 1970s (Wheeler 2012). One of the most popular forms of organized sports is team-based sports, which includes common sports such as soccer, American football, rugby, basketball, baseball, ice hockey, etc, many of which are played at competitive levels among various age groups. Participation in sports comes with a wide range of physical and mental health benefits (Warburton *et al* 2006), but it also has certain risks. Taking part in team sports can lead to acute injuries and even permanent disabilities, with young adults at their physical prime exhibiting the highest injury rate (Kujala *et al* 1995). Sports that involve more frequent and powerful body contact have reported higher overall injury rates, and there is also a clear indication that injury rates are higher during competition than during practice (Kujala *et al* 1995). On top of accidental injuries, participation in team sports can also lead to health drawbacks when it is poorly managed. Overly intense training sessions and competitions can lead to burnouts and overuse injuries (DiFiori *et al* 2014). Burnout due to overtraining can result in declines in physical performance (Cardoos 2015). It can potentially lead to both physiological and psychological symptoms, and even affect the immune system (Cardoos 2015, Keaney *et al* 2018). Recovery time may vary from days to months depending on the severity (Cardoos 2015). Overuse injuries can sometimes lead to a significant loss of time from sports, and severe overuse injuries can even threaten future sports participation (DiFiori *et al* 2014). In the long run, scenarios such as accumulated head injuries can lead to chronic traumatic encephalopathy (CTE) and significantly increase the risk of

developing Alzheimer's disease (AD), Parkinson's disease (PD), and possibly amyotrophic lateral sclerosis (ALS) (Ling *et al* 2015, VanItallie 2019). In addition to having negative health impacts on the athletes, sports injuries are also a huge financial burden. One study shows that the average cost of sports-related medical treatments among youth aged 5–18 years is over £20 million a year in Florida (USA) alone (Ryan *et al* 2019). Due to these health and financial drawbacks, a clear need for developing suitable injury prevention methods and risk management approaches exists. The scale and complexity of the problems faced require sophisticated data-driven and analytical solutions. These

Analytics in sports was first attempted in the 1950s by Charles Reep and Bernard Benjamin, who manually recorded tactical data and game states from professional soccer games (Apostolou and Tjortjis 2019). In recent decades, data analytics in sports have gained popularity thanks to advances made in computer vision and sensor technologies. Early sports analytics devices were made to track players' movements, and help coaches analyze tactical performance post-game (Apostolou and Tjortjis 2019). More recently, player-tracking devices have been made to capture physical and physiological data from athletes unobtrusively in an on-field setting. Data from these player-tracking devices give the coaches the potential to monitor the health and physical states of their players in real-time. This could allow the coaches to actively reduce the injury risks of the players by giving certain players much-needed breaks in training and substituting overexerted players in the game. Being able to capture the players' physical demands in-game can allow coaches to create more game-relevant training routines. In practice, tracking players' physical expenditure in practice can help avoid overtraining and protect the players from injuries and illnesses (Drew and Finch 2016). With all these exciting possibilities in mind, the International Football Association Board principally allowed the usage of wearable player tracking devices during games (Lutz *et al* 2020), and many other sports soon followed (Apostolou and Tjortjis 2019). The purpose of this topical review is to analyze the current practices of on-field data analytics in team-based sports which could help to improve the health and well-being of the athletes. This review will also highlight some of the novel techniques currently in development.

2. Methods

For this review, three databases, Web of Science, IEEE, and PubMed were searched using keywords connected by Boolean operators. The set of keywords used was: 1. (((('team' OR 'team-based') AND ('sport' OR 'sports')) OR ('football' OR 'soccer' OR 'Australian Rules' OR 'baseball' OR 'basketball' OR 'hockey' OR 'rugby')) 2. ('monitor' OR 'monitoring' OR 'track' OR 'tracking') 3. ('health' OR 'well-being' OR 'wellbeing' OR 'injury' OR 'impact' OR 'performance' OR 'exertion' OR 'overexertion' OR 'fatigue' OR 'recovery'), and the three fields are connected by the Boolean operator AND. The keywords were searched in Topic Field for Web of Science, All Metadata for IEEE, and Title/Abstract for PubMed. All papers published before October 2021 were included in this search.

This review aims to investigate how physical and physiological data captured on-field can help improve athletes' health and wellbeing. Studies that use player-monitoring systems to investigate tactical performance, technical performance, or team dynamics are excluded. Papers that describe data capture frameworks without discussing their relevance to improving athletes' health or wellbeing are also excluded. In the search terms, we have specifically included the most popular competitive team-based sports with high revenue generation, based on reports from professional sports leagues, since they are the most likely to invest in or explore player-monitoring techniques, though, studies based on other team-based sports are not excluded if they are on-topic. Only papers published in English are included in this review. The retrieved papers were categorized. A time-series trend analysis was done, using a Mann-Kendall test, to analyze the growth of respective topics within the field.

3. Findings and discussions

The literature search found 2584 papers. After screening through the retrieved papers using the parameters defined above, 252 papers were found to fit the eligibility criteria. Two major categories of monitoring methods were identified, with 200 papers discussing workload tracking, 44 papers discussing impact monitoring, and 6 papers discussing both. Within impact monitoring, there is a strong focus on head impacts ($n = 40$). There were also 6 papers found that reported monitoring methods that do not fall under those two categories, 4 of which reported these methods alongside workload and impact monitoring. Such methods include biochemical sensors for monitoring hydration levels, COVID-19 exposure monitoring via positional data, etc. Figure 1 shows the key locations of monitoring devices found in current literature.

A Mann-Kendall Test on the number of studies published on workload monitoring for the past 10 years gives a Kendall Score of $S = 49$ and a two-sided p -value of $p = 0.00017$, strongly suggesting there has been an

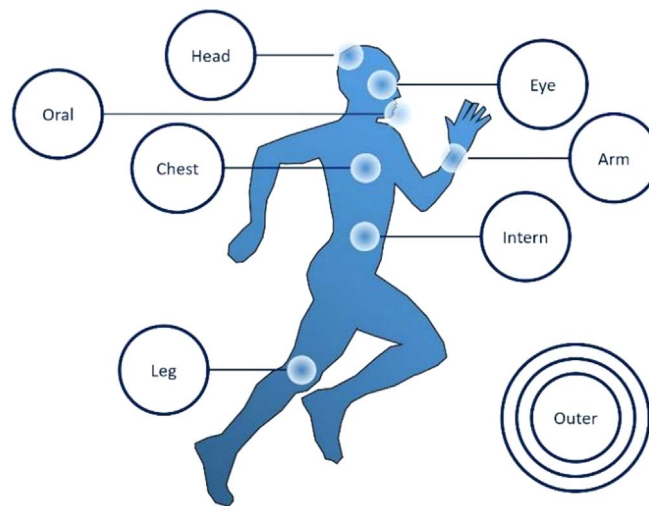


Figure 1. Types of monitoring devices based on placement. Head sensors are placed on e.g. helmets, headbands, caps or stick patches. Eye placement includes smart contact lenses, whilst sensing in the oral cavity is often done by an instrumented mouthguard. A shirt or strap is regularly used for sensing physiological or positional data at the chest level. Ingestible sensors can be used for internal monitoring (such as core temperature). The legs allow for a range of attachment possibilities including epidermal patches. Finally, off-body (outer) techniques can be applied for non-contact sensing for which multi-camera video analysis is one of the most widely used methods.

upward trend in workload related studies. A Mann-Kendall Test on the number of studies published on impact monitoring for the past 10 years ($S = 33, p = 0.011$), suggests that there has also been an upward trend in workload-related studies. It was found that workload monitoring systems and measures have been adopted by major sports teams as a routine part of their training and matches, while head impact monitoring systems are still predominantly used as research devices. The following subsections will give a comprehensive synopsis of the findings.

