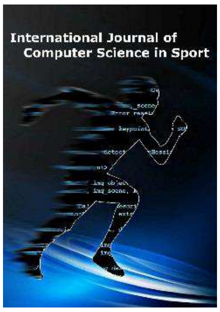
International Journal of Computer Science in Sport

Volume 22, Issue 2, 2023

Journal homepage: http://iacss.org/index.php?id=30

DOI: 10.2478/ijcss-2023-0008



Workload Monitoring Tools in Field-Based Team Sports, the Emerging Technology and Analytics used for Performance and Injury Prediction: A Systematic Review

Georgia Keys (A), Lisa Ryan (B), Maria Faulkner (C) & Michael McCann (A),

(A) Department of computing, Atlantic Technological University (ATU) Letterkenny, Donegal, Ireland

(B) Sport, Exercise and Nutrition, ATU, Galway, Ireland

(C) Department of sport, ATU, Letterkenny, Donegal, Ireland

Abstract

Training load (TL) is frequently documented among team sports and the development of emerging technology (ET) is displaying promising results towards player performance and injury risk identification. The aim of this systematic review was to identify ETs used in field-based sport to monitor TL for injury/performance prediction and provide sport specific recommendations by identifying new data generation in which coaches may consider when tracking players for an increased accuracy in training prescription and evaluation among field-based sports. Data was extracted from 60 articles following a systematic search of CINAHL, SPORTDiscus, Web of Science and IEEE XPLORE databases. Global positioning system (GPS) and accelerometers were common external TL tools and Rated Perceived Exertion (RPE) for internal TL. A collection of analytics tools were identified when investigating injury/performance prediction. Machine Learning showed promising results in many studies, identifying the strongest predictive variables and injury risk identification. Overall, a variety of TL monitoring tools and predictive analytics were utilized by researchers and were successful in predicting injury/performance, but no common method taken by researchers could be identified. This review highlights the positive effect of ETs, but further investigation is desired towards a 'gold standard' predictive analytics tool for injury/performance prediction in field-based team sports.

KEYWORDS: WORKLOAD, TRAINING LOAD, FIELD BASED SPORT, PREDICTIVE ANALYTICS, EMERGING TECHNOLOGY, MACHINE LEARNING.

Introduction

Injuries in a professional sporting environment have proved to have detrimental effects on the sport industry (Sigurdson and Chan 2020). Career ending concussions have been calculated to value players $135 million in terms of opportunity costs (Hiploylee et al. 2016) and another study found 50.9% of all National Hockey League (NHL) players cost $218 per year from missing at least one game due to injury (Donaldson et al. 2014). Injuries as a result, can risk an athlete losing their spot on a team or an increased quality of losses for fans due to a decrease in performance levels. By avoiding injuries among teams, coaches have access to a complete squad during training and matches for a more positive performance as lower injury rates are related to success in both national and international matches (Ekstrand et al. 2021).

Training load monitoring has become a fundamental procedure followed by sporting teams to limit athletic injury, fatigue and optimize physical capacity throughout the season (Rossi et al. 2019). Training load (TL) monitoring provides the practitioner with the ability to determine whether an athlete has successfully completed their planned training and how they coped with the physical stress. A literature review summarizing the impact of TL and fatigue on injury concluded periods of TL intensification and acute changes in load can increase injury risk (Jones et al. 2017). Limitations associated with previous injury prevention models have included the use of linear, generic methods and the lack of incorporation of player workloads (Windt and Gabbett 2017). The current literature surrounding TL for injury has expanded greatly and as a result, the term “load” varies. This includes the measures of load being investigated which provides great difficulty for researchers comparing results from different studies (Staunton et al., 2022). The definition of what constitutes an athletes “load” is still an ongoing debate across different articles but the training-process framework promoted by Impellizzeri (2020) in recent years includes variables necessary for monitoring training which include: 1) External load, 2) Internal load and 3) the training outcome. A study by Ekstrand (2021) that monitored injury rates over 18 years in professional football discovered injury incidence to decrease in training and matches, reinjury rates decreased, and player availability for training increased displaying the potential rewards that investing in player monitoring may have. Injury risk has been predicted using the acute chronic workload ratio (ACWR), which assesses the ratio between the acute TL (workload over the last 7 days) relative to the mean chronic TL (workload over the last 28 days) (Blanch & Gabbett 2016). Recent evidence suggests limitations within the ACWR method and its use is discouraged (Wang et al. 2020). Therefore, other tools should be considered to determine the most accurate method of monitoring athlete workload to predict injury risk and performance.

The combination of technology and sport can be a very rewarding experience for the sport industry as there is a willingness among sport teams to trial sport technology innovations in the hope they improve performance and increase their competitive advantage (Ratten 2019). Non-contact injuries have been regarded as ‘preventable’ and have been associated with internal and external workload which has resulted in an increased desire among coaches and sport practitioners to have quantifiable data documented over time with regards to training and match workload to develop an injury prediction strategy (Vallance et al. 2020). Fanchini et al. (2018) displayed that the potential for prediction cannot simply depend on conventional, linear statistical models such as multivariate linear regression and that predictive analytics needs up to date data mining technologies and techniques to identify unsuspected multifactorial aspects associated with sporting injuries (Mandorino et al. 2021). Numerous computational-based approaches have been investigated and have improved the decision-making process of the trainer (Rajsp and Fister 2020), enabling coaches and practitioners to collect and store larger amounts of data in which they can utilize to monitor and enhance performance. The data avalanche has succeeded the human in analysing and interpreting information and in recent years, emerging technology (ET) is bringing itself to the fore with an emphasis being placed on injury prediction to improve injury reduction strategies (He 2021). Various ETs have been utilized within sport such as Artificial Intelligence (AI), Global Navigation Satellite System (GNSS), Local Positioning Systems (LPS) and Video Tracking Systems (VTS) which have investigated training and match load responses in team sports such as rugby, hurling and soccer (Beato et al. 2018). GNSS is a representation of the most used devices for external TL monitoring and can play a vital role in making decisions for periodisation strategies and athlete's return to play with real time feedback (Beato et al. 2018). This approach may contribute to the identification of sport movement and evaluation of intense activities in sport using devices such as GPS or triaxial accelerometers (Di Credico et al. 2021). VTS combines both experience and contextual information with the expertise of the human user and guided computational analysis to enhance human decision making (Araújo et al., 2021). ML is a branch of AI and is associated with the design and utilisation of algorithms in which computers may learn and uncover patterns, make decisions, and develop predictions without being explicitly programmed (Lopes et al. 2020). With ML, many coaches and sport scientists have opportunity to predict game outcome, their team and players performance and injury (Horvat & Job 2020). The combination of ML and workload monitoring for prediction of injury has shown promising results, especially in soccer (Oliver et al. 2020). ML are commonly classified into three categories: 1) supervised learning, 2) unsupervised learning and 3) reinforcement learning. Supervised learning techniques develop predictive models based on both input and output data to predict future events from unseen data, unsupervised interprets data based on input only (Horvat and Job 2020). Deep learning is a division of ML which involves a deeper neural network model influenced by the biological neural networks within the human brain (Cust et al. 2019). These models avoid the training and testing steps required for ML reducing computational times (Cust et al. 2019). In a previous systematic review evaluating ML to predict match results in team sports, majority of the studies (65%) included artificial neural networks in their investigations (Bunker and Susnjak 2019) which may have been due to the emergence of deep learning techniques. Decision trees were the second most frequently identified technique among the literature (Bunker and Susnjak 2019). Athletic training is moving a lot slower than other domains for prediction modelling in a clinical setting and due to the complexity of sport injuries, ML should be encouraged to be further investigated because of its strength in providing multifactorial predictions. There is limited research in the investigation of TL monitoring for injury prediction when investigating field-based team sports. No model has been established or been recommended as the most accurate method in predicting specific injury types (Carey et al. 2017). The prediction of injuries among athletes would improve player management with regards to weekly training load and promoting injury reduction strategies that could be implemented by coaches and sporting practitioners (Mandorino et al. 2021).

The need for an "injury prevention" strategy, the increased desire in practitioners and sport scientists to find an appropriate workload monitoring tool for teams and the rise of emerging technology all justify this systematic review. The aim of this systematic review is to 1) Identify the ETs being used in field-based sport to monitor TL for injury and performance prediction, 2) Provide sport specific recommendations by identifying new data generation from ET in which coaches can take into consideration when tracking players for an increased accuracy in training prescription and evaluation among field-based sports.

Methods

This SLR was developed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Figure 1 displays the screening process followed.

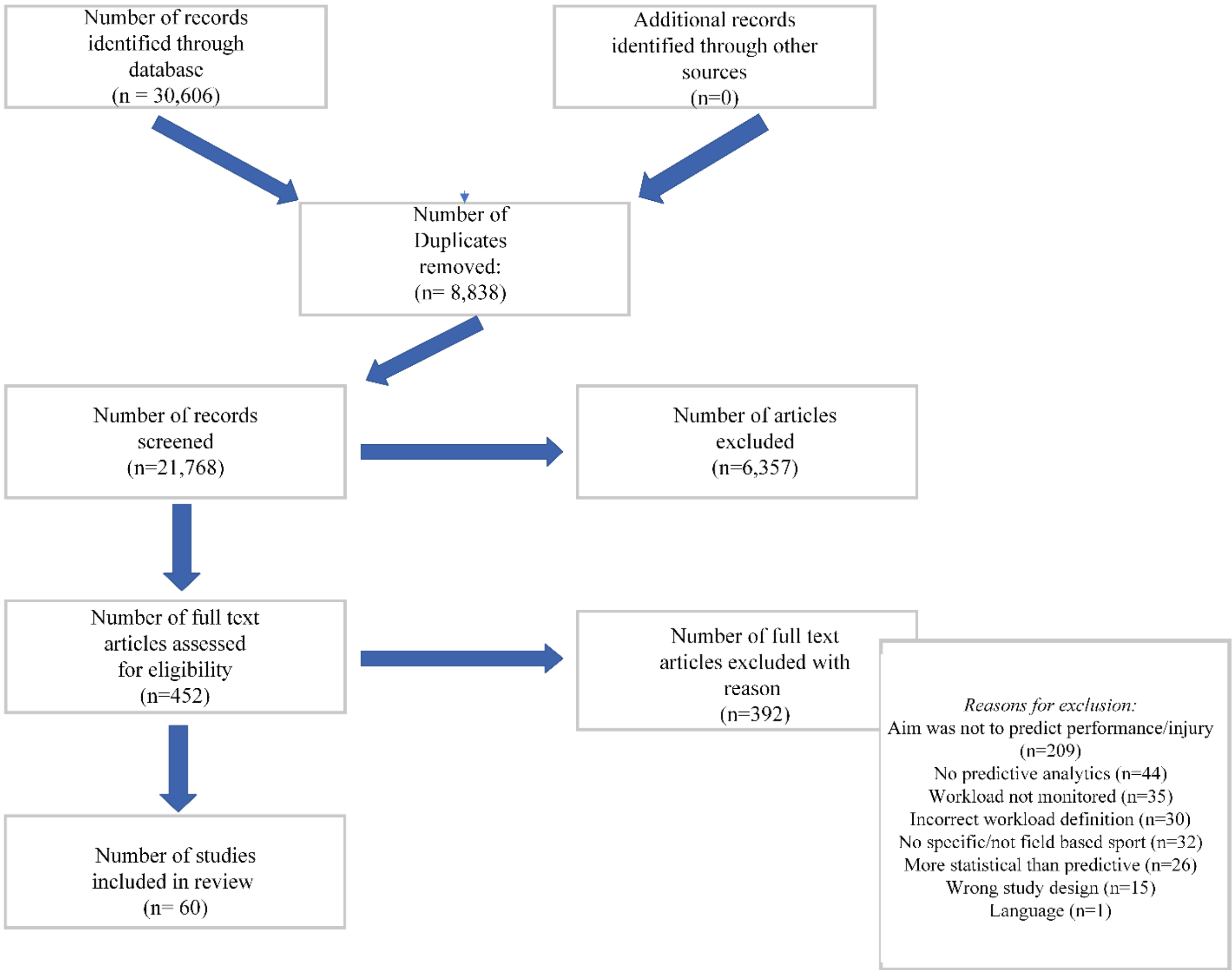


Figure 1: Preferred Reporting Items for Systematic Review and Meta Analysis (PRIMSA) Flow Diagram

Literature search

Studies were identified through a comprehensive search of four databases carried out using the electronic database 'Covidence' from October 2010 to December 2021. Searches were conducted through CINAHL, SPORTDiscus, Web of Science and IEE XPLORE. An initial search was carried out using potential keywords and synonyms displayed in Table 1, initial search terms were further refined to be tested within database searches. Search terms were discussed by the research team (GK, LR, MF and MMC) and keywords and synonyms were agreed. Terms used within the databases were: (emerging technolog* OR integrated technolog* OR global positioning OR artificial intelligence OR machine learning OR internet of things OR support vector machine OR random forest OR decision tree OR regression OR gradient boosting OR neural network OR predictive model OR injury prediction OR injury detection) AND (workload OR training load OR external load OR internal load OR monitor OR athlete monitor OR injur* OR performance) AND (team sport OR field sport OR team* OR club OR football OR Gaelic games OR Gaelic football OR hurl* OR camogie OR Australian football OR field hockey OR athlete* OR player*).

Table 1: Phase 1 literature search key terms, synonyms and related terms

Key Search Terms	Technology	Workload monitoring	Field based sport
Synonyms/Related Terms	emerging technology	workload	team sport
	global positioning	training load	field sport
	artificial intelligence	external load	team sport
	machine learning	internal load	football
	internet of things	athlete monitor	Gaelic games
	support vector machines	load	Gaelic football
	random forest	monitor	hurling
	neural network	injury	camogie
	predictive model	performance	Australian football
	injury prediction		field hockey athlete player
	injury detection decision tree gradient boosting regression		

Inclusion criteria

The criteria for inclusion of studies were: 1) written in English 2) Team based field sport of any level, gender or age, 3) studies that used technology to monitor workload/predict injury or performance, 4) studies that used predictive models for workload, injury or performance and 5) longitudinal, cross sectional or cohort studies, randomized control trials and systematic reviews. Articles were excluded if: 1) they investigated individual sporting athletes or patients, 2) did not use technology or predictive models to monitor load or predict injury/performance 3) studies that were too statistical rather than predictive and 4) case studies, review articles or conference papers. Definitions used to specify the inclusion/exclusion criteria included: “workload” is defined as the amount of cumulative stress than an athlete experiences from one or multiple training sessions/matches over a time period (Soligard et al. 2016) as various articles within the literature utilised this definition, “field-based team sport” was defined as games that are performed on a field/pitch in which two opposing teams have the primary aim of invading their oppositions territory in order to score (Hughes & Bartlett 2002) and “emerging technology” is science based, shows high potential and may be an ongoing process being developed within science (Cozzens et al. 2010).