3.1. Workload monitoring

Sports participation has become an essential part of ensuring healthy living in today's world. Team sports are organized at a variety of skill levels and are played by people in all age groups. Sports participation can bring tremendous benefits to both physical and mental health (Warburton *et al* 2006). However, there are risks that come with participating in sports. Athletes can succumb to musculoskeletal injuries due to overuse of particular body parts (DiFiori *et al* 2014). Muscle injuries can occur when the stresses and strains applied to body tissue exceed the body tissues' maximum capacities (Benson *et al* 2020). In addition to physical injuries, an athlete who is over-reaching or overtraining can experience a drop in physical performance which requires time to recover from, and can sometimes suffer from negative physiological symptoms (DiFiori *et al* 2014). One way of mitigating all these risks is by monitoring the workloads endured by the player.

Athlete workloads can be divided into two types, internal and external loads. External loads are quantifications of physical tasks performed by an athlete and are measured in objective movement-based metrics (Benson *et al* 2020). Internal loads, on the other hand, are physiological and psychological responses an athlete has towards the external workload and incorporate both objective physiological measures and subjective measures of perceived exertion (Bourdon *et al* 2017). Table 1 shows a list of technology used to monitor internal and external loading.

It was found that many workload monitoring methods can apply across a wide range of different sports, and that most methods can be grouped into one of two sports groups, contact sports and throwing sports. The differences in play styles between these two groups of sports have resulted in differently defined workload measures that require the utilization of different monitoring techniques.

3.1.1. External workload monitoring in contact sports

External loads are often determined by positioning and accelerometry-based metrics in contact sports. By capturing the players' in-game external load demands and monitoring their training (external) loads, sports trainers can optimize training sessions to better prepare their players for games (Oliva-Lozano *et al* 2020). Video tracking via multi-camera systems was used to monitor players' movements on the pitch and it was the most common player tracking method in soccer until 2014 (Castellano *et al* 2014, Rico-González *et al* 2020). Due to the high cost and installation difficulties, multi-camera systems were only installed in official match stadia and

Table 1. A list of methods used to measure internal and external loading in the literature.

Technology	Mechanism External load	Measures
Cameras	Multiple cameras placed at different angles around the stadium; footages are used to track player movements	
Global positioning system (GPS)	Signal transmissions from multiple orbital satellites and a ground-based receiver. The relative delay in the signal is used to calculate the position and speed of the receiver	Positioning Data: Distance, Velocity, Acceleration, Jerk
local positioning system (LPS)	Signal transmissions from multiple local antennas and a ground-based receiver. The relative delay in the signal is used to calculate the position and speed of the receiver	Derived Measures: PlayerLoad, Metabolic Power, Number of Jumps, Number of Turning Events, etc * Pitch Count (for wrist-worn technology)
Accelerometer/inertial measurement unit (IMU) that are body-worn*	A mass attached by a spring moves relative to two electrodes under acceleration, changing the capacitance	
Internal load		
Subjective measures	Self-report surveys	Rating of perceived exertion (RPE), session RPE, visual analogue scale, likert scale, hooper's index, etc
Electrocardiogram (ECG)	Electrodes placed in a chest strap to measure electrical activity from the heart	Heart rate, heart rate variability, training impulse, etc
Photoplethysmography (PPG)	Optical sensor place over blood vessels to measure heart rate via light absorption and reflection by the blood	
Surface electromyography (EMG)	Electrodes placed on the skin to measure electrical activity from muscles	Muscle fatigue
Ingestible temperature sensor	Ingestible capsule with a temperature sensor and a transmission circuit	Core temperature
Epidermal patch/Biochemical sensing mouthguard	Biochemical sensors that can measure chemical concentrations in sweat or saliva	Lactate and glucose concentrations as indicators for muscle fatigue Concentration of electrolytes can be used to measure hydration level
Respiratory data sensing mouthguard	Respiratory information can be extracted from breathing audio recorded by a microphone-instrumented mouthguard	Breathing (Sound) volume, breathing rate
Near-infrared spectroscopy	Optical sensor that uses the Beer-Lambert law of light attenuation	Muscle oxygen saturation

were mostly used for match assessments (Rico-González *et al* 2020). To allow sports teams that do not have access to multi-camera positioning systems to track their players' movements both in games and training, radio frequency-based (RF) tracking systems such as global positioning systems (GPS) and local positioning systems (LPS) have been adapted for sports purposes (Rico-González *et al* 2020, Theodoropoulos *et al* 2020). A GPS device can detect the location of its user through signals transmitted by four or more satellites and can determine the user's velocity via Doppler shift. GPS devices require reliable connections to satellites to function, so when a sports facility does not have sufficient satellite coverage, such is the case for many indoor games (Benson *et al* 2020), LPS devices can be used in their place. LPS works on similar principles as GPS, with the satellites being replaced by locally installed antennas. LPS systems are claimed to have pinpoint accuracy, though, at present, their use has been limited due to the high cost of installation and calibration (Theodoropoulos *et al* 2020).

Common sports GPS devices in the present-day sample at 10 Hz, though some can go as high as 18 Hz. While GPS devices can capture the position and velocity of players, they are less useful for observing rapid acceleration and change in direction due to their low refresh rate and their inability to determine orientation. To address this, many GPS-based sports monitoring systems are integrated with inertial sensor units (IMU) that consist of accelerometers, gyroscopes, and magnetometers. Most IMUs used in workload monitoring can record at 100–120 Hz (Theodoropoulos *et al* 2020). Today, the most popular implementation of this technology is an integrated system that consists of a GPS, an IMU, and a heart rate (HR) monitor. An example of this is the

Catapult Vector (Catapult Innovations, Scoresby, Australia) which has an up to 18 Hz GPS, a 100 Hz IMU, an electrocardiogram (ECG) derived HR monitor, and an ultra-wideband LPS receiver.

There is a common set of external load variables derived from the position-tracking systems mentioned above. The basics are the total distance (TD), velocity, and acceleration (Bourdon *et al* 2017, Theodoropoulos *et al* 2020). There are a large number of external load measures derived from these base measurements, often as a data zoning of some sort, or a new measure calculated from the base measures using an algorithm. The frequencies of certain physical actions are derived from these measures and added up as external load measures, such as the frequency of turns and the number of jumps (Benson *et al* 2020). Jerk may be derived from the acceleration and used as an external load measure as is seen in the case of PlayerLoad by Catapult (Boyd *et al* 2011).

A commonly used external load measure calculated from the basic measures is the 'metabolic power'. The 'metabolic power' is an energy exertion estimation obtained from acceleration by establishing an equivalence between accelerating on a plane surface with walking uphill at a constant speed (Di Prampero *et al* 2005). The 'metabolic power' does not account for interpersonal variability. In addition, the 'metabolic power' does not account for the energy used to overcome friction and air resistance at a constant speed.

There exists a large number of external load zoning metrics, such as high-speed distance covered (zoning of speed), sprint-running distance (zoning of either speed or acceleration depending on the study), acceleration intensity (zoning of acceleration), and so on (Benson *et al* 2020, Rago *et al* 2020, Theodoropoulos *et al* 2020). Most papers covering these metrics have their own definition of terms such as 'high-speed' or 'sprint' and have their own ideas of how to set the thresholds for each zone (Benson *et al* 2020, Kupperman and Hertel 2020, Rago *et al* 2020, Theodoropoulos *et al* 2020). One review found that the minimum threshold for 'high-speed' running in the literature varies from 14.4 to 24 km h⁻¹, and the minimum threshold for 'sprinting' varies from 19.8 to 25.3 km h⁻¹ across different studies (Kupperman and Hertel 2020). These discrepancies make comparisons between different external load studies nearly impossible.

3.1.2. Internal workload monitoring in contact sports

Internal loads, in contrast to external loads, are not always captured in objective terms. One of the most frequently used methods to capture internal loads is Borg's scale of perceived exertion (RPE). RPE is used to quantify the conscious sensation of exertion (Nicolò *et al* 2016). There are a few variations of RPE in the literature today, though they are all based on the same principle: subjective numerical measures based on the surveyed responses of the monitored athlete. The RPE has numerical values corresponding to verbal descriptors at some of the points on the scale. One way the RPE variations can differ from one another is the scaling of the numerical values corresponding to different verbal feedbacks. Another difference between some of the RPE variations is the time scale over which the RPE is captured. For example, the session RPE (sRPE), which is commonly used in conjunction with GPS systems in studies that aim to capture sports demands, is a one-off measure taken at the end of a sports session. There are a few other subjective internal load measures like the RPE, which aim to capture the perceived exertion of the athlete. Such measures include the visual analogue scale (VAS), which is a linear scale with two anchor points at the two extremes; and Likert scale, an RPE-like numerical scale with numerical descriptors at every point (Grant *et al* 1999). Some survey-based internal load measures also aim to include the athletes' conditions prior to the match. One example of this is the Hooper's Index, which includes self-perceived ratings of fatigue, stress, delayed onset muscle soreness, and sleep (Haddad *et al* 2013).

Whilst these subjective measures are often linked to the level of physical effort, they are also sensitive to stressors beyond physical effort such as psychological and environmental factors. And the surveying aspect, in practice, often requires a series of training and familiarization sessions between the athletes and dedicated coaches to produce consistent outputs, making them impractical to use at many levels of play (e Bueno *et al* 2021). The surveying aspect also means that these measures are limited to non-realtime use, and cannot perform continuous monitoring throughout a session. All these limitations suggest that while subjective internal load measures provide insightful information on the athletes, they are not suitable as an on-field monitoring method on a session basis, but rather as something tracked over a long period.

On the objective end of internal loading measurement, the rate of oxygen consumption (VO₂) has long been used as a measure of performance and exertion in sports science. However, to directly measure VO₂ requires the use of obtrusive metabolic devices unfit for on-field monitoring. Heart rate (HR) is often used as an on-field measure for evaluating the intensity of exercise and has been shown to have a linear relationship with VO₂ over a large range of submaximal intensities (Li *et al* 2016). Researchers have developed a series of HR-derived measures to evaluate internal loads, these include the ratio between the actual HR and the maximum HR, the ratio between the actual HR and the resting HR, binning of the ratios into different intensity zones, heart rate variability (HRV), and training impulse (TRIMP) which is computed from heart rate and duration (Stagno *et al* 2007, Bourdon *et al* 2017, Colosio *et al* 2020). There are numerous studies on the abilities of HR-related metrics

to capture fatigue and performance in various sports, though the actual effectiveness of these measures has been brought into question. Contradictory findings can be found in the literature and a better understanding of the science behind HR is pointing towards these HR-based measures being potentially a useful part of a multidimensional internal load monitoring system rather than as robust measures of performance, fatigue, and well-being in themselves (Schneider *et al* 2018).

Alternative measures of internal loads have been investigated using different types of physiological sensors. Near-infrared spectroscopy (NIRS) muscle oximeters can measure muscle oxygen saturation (SmO₂) using the Beer-Lambert law of light attenuation. Vasquez-Bonilla *et al* (2021) tested the use of a portable NIRS system with women soccer players in small-sided games, and found that SmO₂ can be a useful measure for evaluating fatigue in players. Biochemical sensors that can detect electrolytes in sweat, and lactate and glucose concentrations in saliva and sweat have been built into integrated mouthguards and epidermal patches (Seshadri *et al* 2016, Seshadri *et al* 2019, 2019). Lactate and glucose concentrations can be used as indicators of fatigue level, and electrolytes can be used to monitor hydration (Seshadri *et al* 2019). A practice that has gained traction at professional levels in recent years is core body temperature sensing in the form of an ingestible pill (Muniz-Pardos *et al* 2021). While this practice is effective, a less invasive and affordable alternative is desired at lower levels of play. A study has shown that respiratory rate (RF) can be used as a marker of physical effort and has a fast response to work-recovery alternation when compared to HR (Nicolò *et al* 2020). An oral-cavity-based sensor system has been developed that captures breathing data (including RF) and found that breathing parameters can be used to accurately estimate one's exertion level (e Bueno *et al* 2021).

There is a wide array of physiological sensors that can offer realtime continuous on-field monitoring of players' internal loads in objective ways, which will allow for more timely intervention that will prevent athletes from harm. Moving forward, internal loads should ideally be determined using more objective measures based on physiological parameters rather than subjective self-reported measures. In addition, future investigations should put a focus on how these measures relate to an athlete's likelihood of injury and long-term health.

3.1.3. Workload monitoring in throwing sports

Throwing athletes, such as baseball and softball pitchers, have a completely different set of physical demands compared to contact team sports athletes. As such, throw athletes require different workload measures and monitoring systems. Overuse injuries, often in the shoulder and elbow of the throwing arm, constitute more than half of the injuries experienced by baseball pitchers (Dowling *et al* 2020). Pitch count is one of the conventional external load measures for baseball pitchers. Higher pitch counts have been linked to higher chances of experiencing pain or injuries (Dowling *et al* 2020). Baseball guidelines have been introduced for adolescent players to restrict pitch counts in hope of reducing overuse injuries in pitchers, though implementing such guidelines requires coaches and players to have the awareness and resources to monitor the players. Schweiger *et al* (2020) developed a wristband with a built-in IMU sensor that can detect and count throwing and pitching events. They demonstrated excellent accuracy in their initial test, successfully identifying all 161 throwing events in their test set with only one false positive. Another way to monitor workloads in pitchers is via surface electromyography (EMG) (Hettiarachchi *et al* 2019). EMG electrodes are not obtrusive to gameplay in baseball as it is a non-contact sport, and can thus be used on-field to monitor players' muscle fatigue. In addition to overuse injuries, pitchers can often injure themselves due to incorrect techniques (Stretch 1995). Along with pitch count and muscle fatigue monitoring, IMUs and surface EMGs can also be used to objectively screen a player's throwing technique (Hettiarachchi *et al* 2019). Surface EMGs can be used to monitor the muscle activation pattern of the relevant muscles during a throw (Hettiarachchi *et al* 2019). This can provide insights into a person's throwing technique. Through observation of low and high-risk muscle activation patterns, potential risk factors can be identified (Hettiarachchi *et al* 2019). Another measurement that can provide a great deal of information regarding a person's throwing technique (and potential risk factors) is the joint angle kinematics, which can be measured using a set of appropriately placed IMUs. These sensors have the potential to improve injury prevention in throwing sports, especially in training for players who have yet to develop any throwing skills.

3.1.4. Workload measures and injury rate predictions

One of the most popular injury prediction measures currently used in sports science is the acute:chronic workload ratio (ACWR) (Kupperman and Hertel 2020). The acute workload is a measure of the current workload and is typically averaged over a week; the chronic workload is a measure of the workload the athlete has been prepared for and is typically averaged over 3–6 weeks. Time windows for both acute workloads and chronic workloads can sometimes vary between different studies (Kupperman and Hertel 2020). The ACWR is based on the theory that the acute workload is analogous to a state of fatigue and the chronic workload is analogous to a state of fitness, and when combining the two into a ratio, an index of athlete preparedness is obtained (Murray *et al* 2017, Kupperman and Hertel 2020). Studies have established correlations between this preparedness index

and injury risks, with a higher ACWR value indicating a higher risk of injury (Murray *et al* 2017, Kupperman and Hertel 2020). In theory, the ACWR can be calculated for any workload measure, either internal or external. Both internal and external load ACWRs have been shown to positively correlate to injury risks (Murray *et al* 2017). The average workloads in ACWR are either calculated as rolling averages (RA) that weigh workloads on all the days equally or as exponentially weighted moving averages (EWMA) that weigh the workloads experienced on more recent days greater than days further back in the past (Murray *et al* 2017, Kupperman and Hertel 2020). It's been found that EWMA-based ACWRs are more sensitive than RA-based ACWRs for detecting changes in injury risks (Murray *et al* 2017). The validity of using ACWR to predict the risk of injury is highly debated within sports science. One concern is that the popularity of ACWR is being propagated by editorials and commentary articles rather than research papers with quantitative analyses and that there currently is not enough evidence to validate its use (Kupperman and Hertel 2020). Another criticism against ACWR is that the acute workload is also a part of the chronic load, which might create a correlation between the two irrespective of any biological or physiological associations (Thornton *et al* 2019). Despite its popularity, there seems to be a pushback against ACWR in recent years, with some recent studies showing strong evidence to reject any correlation between ACWR and injury risk (West *et al* 2021).