Study selection

The database results were exported to Covidence. Phase one included an initial screening of titles and abstracts. Titles and abstracts that did not meet the inclusion criteria were excluded from the study. Reasons for exclusion were documented and displayed in Figure 1. Within phase two of screening, articles were further analyzed and if they did not meet phase two requirements were excluded. If all inclusion criteria were met, articles were included for data extraction. The research team (GK, LR, MF and MMC) were involved in the screening process. One researcher

(GK) executed the collection and initial screening of articles to be further analyzed and discussed by the research team (GK, LR, MF and MMC) and a conclusion was made on articles approved for data extraction.

Data extraction

The aim of this review was to highlight the emerging technologies being used in field-based sport and their efficacy in monitoring workload for performance and injury prediction. Therefore, data extraction was investigated by one author (GK) and information was stored in an Excel document. Data was extracted with regards to study design, participants, devices used, predictive analytics used, workload monitoring tools (internal/external load), field-based sport investigated and the outcome of the predictive model (successful/ unsuccessful in predicting performance/injury). Data extraction was reviewed by authors LR, MF and MMC through a subset selected at random for extraction and discussions were undertaken among reviewers to resolve discrepancies when needed.

Quality assessment

Studies were assessed for quality using the Downs and Blacks quality assessment (the modified version by Andrade (2020)). This checklist consists of 16 questions where "Yes" = 1 point, "No" = 0 points and "Unable to determine" = 0 points. Points were converted to a percentage-based score which was rated as <45.4% signifying "poor" methodological quality, between 45.4%-61.0% as "fair" methodological quality and > 61.0% showing "good" methodological quality. Studies deemed "good" quality were weighed more in the analysis. This tool was chosen as it has been previously validated and used within systematic reviews investigating workload to assess the methodological quality of the study (Andrade et al. 2020; Fox et al. 2018) and has also been validated for investigating the quality of observational study designs (Downs and Black 1998). The quality rating for each paper was considered for result interpretation. Results of the quality assessment are displayed in Table 2.

Technology readiness level

The Technology Readiness Level (RDL) is a monitoring tool utilized to investigate the maturity of new technologies. The purpose of this tool is to assess the performance, reliability, and experience of technologies within their environments (Héder 2017). The tool is mapped to nine levels to four ordinal values (Idea = (TRL 0-3), Validation = (TRL 4-7) and Production = (TRL 8-9). TRL 2-4 indicate the concept is being developed, TRL 5-7 the technology is being validated or presented in its desired environment and TRL 8-9 the technology is fully implemented (Arnouts 2022).

	Bacon (2016)	Bartlett (2016)	Bruce (2021)	Bunn (2021)	Campbell (2020)	Carey, Ong & Morris (2016)	Carey, Ong & Whiteley (2018)	Carey& Crossley (2018)	Chambers (2018)	Colby (2017)	Colby (2018)	Colby (2017)	Crouch (2021)	Di Credico (2021)
Research question stated	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Main outcome clearly measured in methods	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Eligibility criteria/Participants described	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Main findings clearly described	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Loss/addition of participants during clearly described	U	U	U	U	U	U	U	U	U	U	U	U	U	1
Described how missing points were handled	U	U	U	U	U	U	U	U	U	U	U	U	U	1
Significance is reported and confidence intervals provided	1	1	1	1	1	0	0	0	1	1	1	1	1	0
External validity														
Participants representative of population of interest	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Setting of study representative to context of interest	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Multiple settings represented	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Internal validity														
Participants from the same population	1	1	1	1	1	1	1	0	1	1	1	1	1	1
Reliable/valid method for quantification of workload	1	1	1	1	1	1	1	0	1	1	1	1	1	1
Reliable and valid injury surveillance method	1	0	1	0	0	0	1	1	0	1	1	1	1	0
Appropriate statistical analyses applied	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Potential confounding factors adjusted	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Study power														
Sample size and study power to detect statistically sig.	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Total	12	11	13	11	11	10	11	9	11	12	12	12	12	12
%	75	69	81	69	69	63	69	56	69	75	75	75	75	75

Results

The search strategy identified 30,606 articles. Following the screening process, 60 articles were eligible for inclusion in the review. Full text articles that were screened and studies were chosen based on the inclusion and exclusion criteria. Displayed in Figure 1, articles were excluded if the aim was not to predict injury or performance (n=209), no predictive analytics models were used (n=44), workload was not monitored (n=35), the workload did not meet the definition (n=30), there were no participants/ not field based sport (n=32), the studies were more statistical than predictive (n=26), wrong study design (n=15) and were not in English (n=1). Articles included were published between 2010-2022 (Table 3). Most articles included were from 2021 (n=19). There were no articles reported in the year 2012 that met the inclusion criteria.

Quality assessments

A total of 48 studies (80%) included were of "good" methodological quality, Ten studies were classified as "fair" methodological quality (16%) and two studies were of "poor" methodological quality (3%) as these studies did not specify the participants included in the study, they did not include a valid or reliable injury surveillance or quantification of training/ match load (Schmid et al. 2021; Shim et al. 2020).

Participants

Studies comprised of 11,798 participants with the mean age (± STD) of 21.4 ± 4.4 years. The oldest participants recorded were athletes aged 29 (Vallance et al. 2020) and the youngest recorded was 8 years old (Jauhiainen et al.2019). Most articles included investigated male field-based athletes (n=41), four investigated females only (n=4) and three investigated both males and females collectively (n=3). Participants from field-based sports included soccer (n=28), Australian football (n=8), American Football (n=9), Rugby union/ league (n=9), Lacrosse (n=3), Field hockey (n=1) and combinations of soccer and rugby (n=1), Australian football and soccer (n=1) and soccer and American football (n=1). Most articles included in this review investigated athletes competing at an elite level (n=51). Other studies investigated field-based teams at an amateur level including at high school level (n=3), at youth amateur sport level (n=3) and coaches and elite athletes investigating tackle movements in American football (n=1) (Maerlender et al. 2020). A summary of study populations can be viewed in Table 4.

Injury surveillance

With regards to injury tracking, studies included previous injury data collected over previous competitive seasons or preseason (Bacon et al. 2016; Bruce & Wilkerson et al. 2021; Carey et al. 2018; Colby et al. 2018; Gabbett 2010; Mandorino et al. 2021; Mason et al. 2021; Rommers et al. 2020; Rossi et al. 2018; Thornton et al. 2017; Vallance et al. 2020; Wilkerson et al. 2018; Zumeta-Olaskoaga et al. 2021). These injuries were usually tracked by a medical expert such as a physiotherapist or athletic trainer with the clubs. TL and injury data were commonly modelled to determine the relationship between workload and probability of injury. Gabbett (2010) defined an injury as 'any non-contact, soft tissue injury that has been sustained by a player during training or match which has prevented the player from completing the training session or match'. Other classifications of injury included a player missing a match or training as result of an injury (Colby et al. 2018; Mandorino et al. 2021; Zumeta-Olaskoaga et al. 2021). Carey (2018) utilized the Orchard Sports Classification System (OSICS) which categorized injuries into contact or non-contact, injury severity and transient or time loss.

Workload monitoring tools

External load

Contributing to their research, 54 studies included external workload monitoring in their investigations. Devices used within the studies to monitor external workload among field-based sports are shown in Table 5. A variety of combinations of devices were used to investigate external workload for athlete performance and injury identification. GPS (n=24) and accelerometers (n=18) were commonly used across all field-based sports. Table 6 displays studies that utilized one or more devices to measure external workload. With regards to the TRL, Table 5 and 6 display the devices utilised within each study and as all devices are fully implemented within the sporting environment they display a TRL level of 8-9. Eleven studies investigated using GPS only (Bacon et al. 2016; Colby et al. 2017; Colby et al. 2017; Colby et al. 2018; Dijkhuis et al. 2021; Gasparini & Alvaro 2020; Geurkink et al. 2021; Guerrero-Calderon et al. 2021; Klemp et al. 2021;Thorton et al. 2017; Windt et al. 2017), 13 articles utilized GPS and accelerometers (Bartlett et al. 2016; Bunn et al. 2021; Carey et al. 2016; Carey et al. 2018; Chambers et al. 2018; Crouch et al. 2021; Gastin et al. 2019; Gaudino et al. 2015; Geurkink et al. 2019; Gimenez et al. 2020; Rossi et al. 2018; Rossi et al. 2019; Vallance et al. 2020) and five included accelerometers (Di Credico et al. 2021; Gabbett et al. 2011; Jaspers et al. 2018; Peek et al. 2021; Wilkerson et al. 2018). Three studies utilized a combination GPS, accelerometers, magnetometers and gyroscopes (Bunn et al. 2021; Chambers et al. 2018; Crouch et al. 2021). Gaudino (2015) integrated a portable 10-HZ GPS, 100-Hz 3-dimensional accelerometer, a 3-dimenstional gyroscope and a 3-dimensional digital compass which provided valid and reliable estimates of instantaneous velocity during acceleration, deceleration and linear, multidirectional, sport specific activities.

Studies utilized GPS tracking for participants to monitor workload or positional data from training sessions or matches with the aim of capturing all events and movements that occurred on the pitch. Total distance (m) was tracked most using GPS (Bacon et al. 2016; Bunn et al. 2021; Carey et al. 2016; Carey et al. 2018; Chambers et al. 2018; Colby et al. 2017; Colby et al. 2018; Crouch et al. 2021; Gasparini et al. 2020; Gastin et al. 2019; Gimenez et al. 2020; Jaspers et al. 2018; Rossi et al. 2018; Rossi et al. 2019; Thorton et al. 2017). Other measurements investigated using GPS included High speed running (m) (Bacon et al. 2016; Bartlett et al. 2016; Carey et al. 2016; Gaudino et al. 2015; Guerrero-Calderon et al. 2021; Rossi et al. 2019), session duration (min)/ session distance (m) (Bartlett et al. 2016; Crouch et al. 2021; Dijkhuis et al. 2021; Gastin et al. 2019), number of player impacts during elite soccer training (Gaudino et al. 2015) and detecting scrum events in rugby union (Chambers et al. 2018).

Accelerometers are a common quantifiable method used for external workload monitoring in team sports (Di Credico et al. 2021), they have been deemed to have excellent reliability and concurrent validity (Chambers et al. 2018). Accelerometer data from 6 degree-of-freedom X patch accelerometers were used to record tri-axial linear acceleration and angular velocity when investigating head impact exposures on brain changes in soccer (DiCesare et al. 2020) and a 100 Hz triaxial accelerometer calculated head impacts during running, jumping, tackles and collisions when examining the perception of session rating of perceived exertion during elite soccer training (Gaudino et al. 2015).

In studies where GPS or accelerometry devices were not included, other devices such as Head Impact Telemetry Systems (HITS) (Campbell et al. 2020; Rao et al. 2021; Rowson & Duma 2013), 'Tacklytics' (Maerlender et al. 2020), mouthguard devices (Gabler et al. 2020; Wu et al. 2017) and sensored shoulder pads (Schmid et al. 2021) were employed to investigate concussion and tackle identification.

Two studies investigated impact and collisions among contact sports using digital mouthguards (Gabler et al. 2020; Wu et al. 2017). Gabler (2020) investigated on field performance of American footballers with custom fit mouthguards using a three-dimensional scan of participants upper dentition for triaxial linear and angular acceleration to detect head impacts. Sensor recall increased from 18.8% to 49.6% when the trigger threshold decreased from 25g -11g as a greater number of events could be identified by the sensor. Wu (2017) also examined head impacts in American football using digital mouthguards to record angular and linear accelerations. These results were time stamped and synchronized with video and support vector machines (SVM) contributed to the classification of 1219 recordings to identify 156 impacts and 231 non impacts (Wu et al. 2017).

Three articles investigated American football using HITS (Campbell et al. 2021; Rao et al. 2021; Rowson & Duma 2013). Rao (2021) explored the predictive changes in optic nerve sheath diameter in contact sports such as soccer and American football. The number of impacts per week, the cumulative number of hits and the magnitude of the hits were documented. These results were combined with ImPACT scores and eye movement data recorded by an eye tracker. Rowson and Duma (2013) introduced a new injury metric utilizing HITS among American football which consisted of data from linear and rotational acceleration. 62,974 sub-concussive impacts and 37 diagnosed concussive impacts were recorded by digital helmets. A combination of the HITS system with synchronized video monitoring on collegiate football players had 69% sensitivity, 72% specificity, 70% accuracy in classifying true and non-head impact data and observed 64% of 129 impacts (Campbell et al. 2021).

Internal load

A total of 29 studies (48.3%) included internal workload monitoring. Heart rate monitoring was utilized by five articles (Bunn et al. 2021; Carey et al. 2016; Crouch et al. 2021; Di Credico et al. 2021; Geurkink et al. 2019; Jelinek et al. 2014), 14 studies included Rated Perceived exertion (RPE) before/after training sessions to measure internal load of players and nine articles included subjective questionnaires investigating athlete’s wellness, motivation and previous injury data (Colby et al. 2017; Crouch et al. 2021; Juahiainen et al. 2019; Mandorino et al. 2022; Mandorino et al. 2021; Thorton et al. 2016; Rommers et al.2020; Wilkerson et al. 2018; Vallance et al. 2020).

RPE is a subjective form of monitoring an athlete's physical activity (Foster et al. 2001). Reliability of the RPE tool has shown moderate positive correlations and has been identified in previous studies investigating wellness and RPE in male Australian footballers (r=0.59) (Gallo et al. 2017) and elite male soccer players (r=0.59) (Malone et al. 2018). The athlete is provided with a scale in which they have approximately 30 minutes to complete at the cessation of training. The athlete is asked ‘’how was your workout?’’ and athletes will respond with a single number that corresponds to a description on the scale between 1-10, where 1 describes ‘very, very easy’ and 10 as ‘maximal’ difficulty (Foster 2001).

Two articles used RPE only when investigating internal workload of elite male soccer (Fanchini et al. 2018) and elite male Rugby League (Gabbett 2010) to predict non-contact injuries. Two articles used RPE and subjective questionnaires only (Perri et al. 2021; Thornton et al. 2016). In a study by Perri (2021), soccer players filled out RPE and a wellness questionnaire (WELQUE) 30 minutes at the end of each session or match. WELQUE consisted of 5 items (fatigue, sleep, pain, stress and RPE). RPE and machine learning technique such as Logistic regression predicted work intensity for the following day based on the results given by players that day and a high accuracy and precision of 41% was detected, indicating the successful combination of subjective questionnaires and logistic regression to predict recovery status of players with regards to their scheduled TL throughout their training week (Perri et al. 2021). Thornton (2016) utilized RPE and a self-reported sleep and well-being questionnaire for 29 weeks during the rugby season. Decision trees and random forests were modelled and developed 556 observations which identified internal TL measures strain, weekly TL and monotony as main contributors to subjects internal ratings (Thornton et al. 2016).