Internal load measures and external load measures can be combined to paint a better picture of a player's physical state. The ratio between a player's external load and internal load during a training session can be used as a measure of the player's workload efficiency, which can indicate the player's fitness level (Grünbichler *et al* 2020). Internal loads and external loads can also be combined to train a machine learning model that is capable of predicting injury risks. Vallance *et al* (2020) trained and compared various injury prediction machine learning models based on internal and external load measures, and found models that use a combined input of internal and external loads performed better than models that use either internal or external loads alone.

Currently, there is no consensus on how workload should be determined. There exists a large number of variants of the base metrics as well as numerous ways different workload measures can be combined into hybrid measures; one study reports up to 756 different combinations (Benson *et al* 2020). No clear conclusion can be drawn on how to utilize workload monitoring for injury prevention, due to the heterogeneity of analytic approaches in the literature, and this issue is worsened by the fact that not all studies have the same definition of what constitutes an injury (Benson *et al* 2020). There is an overwhelmingly strong need for standardization in the field of workload monitoring.

Nonetheless, there is little doubt that workload monitoring will become a standard practice in organized sports in the future. Monitoring players' workloads can potentially benefit the players' health as well as their growth as athletes. Such potential benefits include more optimized training based on game demands, lowered risk of overtraining, injury prevention, and smoother return-to-play transitions after injuries in the future. However, most studies on workload monitoring are based on statistically small data sets and are disproportionately skewed towards high-level male athletes (Benson *et al* 2020, Kupperman and Hertel 2020, Rago *et al* 2020). There is a need to collect data from a wider range of demographics. One of the potential limitations to data collection right now is the existing monitor systems are only affordable to well-funded sports entities. Future research should also include more developments of devices capable of measuring both internal and external loads, especially affordable devices that will be accessible at all levels of play.

3.2. Impact monitoring

3.2.1. Miscellaneous collisions monitoring

Physical collisions between players as well as impacts between a player and the play surface are a common occurrence in full-contact sports such as rugby football, Australian rules football, American football, and ice hockey. Collisions can often take place during tackling and checking actions which are integral to these games. These collisions can lead to soreness and muscle damage which may result in attenuated neuromuscular performance and recovery (Naughton *et al* 2018). Tackling can also lead to injuries that cause players to miss training and matches (Gabbett *et al* 2011). Monitoring collisions that contact sports players have to endure may help to mitigate the risk of injury. As with in-game workload monitoring, learning more about in-game collision loads can aid coaches in designing more specialized training and recovery strategies to better prepare their players (Wellman *et al* 2017).

Collision loads are often quantified by the frequency and intensity of collisions (MacLeod *et al* 2018, Naughton *et al* 2020). In the past, collision load monitoring was done via video analysis, the number of collisions would be manually counted, and a perceived measure of collision intensity would be given following a quantitative analysis of the footage (Naughton *et al* 2020). In more recent years, researchers have attempted to quantify collision intensity more objectively by extracting collision velocity and acceleration from videos frame-by-frame (Naughton *et al* 2020). These methods are time-consuming and can be prone to human errors and biases.

GPS systems for external load tracking have become widely accepted by most football-code sports at a professional level. As stated previously, there are commercial systems that combine GPS with IMUs, which often include a 100 Hz tri-axial accelerometer, a gyroscope, and a magnetometer. Due to the popularity of these systems, many researchers have been attracted to investigate the viability of tracking collision load using IMUs (Gabbett *et al* 2011, Gabbett *et al* 2014, Hulin *et al* 2017, MacLeod *et al* 2018). Attempts were made to identify collision events from the kinematic data captured by IMUs, though there is only limited validation of such systems in the literature (Naughton *et al* 2020). One validated collision detection algorithm found in the literature works by thresholding the jerk-based PlayerLoad external load measure and detecting changes in orientation of the IMU (Gabbett *et al* 2011, 2014, Hulin *et al* 2017, Naughton *et al* 2020). A collision is flagged when the PlayerLoad spikes above 2 AU (Arbitrary Units) following a change in orientation of the IMU (Hulin *et al* 2017). This algorithm performs poorly when short-duration collisions (<1 s) and low-intensity collisions (<1 AU) are included (Hulin *et al* 2017). When short-duration collisions and low-intensity collisions are excluded, the algorithm achieves a sensitivity of 93.9% and a specificity of 91.7% (Hulin *et al* 2017). The inability of this algorithm to accurately detect so-called short-duration collisions and low-intensity collisions is an innate problem with thresholding. Perhaps, in the future, collision event detections can be made more accurate using more dynamic algorithmic approaches.

When monitoring collision events using accelerometers, the collision intensity is determined by the acceleration of the player due to the collision (Gabbett *et al* 2014, Wellman *et al* 2017, Naughton *et al* 2020). In most studies, different ranges of acceleration are categorized into three severity levels, mild, moderate, and heavy (Gabbett *et al* 2014, Wellman *et al* 2017, Naughton *et al* 2020). However, the acceleration ranges used for each severity level vary across different studies, which makes it difficult to meaningfully compare their outputs (Naughton *et al* 2020). Presently, there's a clear need to standardize how collision intensity is quantified. In addition, current collision monitoring methods do not discriminate between different types of collisions: different types of collisions could have different implications on the athlete. Future work in collision monitoring should include applying more sophisticated methods, such as machine learning, to differentiate types of collisions (Naughton *et al* 2020).

3.2.2. Head impact monitoring

Shocks to the head are often of special interest when it comes to monitoring body impacts due to their potential medical implications. Head impacts are often monitored with dedicated devices, separate from those measuring general impacts. Whether it occurs through direct collisions between athletes in tackling and checking, contact with the playing surface, or because of a blow to the head by a ball, traumatic brain injuries (TBIs) due to head impacts are of great concern as they can compromise the athletes' short and long-term health.

An estimated 300 000 sport-related concussions (mild TBIs) occur annually in the US alone, making up for 8.9% of all high school athletic injuries and 5.8% of all collegiate athletic injuries (Gessel *et al* 2007). Some studies suggest that concussions only make up for between 8% to 19.2% of sports-related TBIs, making the number of US annual sports-related TBIs somewhere between 1.6 million and 3.8 million (Langlois *et al* 2006). On-field diagnoses of TBIs often rely on self-reports from the affected athletes. This can sometimes lead to underreporting of TBIs, potentially due to transient or delayed symptoms, or players' unwillingness to leave play (McCrea *et al* 2004, Williamson and Goodman 2006, LaRoche *et al* 2016). Despite the recent evidence that has shown that policy changes can help reduce underreported incidents (LaRoche *et al* 2016), an objective way to detect injurious head impacts in real-time is still warranted.

Head impacts are often analyzed as two separate mechanisms, translational (linear) movements and rotational (angular) movements. Both large linear accelerations (LA) and angular accelerations (AA) of the head can lead to injurious strains on the brain, with the latter associated with a higher risk of injury (Bailes and Cantu 2001). Due to the nature of TBIs, human experiments with deliberate injurious head impacts cannot be carried out, making acquiring data for TBI studies difficult. Human cadavers and medical phantoms have been used in place of a live human in many past studies to grant insight on TBIs (Hardy *et al* 2007, McAllister *et al* 2012, Yang *et al*), though, how representative these substitutes are of the biomechanics of live humans remains an open question (Hardy *et al* 2007, McAllister *et al* 2012, Yang *et al*). And as of now, many of the clinical implications associated with head impacts sustained by athletes remain unknown (Bartsch *et al* 2020, Mihalik *et al* 2020).

In recent years, sensor systems have been developed to capture head kinematics of contact-sport athletes on-field to help bridge the gap between head impact data and TBIs, while simultaneously offering solutions to help flag TBIs in athletes in real-time. Development of such systems first started in American football, taking the forms of accelerometer arrays, such as the Head Impact Telemetry (HIT) System (Simbex, Lebanon, NH, USA), or inertial sensor units (IMU), such as the gForce Tracker (GFT) (Artaflex Inc., Markham, Ontario, Canada), which could be integrated into American football helmets (Campbell *et al* 2016, Siegmund *et al* 2016, Brennan *et al* 2017, O'Connor *et al* 2017). These helmet-mounted sensor systems can measure kinematics in six degrees of

freedom, three linear and three rotational, and can estimate the location of head impact based on the kinematics. Raw kinematic data from these systems are often put through a correction algorithm to output the LA and AA at the center of mass of the head (Campbell *et al* 2016). These techniques have also been adopted by other sports that include helmets in their kits, such as ice hockey and lacrosse. It has been reported that the accuracy of these systems is heavily influenced by the shape of the helmets they are in (Siegmund *et al* 2016, Buice *et al* 2018). Many limitations of these systems have been identified, with one of the greatest limitations being that helmets can move relative to the players' heads, especially when under impact. The helmet-mounted systems cannot account for the relative movements between the helmet and the head, which can lead to overestimated acceleration values when the helmet moves more than the head (O'Connor *et al* 2017). The HIT system, in particular, has also been critiqued for its high price and limited compatibility with different helmet models (Merrell *et al* 2017). Furthermore, these systems can only be deployed in sports that use helmets, but TBIs are present in many sports that do not use helmets.

To accommodate for more sports, nonhelmeted systems with IMUs have been developed in the form of headbands, skullcaps, mouthguards, or xPatch (X2 Biosystems, Seattle, WA, USA)—a stick-patch that goes behind the ear (Brennan *et al* 2017, Cummiskey *et al* 2017, Merrell *et al* 2017, O'Connor *et al* 2017, Bartsch *et al* 2020), with the latter two also addressing the issue of relative motions between the sensors and the player's head. Like their helmeted counterparts, these nonhelmeted systems are designed to measure head kinematics and impact locations. These systems come with their own limitations. The accuracy of the stick patches can be affected by skin motions. And data transmission from the mouthguards can be affected by saliva accumulation (O'Connor *et al* 2017).

In validation studies for these head-kinematics-based impact-monitor-systems, a Hybrid III (General Motors, Detroit, Michigan, USA) headform instrumented with sensors is often used as a reference for the measured kinematics (Duma *et al* 2005, Jadischke *et al* 2013, Campbell *et al* 2016, Siegmund *et al* 2016, Cummiskey *et al* 2017, Merrell *et al* 2017, O'Connor *et al* 2017, Buice *et al* 2018, Bartsch *et al* 2020). The design of validation studies can sometimes be over-idealized and not representative of real-world usages. For instance, press-fitting a helmeted system onto the headform and effectively making the helmet and headform move as a single rigid unit (Duma *et al* 2005, Cummiskey *et al* 2017). Validation of the same device under more realistic conditions found much higher errors in the measurements (Duma *et al* 2005, Jadischke *et al* 2013, Cummiskey *et al* 2017). Cummiskey *et al* (2017) compared the accuracy of 2 commercially available helmet-mounted systems and 3 commercially available head-mounted systems and found that the head-mounted systems consistently outperformed helmet-mounted systems under lab settings. They suggested this was due to relative motions between the helmet and the headform, and since relative motions between the helmet and the player's head are present in real life, this finding cannot be dismissed. Thus, Cummiskey *et al* concluded that to most accurately capture head acceleration events, it is necessary to mount the sensor system directly to the head. Cummiskey *et al* further suggested that under real-world conditions, the accuracy of the head-mounted systems such as the xPatch can be affected by skin motion, and therefore, moving forward, mouthguard-based sensors may be the most promising.

In terms of the actual measurement accuracies of these systems, the measurement quality can differ for different impact locations. Furthermore, inconsistent measurement accuracies of identical systems have been reported across different peer-reviewed works. The HIT System, for example, when compared with the Hybrid III, has been reported to have a relative error rate ranging from less than 4% to greater than 15% for LA measurements, according to studies from different researchers, and some have even observed peak linear acceleration measurements with root mean squared errors (RMSE) greater than 100% (Jadischke *et al* 2013, Cummiskey *et al* 2017, O'Connor *et al* 2017). Based on this observation, a meta-analysis is likely needed to fully validate the accuracy of these systems, and till then, research teams intending to use these devices for data capture should perhaps carry out their own validation study whenever possible. Most IMU-based devices cannot measure angular acceleration directly but measure angular velocity via gyroscopes instead, and the angular acceleration is often numerically obtained via differentiating the angular velocity (Cummiskey *et al* 2017, Buice *et al* 2018, Rich *et al* 2019). Head acceleration events often happen on a scale of milliseconds, as such, a minimum sampling rate of 1 kHz is desired, and higher sampling rates have been shown to further improve measurement accuracy (Cummiskey *et al* 2017, Rich *et al* 2019). Impact locations are estimated based on the LA and AA measurements, and the outputs are divided into discrete impact zones. There's a fundamental flaw in the way the impact location is calculated, as both the impact location and the force direction are unknown, and it is, therefore, impossible to obtain a unique impact location using just the head kinematics (Cummiskey *et al* 2017). This issue is slightly alleviated by the fact that the human head is not isotropic which makes some impact locations more likely than others for different head kinematics, but the issue is still ever-present. Helmets can be instrumented with tactile sensors to better measure the location of impact (Merrell *et al* 2017), though there is no equivalent solution for non-helmeted systems such as mouthguards.

In certain sports, such as soccer, players are often reluctant to adopt additional accessories that are not already a part of their kit. To address this issue in soccer, Stone *et al* (2018) proposed the development of a smart soccer ball with integrated IMUs for heading detections. In their study, the smart ball showed promise for heading detections under controlled testing conditions, though, Stone *et al* stated that better sensors are needed to make their system viable in the real world.

For the reasons listed above and more, the aforementioned sensor systems are not currently widespread amongst athletes outside of research studies. At a professional level, many sports have already adopted monitoring systems for capturing internal and external loads, and some researchers have proposed to detect and measure head impacts using data captured by some of these systems.