Internal subjective wellness questionnaires

Articles that met the inclusion criteria included subjective wellness questionnaires to investigate the internal workload of team athletes (n=13) (Carey et al. 2016; Colby et al. 2017; Colby et al. 2021; Crouch et al. 2021; He et al. 2021; Jauhiainen et al. 2019; Mandorino et al. 2021; Mandorino et al. 2021; Perri et al. 2021; Revie et al. 2017; Rommers et al. 2020; Thornton et al. 2016; Thornton et al. 2017; Vallance et al. 2020; Wilkerson et al. 2018). Colby (2017) included a 5-point Likert scale including items on fatigue, sleep quality, muscle soreness, stress levels, mood and perceived performance. Similarly, as mentioned above, Perri (2021) used WELQUE consisting of five items (fatigue, sleep, pain, stress and RPE) and Crouch (2021) included a wellness score on self-reported muscle soreness, energy, sleep quality and stress. Other studies determined internal workload through the utilization of self-reported questionnaires such as the athletes perceived recovery status (Mandorino et al. 2022; Mandorino et al. 2021), self-reported sleep (Thorton et al. 2016) and motivation (Juahiainen et al. 2019). Articles also took the approach of using questionnaires to collect demographic information and injury history in comparison to an athlete's perceived recovery or wellness following a training session (Rommers et al.2020; Wilkerson et al. 2018; Vallance et al. 2020). Four articles combined internal questionnaires with GPS (Carey et al. 2016; Colby et al. 2017; Crouch et al. 2021; Vallance et al. 2020) and two articles with accelerometers (Vallance et al. 2020; Wilkerson et al. 2018).

Combination of internal and external monitoring

Combinations of both internal and external workload monitoring tools were used in 23 articles to investigate their impact on injury and performance prediction (n=23). Six studies investigated internal using RPE and external using GPS monitoring devices (Bartlett et al. 2016; Carey et al. 2018; Colby et al. 2018; Gaudino et al. 2015; Rossi et al. 2019; Thornton et al. 2017), two studies used heart rate monitoring and GPS (Bunn et al. 2021; Jelinek et al. 2014) and two studies used RPE, subjective questionnaires and GPS (Carey et al. 2016; Vallance et al. 2020). A summary of internal and external monitoring tools used within studies is displayed in Table 7.

Predictive analytics

Receiving operating characteristics (ROC) was the most frequently used form of predictive analytics with fifteen studies incorporating this analytics method. Thirteen studies utilized Random Forest (RF) and eleven studies utilized Logistic Regression models. R statistic software was the most used programming platform, followed by Python. Other methods of predictive analytics used in studies are displayed in Table 7.

No pattern could be identified with regards to the combination of workload monitoring tools and predictive analytic tools used. Two forms of predictive analytics were combined by 13 studies, combinations included: Generalized Estimating Equations (GEE) and Artificial Neural Networks (ANN) (Bartlett et al. 2016), linear Regression and GEE (Carey et al. 2018), GEE and logistic regression (Colby et al. 2017), ROC and RF (Chambers et al. 2018), logistic regression and ROC (Di Cesare et al. 2020; Wilkerson et al. 2016; Wilkerson et al. 2018), RF and Decision Trees (DT) (Dijkuis et al. 2021), GEE and RF (Gastin et al. 2019), Support Vector Machine (SVM) and ROC (Jauhiainen et al. 2019), logistic regression and ROC (Mason et al. 2021), linear regression and SVM (Revie et al. 2017) and logistic regression and ANN (Schmid et al. 2021). The incorporation of 3 or more predictive analytics models to investigate prediction strategies for performance and injury in team-based field sport was used by 12 studies (Bruce & Wilkerson et al. 2021; Carey et al. 2016; Carey et al. 2018; Colby et al. 2018; Fanchini et al. 2018; Gasparini & Alvaro 2020; Geurkink et al. 2019; Mandorino et al. 2021; Mandorino et al. 2021; Reyers & Swartz et al. 2021, Rowson & Duma 2013; Thornton et al. 2016;

ROC, RF and logistic regressions were the most common models developed for injury and performance prediction among field-based team sports. These models have been used collectively and separately throughout these studies.

Combinations of workload monitoring tools and predictive analytics had been frequently identified in studies. Internal workload monitoring tools such as RPE and subjective questionnaires were modelled using ROC and RF collectively to develop predictive outcomes in elite male youth soccer (Mandorino et al. 2021; Mandorino et al. 2021) and Rugby League (Thornton et al. 2016). Four studies investigated prediction of performance and injury in players using GPS and RF (Dijkhuis et al. 2021; Gasparini &Alvaro 2020; Geurkink et al. 2019; Thornton et al. 2017) and three studies combined GPS and accelerometers with RF displayed in Table 7 (Carey et al. 2016; Gastin et al. 2019; Vallance et al. 2020). In the study by Chambers (2018) all external workload monitoring tools (GPS, Triaxial accelerometer, gyroscope, magnetometer) were modelled using ROC and RF to establish a microsensor algorithm for detecting scrum events in Rugby Union. Four studies utilized GPS measurements with logistic regression (Colby et al. 2017; Colby et al. 2018; Gasparini & Alvaro 2020; Windt et al. 2017). Logistic regression was used by studies investigating tackles, collisions for prediction head impacts and concussion combined with X patch accelerometer (Di Cesare et al. 2020). Rowson and Duma 2013 utilized accelerometers to identify peak linear and rotational head acceleration and multivariate logistic regression analysis to develop an injury risk curve to determine the likelihood of a player sustaining a concussion from that impact. Rossi (2018) constructed a multi-dimensional injury model to predict injury likelihood of players combining training workload data and decision trees which had the ability to predict 80% of injuries and significantly improved throughout the season.

Predictive ability

The successful prediction of injury/performance during their investigations was identified in 54 studies (88%). Three studies were not successful in prediction (Bacon et al. 2016; Carey et al. 2018; Klemp et al. 2021) and four articles had the potential to predict injury/performance if alterations were made to the predictive methods used or data size was increased (Bartlett et al. 2016; Carey et al. 2018; Reyers & Swartz 2021; Zumeta-Olaskoaga et al. 2021). A study that combined internal load (RPE), external load (GPS), GEE and ANN in professional Australian football displayed potential to identify session distance as an injury risk predictor but errors in prediction were identified due to an individualized ANN (Bartlett et al. 2016). Other issues affecting predictive ability with studies in this review included 1) Player's decisions impacting realistic options that could be predicted by algorithms with a small dataset (Reyers & Swartz 2021), 2) no pre-game information was documented (Klemp et al. 2021) and 3) data size limiting the suitability for prediction of injuries (Zumeta-Olaskoaga et al. 2021).

Machine learning (ML) utilization in studies contributed to increased precision (85%), recall (85%) and accuracy (85%) with limited false positives (15%) and misclassification (15%) of injuries when an algorithm was developed to identify injured footballers (Rossi et al. 2020). Similarly, ML combined with sensors and video analysis displayed a 98.3% precision and 81.6% recall when investigating head impacts in American footballers (Gabler et al. 2020) and a true positive prediction of 62.3% was displayed when TL and RPE documentation was modelled using logistic regression with rugby union players (Gabbett et al. 2010).