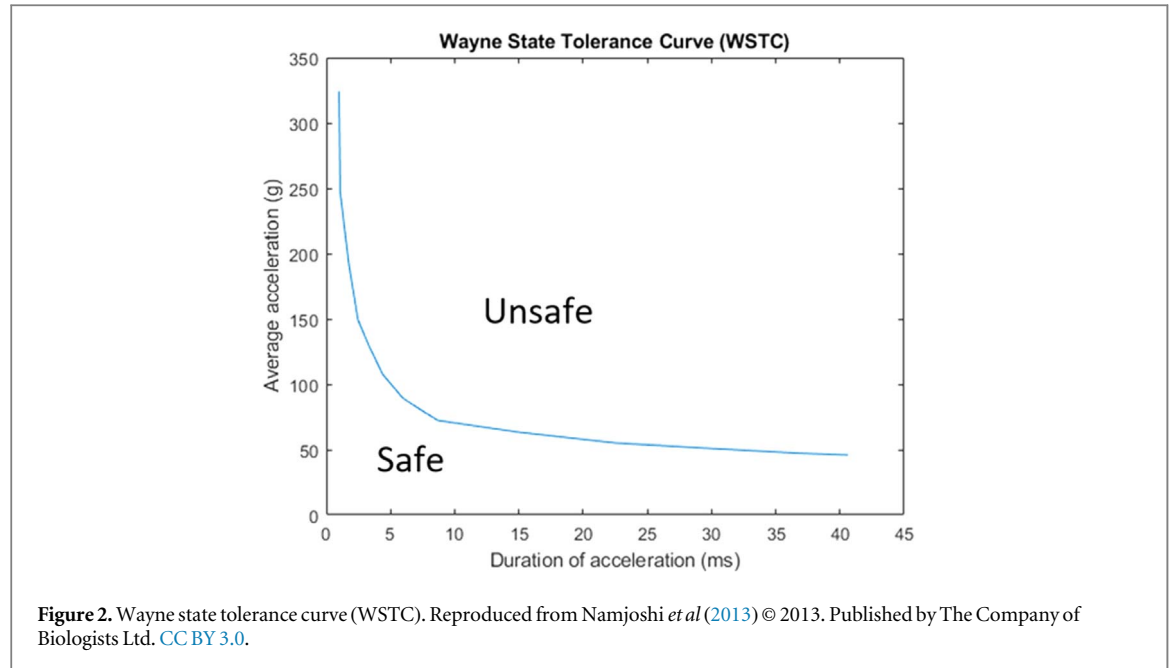
In soccer, it is already common for professional players to wear GPS vests with a built-in IMU located above the third thoracic vertebra (T3) of the spine. Worsey *et al* (2020) investigated the potential to use that T3 IMU as a detection device for heading events in soccer. In their study, they found that the T3 IMU can only make reliable heading detections in athletes when certain techniques are used, and it cannot make any accurate head kinematics measurements, making it, unfortunately, not suitable for heading detection and monitoring.

In American football, while the aforementioned head impact monitoring systems are not commonly employed by professional athletes, professional stadiums are equipped with high-quality camera systems that can capture game footage which will allow for analyses of impacts sustained by players. Bailey *et al* (2020) demonstrated a model-based image-matching technique to calculate head kinematics. In their study, a ray-tracing technique was used to obtain the movement trajectories of the helmets. A helmet model was then manually superimposed onto the video images frame-by-frame to obtain the rotational movements of the helmets. Bailey *et al* found that cameras with a higher frame rate (240 Hz) are better for calculating the head kinematics than cameras with a lower frame rate (60 Hz), and their technique is more accurate at measuring the pre-impact velocities than during the impact. One of the shortcomings of this technique, when compared to the IMU-based sensor systems, is its reliance on a large amount of manual input, making it unsuitable for real-time monitoring in its current form. It is, however, still useful for capturing kinematics data for TBI studies and acquiring in-game helmet loading data for advising helmet testing.

While the aforementioned devices all come in different formats, they all aim to capture translational and rotational movements of the head, and impact locations. And as such, they all aim to assess the severity of head impacts under the same metrics. To rate the severity of a head impact, one needs to first be able to differentiate an actual impact from miscellaneous head accelerations in the kinematics data. To achieve that, many systems have simply set a threshold for the LA measurement (Siegmund *et al* 2016, O'Connor *et al* 2017, Wu *et al* 2017). The threshold is often set to 10 g (ten times the gravitational acceleration), though other threshold values have also been suggested by researchers (Siegmund *et al* 2016, O'Connor *et al* 2017). This approach raises several concerns. When the threshold value is set too low, it will result in a higher number of false positives, and when the value is set too high, some true positives will be missed out (Wu *et al* 2017). In addition, since the cutoff is based on the LA, many impacts that are predominantly rotational with high AA values and low LA values will likely be missed out (Siegmund *et al* 2016).

Two commercially available systems, HIT System and xPatch, have built-in software for identifying the legitimacy of a hit based on the acceleration waveform (Cumiskey *et al* 2017). However, validation of this method is currently lacking in peer-reviewed literature. As an alternative, Wu *et al* (2017) demonstrated a machine learning (ML) method for identifying head impacts in kinematic data. In their study, a support-vector-machine (SVM) classifier was trained using American football data collected on-field via IMU instrumented mouthguards. The trained SVM classifier achieved over 90% precision and recall when tested on an independent dataset. This shows promise as a more objective way to detect head impacts than arbitrary thresholding, and similar approaches can perhaps be implemented with future sensor systems to improve the accuracy of head impact detections.

Once an impact has been identified, the severity of the individual impact can be assessed. There has also been strong evidence in the literature that the accumulation of repeat head impact exposures can lead to certain risks (Nauman *et al* 2015, Bari *et al* 2019, Caccese *et al* 2019, Mihalik *et al* 2020), though there is still a large gap in that knowledge. As of now, the majority of head impact severity models only account for individual impacts. The most basic models are simply thresholds for either the peak LA or the peak AA at values that present a risk of concussion. These models are, however, extremely unreliable. At greater than 50% correct injury prediction levels, for every correct prediction made, hundreds if not thousands of false positives are also flagged (Greenwald *et al* 2008). An NFL study has also attempted to correlate the peak LA to head injury rate using on-field data (Pellman *et al* 2003). This paper claims that 75% of all impacts greater than 98.9 g would result in a concussion. However, an independent study by Greenwald *et al* found that out of the 3476 impacts of greater than 98.9 g they have recorded, only 11 of them (0.3%) have resulted in clinically diagnosed concussion (Pellman *et al* 2003, Greenwald *et al* 2008). While the discrepancy could have been caused by data biased towards injurious impacts, it also indicates that it is likely that there isn't a clear TBI threshold.



Through a series of experiments carried out with human and dog cadavers at Wayne State University, it was found that head injury, defined as the occurrence of a skull fracture, correlated with the magnitude of LA and exposure duration. These data were plotted up as the famous wayne state tolerance curve (WSTC), see figure 2 (Hutchinson *et al* 1998). In 1966, Charles W Gadd analyzed this set of data, and by plotting the data on a log paper, fitted the data to the following equation,

$$\bar{a}^{2.5} \cdot T = 1,000, \quad (1)$$

where \bar{a} is the average acceleration in g-force, and T is the exposure duration in seconds (Gadd 1966).

Gadd then expressed this fit in an integral form

$$I = \int_{\Delta t} a(t)^{2.5} dt \quad (2)$$

and called it the Gadd severity index (GSI). Later, out of consideration for the appropriateness of the GSI, Versace re-expressed Gadd's fit of the WSTC as

$$HIC = \left[\frac{\int_{t_1}^{t_2} a(t) dt}{(t_2 - t_1)} \right]^{2.5} (t_2 - t_1), \quad (3)$$

where HIC stands for Head Injury Criterion (Versace 1971). Although both GSI and HIC were developed for predicting life-threatening head injuries, they are, to date, two of the most commonly used measures of impact severity in sports science for studying mild TBIs. While they have had great implications for regulations in the automobile industry, they have not proven to be any more reliable, statistically, than peak LA or RA thresholding for TBI prediction (Greenwald *et al* 2008).

There are many criticisms of GSI and HIC, and many alternative measures of impact severity have been developed to address these criticisms. One of these criticisms is that neither GSI nor HIC accounts for rotational motion. As such, models that combine both linear and rotational measurements have been proposed. Such models include Kleiven's linear combination (KLC), a linear combination of HIC and the maximum resultant angular velocity (Kleiven 2007); the generalized acceleration model for brain injury threshold (GAMBIT) which regards LA and AA as proxies for stresses on the brain (Newman 1986); and the combined probability of concussion (CP), a function of LA and AA developed from a head-impact dataset using multivariate logistic regression analysis (Rowson and Duma 2013).

Another criticism of GSI and HIC is that these models were loosely empirically fitted by hand and the dimensions of these measures are physically meaningless (Newman and Shewchenko 2000). Newman *et al* proposed to instead measure head impact severity using the rate of change of kinetic energy of the head and created the head impact power (HIP) index (Newman and Shewchenko 2000). While HIP is physically more sound than some of the other head impact measures, it still neglects some physical properties of the head. The human head is not isotropic and therefore responds differently to different directions of impact. A modified HIP

was proposed to address this issue. The modified HIP has an additional scaling coefficient for each component of the original HIP, accounting for the various directions and differentiation between positive and negative accelerations (Kleiven 2003).

Greenwald *et al* (2008) had also proposed a kinematics-based head impact measure that considers the anisotropic properties of the head, though via a different approach. By using principal component analysis, Greenwald *et al* constructed a head impact score that is a combination of GSI, HIC, LA, and AA. This score is then multiplied by a weighting factor based on the location of the impact to give what Greenwald *et al* called a weighted principal component score (wPCS). The wPCS is sometimes also referred to as the HIT severity profile (HITsp) since it was developed using the HIT system. Greenwald *et al* demonstrated that HIPsp performs better than the classical measures (LA, AA, and HIC) in predicting mild TBI. However, the prediction power of the HITsp is still insufficient for monitoring head traumas in practice as it has a positive predictive value (PPV) of 0.9% at the 50% sensitivity threshold (Greenwald *et al* 2008). (The definitions of PPV and sensitivity are as follows. A 75% PPV at a threshold means that on average three of four impacts above this threshold result in mild TBIs. A 75% sensitivity at a threshold means that on average three of four mild TBIs are resulted from impacts above this threshold.) Greenwald *et al* also noted that a 'safe' HITsp value for one player may correspond to a mild TBI diagnosis for another player (Greenwald *et al* 2008). These findings showcase the problem with regards to a 'one-size-fits-all head injury threshold'.

Studies have shown that rotational movements contribute more to brain injuries than linear motions (Ji *et al* 2014). As a result, some head impact measures were developed while only considering rotational kinematics. Takhounts *et al* introduced the Brain Injury Criterion (BRIC) which is the sum of normalized maximum angular velocity and acceleration, and later introduced an updated version (BrIC) which only uses angular velocity after finding a low correlation between angular acceleration and strain on the brain (Takhounts *et al* 2013, Takhounts *et al* 2011). Later studies have, however, found the contrary and shown BRIC and BrIC to perform poorly under certain impact conditions (Gabler *et al* 2016, Shi *et al* 2020). Ommaya *et al* (Ommaya *et al* 1967) constructed a tolerance curve for angular acceleration using data on concussed monkeys. The acceleration tolerance curve resembles the WSTC, and using this similarity, Kimpara and Iwamoto (Kimpara and Iwamoto 2012) proposed two head impact measures similar to HIC. The first of the two is the power rotational head injury criterion (PRHIC) which replaces the LA term in HIC with the rotational component of HIP. The second is called rotational injury criterion (RIC) which replaces the LA term in HIC with AA. While both measures produced promising results on the initial study, the authors of RIC and PRHIC are concerned with the unusual physical dimensions of these measures and their implications on the physical interpretation. There are many more kinematics-based measures of head impact severity, though the sentiment here holds. The table below (table 2) lists some of the commonly used kinematics-based measures of head impact severity within the field.

Despite all these efforts to establish new kinematics-based head impact severity measures and an injury threshold, no consensus has been reached within the field (Ji and Zhao 2015). New sensor systems have been developed to capture a wider range of data in hopes of further improving upon current head impact severity measures. Merrell *et al* (2017) demonstrated a helmet-based sensor system fitted with an array of nano-composite foam (NCF) sensors. The NCF sensors can measure impacts through a triboelectric response. Merrell *et al* demonstrated that the NCF sensor system can accurately measure the impact location as well as the head kinematics. In addition to the information that conventional helmeted systems can capture, the NCF sensor system can also capture the impact energy. Future studies could investigate the relationship between impact energy and concussion, and potentially use the impact energy measures to improve head injury prediction accuracy.

3.2.2.1. Finite element models for head impact

One of the likely reasons behind the failures of the kinematics-based head impact severity measures is that these models, based on head kinematics, simply are not representative of the motions of the brain. Meng *et al* (2020) investigated the correlations between skull movements and movements of different sections of the brain and found R-squared values of less than 0.4 across the board. To reasonably predict the actual impact on the brain due to external energy on a microstructural level, many finite element (FE) models have been constructed using (head impact) data from various sources, including MRI images of the human brain (Ji *et al* 2014). These FE models can predict deformations on different parts of the brain based on kinematic inputs. FE models are often complex and computationally costly. It can take hours to process a single head impact on a modern high-spec computer (Ji and Zhao 2015, Gabler *et al* 2019, Wu *et al* 2019, Gabrieli *et al* 2020, Zhan *et al* 2021). The long processing time not only makes the FE models unfeasible for on-field player monitoring at the moment but also limits the scale of head impact studies that require the use of them (Ji and Zhao 2015, Gabler *et al* 2019, Wu *et al* 2019, Gabrieli *et al* 2020, Zhan *et al* 2021).

Several different approaches have been proposed to either reduce the computational time of an FE model or to offer a less time-consuming alternative. These efforts can be classified as either reduced-order models or pre-

Table 2. A list of some of the commonly accepted kinematics-based measures of head impact severity, where a represents linear acceleration, α represents angular acceleration, ω represents angular velocity, and t represents time. In GAMBIT, n , m , and s are assigned constants and are often taken to be 1. In CP, α_i are regression coefficients with i indicating the index number. In HIP, m stands for mass and I stands for moment of inertia. In HITsp, i is the impact location coefficient, and In PRHIC HIP_rot is the rotational component of HIP.

Name	Measure
Peak LA	a_{peak}
Peak AA	α_{peak}
GSI	$I = \int_{\Delta t} a(t)^{2.5} dt$
HIC	$HIC = \left[\frac{\int_{t_1}^{t_2} a(t) dt}{(t_2 - t_1)} \right]^{2.5} (t_2 - t_1)$
GAMBIT	$G(t) = \left[\left(\frac{a(t)}{\alpha_c} \right)^n + \left(\frac{\alpha(t)}{\alpha_c} \right)^m \right]^{1/s}$
KLC	$KLC = 0.004718 \cdot \omega_r + 0.000224 \cdot HIC$
CP	$CP = \frac{1}{1 + e^{-(\beta_0 + \beta_1 a + \beta_2 \alpha + \beta_3 a \alpha)}}$
HIP	$HIP = m \sum_i a_i \int a_i dt + \sum_j I_{ij} \alpha_j \int \alpha_j dt$
HITsp	$wPCS = x_n \cdot 10 \cdot ([0.4718 \cdot sGSI + 0.4742 \cdot sHIC + 0.4336 \cdot sLA + 0.2164 \cdot sAA] + 2)$
BRIC, BrIC	$BRIC = \frac{\omega_{max}}{\omega_{cr}} + \frac{\alpha_{max}}{\alpha_{cr}}, BrIC = \sqrt{\left(\frac{\omega_x}{\omega_{xc}} \right)^2 + \left(\frac{\omega_y}{\omega_{yc}} \right)^2 + \left(\frac{\omega_z}{\omega_{zc}} \right)^2}$
RIC	$RIC = \left[\frac{\int_{t_1}^{t_2} \alpha(t) dt}{(t_2 - t_1)} \right]^{2.5} (t_2 - t_1)$
PRHIC	$PRHIC = \left[\frac{\int_{t_1}^{t_2} HIP_{rot} dt}{(t_2 - t_1)} \right]^{2.5} (t_2 - t_1)$