Discussion

The aim of this systematic review was to identify the ETs being used to monitor TL for injury and performance prediction in field-based sports and provide sport specific recommendations through the identification of new data generation from ET through the research available. Although it is evident in recent years that an increased demand has been placed on workload management and data analytics, a combination of different monitoring techniques has been employed by coaches and sport scientists for injury risk and performance prediction. As a result of this, it is difficult to recognize a recurrent approach among studies. A variety of workload monitoring and predictive analytics methods have been successfully applied by researchers but recommendations on the most effective method towards injury and performance prediction in sport is limited as no pattern can be identified with regards to the most utilized data analytics technique.

Soccer is the most frequently investigated sport in this review (n=28). With more than 265 million participants in soccer internationally, in both sexes and all age groups (Hennessy and Jeffreys 2018), numerous physical features and technical abilities are favorable for success in soccer (Jauhiainen et al. 2019) and are required when performing at a high standard. This may be why an emphasis is placed on the evaluation of physical demands during training sessions in this sport using both internal and external assessments of load (Gaudino et al. 2015). GPS tracking, although still in its infancy, was the most common external workload monitoring tool used when investigating soccer (Bacon et al. 2016; Dijkhuis et al. 2021; Gasparini & Alvaro 2020; Gaudino et al. 2015; Geurkink et al. 2021; Geurkink et al. 2019; Gimenez et al. 2020; Guerrero-Calderon et al. 2021; Rossi et al. 2018; Rossi et al. 2019; Vallance et al. 2020), RPE for internal workload monitoring (Fanchini et al. 2018; Gaudino et al. 2015; Geurkink et al. 2019; Jaspers et al. 2018; Mandorino et al. 2021; Mandorino et al. 2021; Perri et al. 2021 Rossi et al. 2019; Vallance et al. 2020) and a combination of both internal and external load monitoring was included by nine studies (Di Credico et al. 2021; Gaudino et al. 2015; Geurkink et al. 2019; He et al. 2021; Jaspers et al. 2018; Mandorino et al. 2021; Rommers et al. 2020; Rossi et al. 2019; Vallance et al. 2020). A variety of models were developed to predict injury or performance using different data analytics tools. Linear regression was utilized by three articles (Bacon et al. 2016; Gaudino et al. 2015; Guerrero-Calderon et al. 2021;), SVM (n=1) (Di Credico et al. 2021), Decision Trees/ RF (n=3) (Geurkink et al. 2021; Gimenez et al. 2020; Rossi et al. 2018), ML (n=3) (He et al. 2021; Rommers et al. 2020; Rossi et al. 2019), logistic regression (n=3) (Klemp et al. 202; Philp et al. 2020; Zumeta-Olaskoaga et al. 2021), three studies combined two methods (Goes et al. 2021; Jaspers et al. 2018; Oliver et al. 2020; Perri et al. 2021) and 11 studies utilized more than three tools (Bruce & Wilkerson 2021; Di Cesare et al. 2020; Dijkhuis et al. 2021; Fanchini et al. 2018; Gasparini & Alvaro 2020; Geurkink et al. 2019; Jaspers et al. 2018; Jauhiainen et al. 2019; Mandorino et al. 2021; Mandorino et al. 2021; Vallance et al. 2020) in which no similar predictive tools were included in each methodology. Therefore, although several prediction and modelling strategies have been proposed for injury and performance modelling, no 'gold standard' approach can be advocated. A study by Philp (2020) in which the aim was to investigate the effect of using zero-inflated Poisson to improve injury prediction models in soccer had hoped to compare it's results against the existing literature available but this was not possible as 1) the datasets had significant differences with regards to independent and dependent variables being investigated, 2) there was variance in injury classification and documentation and 3) modelling methods utilized displayed limited explanatory validity and clinical applicability (Philp et al. 2020).

Similarly, modeling procedures utilized by teams from the same sporting population followed no pattern in this review. Workload monitoring tools used were similar to studies investigating soccer in which GPS and RPE were most frequently used in Australian football, rugby league/union, American football, lacrosse, and field hockey which is shown in Table 4. This may be a result of most articles included in this review investigating athletes at an elite level (n=51) and therefore having access to devices such as GPS and accelerometers to quantify multidirectional movements to assess external load and analyze the collected information through a specific software designed to investigate quantitative data (Di Credico et al. 2021). It is also important to note that although it was expected elite sport would have more access to current ETs based on the expected monetary costs of technology, within the studies including amateur sporting participants (n=7), two studies had access to accelerometers (Campbell et al. 2020; Dicesare et al. 2020) and one utilised HITS (Rao et al. 2021) which displays amateur sport is not at a disadvantage with technology as it evolves. A combination of internal and external load tools showed promising results and contributed to the accuracy in differentiating TL, but no consensus has been established on the importance of one variable over another yet, but past researchers have distributed questionnaires and carried out statistical analysis on experts in the field (Bunn et al. 2021). This may be due to difference in definitions of “load” across the literature and workload and TL are used interchangeably (Staunton et al. 2022). It is evident from this review that TL is being considered in all aspects with relevance being given to athlete’s well-being and physical demands for performance and injury risk as both internal and external loads are considered. Although GPS is very popular among field-based team sports for workload monitoring, it has been identified as having reasonable accuracy and reliability for total distance (Hennessy et al. 2018) which was the most common variable investigated by studies in this review. A recent systematic review concluded that using GPS tracking for injury prediction in field-based team sports reported inconclusive evidence to support it when assessing injury due to factors including injury definitions, workload tools and statistical analysis used (Kupperman and Hertel 2020). Although GPS technology shows potential and is favorable among sport teams to utilize during their seasons, further validity and reliability of sensor devices needs to be further investigated. Therefore, researchers, sport scientists and coaches may need to increase their knowledge in sensor-based technology for injury prediction in order to improve modeling strategies (Kupperman & Hertel 2020).

Measures have been taken in sport to decrease the number of head impacts occurring such as rule changes and educating appropriate concussion identification and management skills, but collisions are still likely to occur due to the nature of contact sports (Rowson & Duma 2013). Success in rugby is determined by physiological and anthropometric qualities but also a player’s ability to withstand physical collisions (Gabbett et al. 2011). A study completed on rugby sevens presented that most acute match injuries were a result of physical collisions both in men and women, therefore, the careful monitoring of physical contact load among players should be supervised for appropriate player management (Clarke et al. 2017). Research has highlighted there is currently no valid method for quantifying scrum workload during matches or training sessions only video-based motion analysis (Chambers et al. 2018). From this review, there are numerous impact monitoring systems to identify collisions, tackles and head impacts using helmets (Campbell et al. 2020; Rao et al. 2021; Rowson and Duma 2013), mouthguards (Gabler et al. 2020; Wu et al. 2017), accelerometers (Di Cesare et al. 2020) and GPS (Chambers et al. 2018) combined with video analysis (Campbell et al. 2020; Chambers et al. 2018; Di Cesare et al. 2020; Gabler et al. 2020; Peek et al. 2021). As repeated collisions contribute to players total workload in rugby, Chambers (2018) developed a scrum detection algorithm using GPS tracking which has given coaches and sport scientists the opportunity to quantify scrum events more easily during matches and training (Chambers et al. 2018). Logistic regression shows promise when detecting tackles, collisions and head impacts when combined with accelerometers (Chambers et al. 2018; DiCesare et al. 2020; Rowson & Duma 2013; Schmid et al. 2021) when investigating determinants for likelihood of concussion from impact in team sports and therefore, should be considered in predictive models moving forward.

A sport similar in nature with regards to physiological demands and repeated collisions is the Gaelic Athletic Association (GAA), Ladies Gaelic Football Association (LGFA) and Camogie Association which are Ireland's largest sporting organizations involving field-based team sports played at club, collegiate and County level from preschool level (4-7 years) through to adulthood (O Connor et al. 2019). Gaelic football, although deemed an amateur sport is a multi-directional, high intensity field-based contact team sport which places a high physical and psychological demand on players which must be maintained while athletes also study or work. (Dekkers et al. 2021). In a systematic review, match injury incidence was reported to be higher in Gaelic football (55.9/1000h) than Australian rules (30.3/1000h), amateur soccer (20.4/1000h) and amateur rugby union (46.8/1000h) (Dekkers et al. 2021). Although a field-based team sport with high match injury incidence rate, there is a lack of Gaelic games specific research (Malone et al. 2017) with regards to workload monitoring and the modelling of injury and performance prediction. As this review has showcased the potential and success in combining both workload monitoring tools and predictive analytics in field-based team sports, it may be worthwhile to investigate this further in the area of the Gaelic games with regards to concussion monitoring, injury and performance prediction.

Concussion frequently goes underreported in team sports and HITS has been identified as an effective measurement tool through identifying injury tolerance curves, severity cues and whether a player may need further medical attention. (King et al. 2014). AI has helped to distinguish positive impacts and collisions from false positives which is a limitation shown in research when working with sensor systems for head impact identification in American football (Campbell et al. 2020; Gabler et al. 2020; Rawson & Duma 2013) and soccer (Rao et al. 2021). Results from evaluating different ML models and predictive variables to differentiate between positive and false positive head impacts concluded that a head impact detection system (the combination of sensors and machine learning models) has the ability to outperform human reviewers and increase sensitivity towards screening protocols for head injuries in football (Gabler et al. 2020). Success with separating true and false impacts in soccer was investigated by Di Cesare (2020) by developing a ML learning model to classify verified head impacts using 6-degree-of-freedom X patch accelerometers to record tri-axial linear acceleration and angular velocity. Results displayed effectiveness in true and false impacts through an area under the curve (AUC) model developed measured 90.3 (out of 100). This shows promising results and researchers should consider the implementation of HITS and ML models to detect impacts among other collision field-based sports such as rugby and GAA as there is limited research available.

Data collection in sport has increased opportunities for sport management, sport scientists and researchers in the analysis and development of players to improve training environments. More sporting teams are increasing their data collection to take advantage of the advances being made in data collection technologies and workload monitoring devices. Although analytics in sport is developing area, it is rapidly expanding and a variety of approaches and data techniques are becoming available and documented within the literature (Jauhiainen et al. 2019). From the research available so far, it is evident the predictive analytics models included in studies have a high precision and accuracy, such as a study completed by Campbell (2020) identifying head impact location accuracy using HITS as having 69% sensitivity, 72% specificity and 70% accuracy (Campbell et al. 2020), Rossi (2018) and Rossi (2020) developing a decision tree for elite soccer players that predicted 80% of injuries (Rossi et al.2018) and a ML algorithm identifying injuries with 85% precision, 85% sensitivity and 85% accuracy (Rossi et al. 2020). ML methods are widely utilized to identify both linear and non-linear patterns between various TL without having expert knowledge in that area (Jaspers et al. 2017). ML also provides the investigator with the tools to identify potential inter-player differences (Jaspers et al. 2017) while also recognizing predictive variables with regards to TL, injury and performance (Geurkink et al. 2021).

With large sums of data being recorded regarding internal and external workload, ML has become relevant in the management of large complex pre-existing datasets and training tools for injury and performance identification patterns (Vallance et al. 2020). ML is proving to be a more objective method of data examination. A simple solution to modeling TL and injury is not the case, injury prevention and TL monitoring is a complex phenomenon and there are multiple factors to consider.

Limitations and future directions

From results of this review, it is important to consider some limitations within this work. The heterogeneity among studies such as the variety of athlete populations, field-based team sports, technologies and TL tools utilized and study designs made it challenging to make direct comparisons and identify the most effective TL tools and predictive models to recommend for coaches to implement with their teams. As ETs present a broad spectrum as by the definition utilised in this review, the compatibility and comparability of various technologies was difficult to establish based on the numerous devices and predictive models investigated. This resulted in a comprehensive and complex search strategy. The absence of a standardised protocol for data collection, processing, and analysis across studies may hinder the definitive conclusion on the most effective TL tools and successful predictive models based on the diversity of risk factors and variables being investigated. The large selection of player monitoring tools available to coaches and both the various and debatable definitions associated with "training load" and "workload" may be the reason for the lack of consistency among the literature. The large number of prospective cohort studies, although statistically significant, display the complexity that is athletic injury and its dependence on internal and external factors, highlighting the task of accurate injury prediction to be quite challenging. There is no way to confirm a prediction if an athlete is pulled from play based on recommendations from a predictive model. The literature should focus on understanding patterns within the data to detect injury risk rather than predicting injury itself, to make considerations for the inconsistencies and correlations between predictors and risk factors for injury.

Conclusion

This review demonstrates the potential of advanced analytical techniques such as ML for predicting injury and performance outcomes among field-based sports but as this area is still relatively new, therefore it is still developing across multiple areas. With the rapid expansion of research becoming available regarding ETs role in team sports, there is a need for guidance and support among coaches and practitioners. Sport injury prediction although is interesting, is very challenging due to the unpredictable elements of injury and performance which is also an enjoyable aspect of sport for many people. Field-based sports are positively utilizing a wide variety of workload monitoring tools combining both internal and external, which has displayed successful results by increasing accuracy in TL documentation. Recommendations for the most effective parameters for injury and performance prediction and the most valuable combinations of different predictive models should be further evaluated so that variables being collected from athletes are of value and contribute to the planning of sessions and decisions for return to play among teams. The variability in workload documentation may be a result of the many definitions "Workload" and "Training Load" has within the literature. ML is the most accurate method in detecting high false positive rates and true head impacts and should be investigated further within field-based sport. The lack of utilisation of predictive analytics in GAA and head impact and collision detection in both rugby and GAA is brought to the spotlight especially with regards to concussion detection and monitoring strategies. The review displays the availability of these tools to detect true and false impacts but are not being utilized to their full potential. With data-driven solutions being brought to the fore predictive models are likely to provide competitive advantage for teams. Although ET shows to be quite promising, more direction and guidance should be given on where researchers should investigate further with regards to workload monitoring and injury prediction. Various ETs have been identified within this review, but no recommendations can be made on the most effective devices for coaches to implement with teams. A focus should be placed on defining workload monitoring in sport, highlighting the most effective internal and external monitoring tools to develop a predictive model that incorporates variables of value to detect injury risk among field-based sport.

References

Andrade, R., Wik, E. H., Rebelo-Marques, A., Blanch, P., Whiteley, R., Espregueira-Mendes, J., & Gabbett, T. J. (2020). Is the acute: chronic workload ratio (ACWR) associated with risk of time-loss injury in professional team sports? A systematic review of methodology, variables and injury risk in practical situations. *Sports medicine*, *50*, 1613-1635.

Araújo, D., Couceiro, M., Seifert, L., Sarmento, H., & Davids, K. (2021). *Artificial intelligence in sport performance analysis*. Routledge

Arnouts, S., Brown, S., de Arriba, M. L., Donabedian, M., & Charlier, J. (2022). Technology Readiness Levels for vaccine and drug development in animal health: From discovery to life cycle management. *Frontiers in Veterinary Science*, *9*, 1979.

Bacon, C. S., & Mauger, A. R. (2017). Prediction of overuse injuries in professional U18-U21 footballers using metrics of training distance and intensity. *The Journal of Strength & Conditioning Research*, *31*(11), 3067-3076.