computed models, with both aiming to provide some form of brain strain prediction using head kinematic measures (Zhan *et al* 2021). The reduced-order models are based on multibody modelling, in which the brain is modelled as a system of masses connected by springs with damping (Gabler *et al* 2019, Gabrieli *et al* 2020). The physical characteristics of the multibody systems such as the spring stiffness and damping matrices are determined using a set of FE simulation results. The reduced-order models are less computationally taxing, but as a trade-off, reduced-order models are limited in accuracy and cannot predict brain deformation on a detailed level (Zhan *et al* 2021). Gabrieli *et al* (2020) attempted to reduce the discrepancy between the outcomes of their multibody brain model and those of a FE model by linking the two using machine learning. They were able to show an improvement in the accuracy of the predicted strain using machine learning, achieving an average absolute relative error greater than 15% when applied to a test set. In contrast to reduced-order models which are simplified mechanical models of the brain, pre-computed models are data-driven computational models built on large kinematic data sets and their FE simulation results. One example of a pre-computed model is the pre-computed brain response atlas (pcBRA) presented by Ji and Zhao (Ji and Zhao 2015). Other pre-computed models include deep-learning models that take kinematic inputs and output brain strain predictions (Wu *et al* 2019, Zhan *et al* 2021). Banking on the fact that the brain is much more sensitive to strains due to rotational motions than strains due to linear motions (Kleiven 2013), the reduced-order models and the pre-computed models described above, all opted to only take rotational kinematics into account (Ji and Zhao 2015, Gabler *et al* 2019, Wu *et al* 2019, Gabrieli *et al* 2020, Zhan *et al* 2021). While linear kinematics should in theory only have a minor effect on brain strain predictions, the exact extent of its effect can differ from model to model and should be verified in future studies. Direct comparisons between pre-computed these models are difficult to carry out since many of them are created using different FE models, and the reliability of these pre-computed models is limited by the FE models they are based on. Another issue faced by all of these models is the lack of on-field injury data to further tune and validate the models. This is especially true for the machine learning models, as they will likely need retraining for different sports or even different demographics.

3.2.2.2. Alternative monitoring head impact solutions

In contrast to the software solutions above, Meng and Prather *et al* (Meng *et al* 2020, Prather *et al* 2019) presented a novel hardware approach. In the same study where Meng *et al* (2020) showed that the skull kinematics do not correlate to the movements of the brain, they also found that the movements of the eyes are well correlated to the brain, especially for the posterior part of the brain where R-squared value is as high as 0.983. Meng and Prather *et al* (Meng *et al* 2020, Prather *et al* 2019) proposed to build a micro IMU in a contact lens as a way to monitor the movements of the brain due to an impact. However, sensor technology has a long way to go before this system can be safely realized outside of the lab.

Lab-based electroencephalography (EEG) where signals from the brain are measured via epidermal-electrodes has shown promise in aiding head injury detections (Seshadri *et al* 2016). Helmets embedded with EEG in addition to accelerometers have been proposed as a means to capture additional information related to TBIs (Ramasamy and Varadan 2016). However, the usefulness of such a system is still lacking scientific evidence. EEG data can be noisy and difficult to work with even when recorded under well-controlled lab environments, and one can question the reliability of EEG data captured with a helmet that can move relative to the head in a high-impact sport. Likely, EEGs will not be easily utilized during live-game action (Seshadri *et al* 2016).

While current on-field head injury monitoring systems leave much to be desired, there are many exciting novel pieces of research happening in both sensor technology as well as data modelling. More accurate sensor systems are being developed with a wider range of sports in mind. This will allow researchers to capture data in both higher quality and quantity, enabling us to better study and understand the biomechanics of the brain. Together with advancements in computational units, it is hopeful that in the future we will have a representative biomechanical model of the head that can process head impact data captured by sensor systems, output strains on different regions of the brain, and accurately predict the risk of TBI in realtime.

4. Further considerations

With the growing public awareness of the short and long-term consequences of various sports-related injuries, the need to objectively safeguard and manage the athletes is clearer now, more than ever. There is a growing interest in understanding the well-being and mental health of athletes, which is affected by the ability to cope with both impacts and workload. A more holistic view is appropriate in the management of athletes and this indicates the necessity of a multi-modal approach for monitoring. At the moment there is a lack of research that aims to monitor across domains (e.g. impact, workload and well-being), which makes it hard to generate better models for player management. However, this approach also requires the individual tracking components to be well understood. This review has identified a few issues with on-field monitoring that need to be addressed moving forward. The first issue is a general lack of data to help build and validate injury rate prediction models. There appear to be a lot of models in sports monitoring that were created from limited-sized and homogenous data sets. With developments of better sensor systems, high-quality data needs to be captured both in higher quantity and from a wider range of demographics to create models that are more accurate and more applicable across the sports community. The second issue is that there is a lack of consensus on how measurement data should be processed and presented. Inconsistent data presentations across related studies make comparing and combining outcomes of different studies difficult, and this may result in some researchers' hard work becoming much less impactful than they intended. Moving forward, standardized definitions and data formats that can facilitate meaningful comparisons between studies and meta-analyses are needed for the field to grow meaningfully and effectively.

An athlete's lifestyles and behaviours outside of sports can also have meaningful impacts on their on-field performance, and conversely, their involvement in sports can impact their general wellness and behaviours off-field. So, to improve players' wellness and to optimize their on-field performance, future studies and practices should consider combining on-field monitoring with player wellness data collected off-field. Such off-field data collections may include aspects such as sleep and stress.

Poor sleep can negatively affect an athlete's physical and mental abilities resulting in poor athletic performance and has been linked to increases in injury rate (Chandrasekaran *et al* 2020, Seshadri *et al* 2021). Thus, there's a clear incentive to monitor sleep in sports. Current practices of sleep monitoring in sports and sports studies are often reliant on self-reports via sleep questionnaires, the reliability of which can be questionable as it depends on the participant's ability to recall and is subject to the participant's bias (Chandrasekaran *et al* 2020). More objective measures can be taken through technological means. In the future, devices can be utilized to monitor athletes in conjunction with on-field monitoring techniques to optimize player performance and better prevent injuries.

In regard to the current state of the world, the COVID-19 pandemic caused by the SARS-CoV-2 virus has led to the cancellation of most amateur and semi-professional team sports and has changed the way professional team sports are organized dramatically around the globe. With lockdown measures being gradually loosened in several parts of the world, many team sports are being reinstated, with extra measures taken to minimize the risk of spreading the SARS-CoV-2 virus. Tracking interpersonal contact exposures between players can allow for early intervention when new suspected or confirmed COVID-19 cases surface and thus limit the spreading of the disease. Gonçalves *et al* showed that player positioning tracking systems can be used to track COVID-19 related interpersonal contact exposures (Gonçalves *et al* 2020). The European Centre for Disease Prevention and Control (ECDC) defined high-risk exposure as having had face-to-face contact with a SARS-CoV-2 carrier within 2 m for more than 15 min. To monitor exposure using the ECDC recommendations, Gonçalves *et al* had

devised two exposure measures. Measure one is the duration of direct contact between players within 2 m; measure two takes into account the respiratory droplets left behind by moving individuals and tracks the duration of indirect exposure with a half-life of 2 s (Gonçalves *et al* 2020). A contact exposure tracking method as such has the potential to improve sports team risk management during the COVID-19 pandemic and facilitate sports returning to normal. Another concern with players returning to training and play is that after a long lockdown, the players might not adapt to a sudden increase in exercise intensities well (Seshadri *et al* 2021). Workload monitoring should be employed by teams as players are returning to play to minimize the risk of overtraining.

5. Conclusion

This review provides an overview of on-field sports monitoring techniques that aim to improve the health and wellness of athletes. Most of the current monitoring methods are either tracking the athlete's workload or monitoring physical impact. Current sports monitoring practices are being held back by a lack of standard metrics and definitions, and the size and diversity of data needs to increase to develop ecologically valid approaches. The future of on-field sports monitoring will most likely consist of well packaged wearable sensor systems that can measure both physical and physiological parameters. Big data approaches should be adopted to build models that can meaningfully process the data captured by these systems and provide effective injury prevention and player management.

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