Bartlett, J. D., O'Connor, F., Pitchford, N., Torres-Ronda, L., & Robertson, S. J. (2017). Relationships between internal and external training load in team-sport athletes: evidence for an individualized approach. *International journal of sports physiology and performance*, *12*(2), 230-234.

Beato, M., Coratella, G., Stiff, A., & Iacono, A. D. (2018). The validity and between-unit variability of GNSS units (STATSports Apex 10 and 18 Hz) for measuring distance and peak speed in team sports. *Frontiers in physiology*, *9*, 1288.

Bourdon, P. C., Cardinale, M., Murray, A., Gastin, P., Kellmann, M., Varley, M. C., ... & Cable, N. T. (2017). Monitoring athlete training loads: consensus statement. *International journal of sports physiology and performance*, *12*(s2), S2-161.

Bruce, S. L., & Wilkerson, G. B. (2021). Whole-body reactive agility metrics to identify football players with a core and lower extremity injury risk. *Frontiers in sports and active living*, 292.

Bunker, R., & Susnjak, T. (2022). The application of machine learning techniques for predicting match results in team sport: A review. *Journal of Artificial Intelligence Research*, *73*, 1285-1322.

Bunn, J. A., Myers, B. J., & Reagor, M. K. (2021). An evaluation of training load measures for drills in women's collegiate lacrosse. *International Journal of Sports Physiology and Performance*, *16*(6), 841-848.

Campbell, K. R., Marshall, S. W., Luck, J. F., Pinton, G. F., Stitzel, J. D., Boone, J. S., ... & Mihalik, J. P. (2020). Head impact telemetry system's video-based impact detection and location accuracy. *Medicine and science in sports and exercise*, *52*(10), 2198.

Carey, D. L., Ong, K., Morris, M. E., Crow, J., & Crossley, K. M. (2016). Predicting ratings of perceived exertion in Australian football players: methods for live estimation. *International Journal of Computer Science in Sport, 15 (2): 64, 77*.

Carey, D. L., Crossley, K. M., Whiteley, R. O. D., Mosler, A., Ong, K. L., Crow, J., & Morris, M. E. (2018). Modeling training loads and injuries: the dangers of discretization. *Medicine & Science in Sports & Exercise*, *50*(11), 2267-2276.

Chambers, R. M., Gabbett, T. J., & Cole, M. H. (2019). Validity of a microsensor-based algorithm for detecting scrum events in rugby union. *International Journal of Sports Physiology and Performance*, *14*(2), 176-182.

Colby, M. J., Dawson, B., Heasman, J., Rogalski, B., Rosenberg, M., Lester, L., & Peeling, P. (2017). Preseason workload volume and high-risk periods for noncontact injury across multiple Australian football league seasons. *The Journal of Strength & Conditioning Research*, *31*(7), 1821-1829.

Colby, M. J., Dawson, B., Peeling, P., Heasman, J., Rogalski, B., Drew, M. K., ... & Lester, L. (2017). Multivariate modelling of subjective and objective monitoring data improve the detection of non-contact injury risk in elite Australian footballers. *Journal of science and medicine in sport*, *20*(12), 1068-1074.

Colby, M. J., Dawson, B., Peeling, P., Heasman, J., Rogalski, B., Drew, M. K., & Stares, J. (2018). Improvement of prediction of noncontact injury in elite Australian footballers with repeated exposure to established high-risk workload scenarios. *International journal of sports physiology and performance*, *13*(9), 1130-1135.

Cozzens, S., Gatchair, S., Kang, J., Kim, K. S., Lee, H. J., Ordóñez, G., & Porter, A. (2010). Emerging technologies: quantitative identification and measurement. *Technology Analysis & Strategic Management*, *22*(3), 361-376.

Crouch, A. K., Jiroutek, M. R., Snarr, R. L., & Bunn, J. A. (2021). Relationship between pre-training wellness scores and internal and external training loads in a Division I women's lacrosse team. *Journal of sports sciences*, *39*(9), 1070-1076.

Cust, E. E., Sweeting, A. J., Ball, K., & Robertson, S. (2019). Machine and deep learning for sport-specific movement recognition: A systematic review of model development and performance. *Journal of sports sciences*, *37*(5), 568-600.

Dekkers, T., O'Sullivan, K., Blake, C., McVeigh, J. G., & Collins, K. (2022). Epidemiology and moderators of injury in Gaelic football: a systematic review and meta-analysis. *Journal of science and medicine in sport*, *25*(3), 222-229.

Di Credico, A., Perpetuini, D., Chiacchiaretta, P., Cardone, D., Filippini, C., Gaggi, G., ... & Izzicupo, P. (2021). The prediction of running velocity during the 30–15 intermittent fitness test using accelerometry-derived metrics and physiological parameters: a machine learning approach. *International Journal of Environmental Research and Public Health*, *18*(20), 10854.

DiCesare, C. A., Green, B., Yuan, W., Diekfuss, J. A., Barber Foss, K. D., Dudley, J., ... & Myer, G. D. (2020). Machine learning classification of verified head impact exposure strengthens associations with brain changes. *Annals of biomedical engineering*, *48*, 2772-2782.

Dijkhuis, T. B., Kempe, M., & Lemmink, K. A. (2021). Early Prediction of Physical Performance in Elite Soccer Matches—A Machine Learning Approach to Support Substitutions. *Entropy*, *23*(8), 952.

Donaldson, L., Li, B. and Cusimano, M.D. (2014), "*Economic burden of time lost due to injury in NHL hockey players*", Injury Prevention, Vol. 20, pp. 347-349, doi: 10.1136/injuryprev-2013-041016.

Downs, S. H., & Black, N. (1998). The feasibility of creating a checklist for the assessment of the methodological quality both of randomised and non-randomised studies of health care interventions. *Journal of epidemiology & community health*, *52*(6), 377-384.

Ekstrand, J., Spreco, A., Bengtsson, H., & Bahr, R. (2021). Injury rates decreased in men's professional football: an 18-year prospective cohort study of almost 12 000 injuries sustained during 1.8 million hours of play. *British journal of sports medicine*, *55*(19), 1084-1092.

Fanchini, M., Rampinini, E., Riggio, M., Coutts, A. J., Pecci, C., & McCall, A. (2018). Despite association, the acute: chronic work load ratio does not predict non-contact injury in elite footballers. *Science and Medicine in Football*, *2*(2), 108-114.

Foster, C., Florhaug, J. A., Franklin, J., Gottschall, L., Hrovatin, L. A., Parker, S., ... & Dodge, C. (2001). A new approach to monitoring exercise training. *The Journal of Strength & Conditioning Research*, *15*(1), 109-115.

Fox, J. L., Stanton, R., Sargent, C., Wintour, S. A., & Scanlan, A. T. (2018). The association between training load and performance in team sports: a systematic review. *Sports Medicine, 48*, 2743-2774.

Gabbett, T. J. (2010). The development and application of an injury prediction model for noncontact, soft-tissue injuries in elite collision sport athletes. *The Journal of Strength & Conditioning Research*, *24*(10), 2593-2603.

Gabbett, T. J., Jenkins, D. G., & Abernethy, B. (2011). Correlates of tackling ability in high-performance rugby league players. *The Journal of Strength & Conditioning Research*, *25*(1), 72-79.

Gabler, L. F., Huddleston, S. H., Dau, N. Z., Lessley, D. J., Arbogast, K. B., Thompson, X., ... & Crandall, J. R. (2020). On-field performance of an instrumented mouthguard for detecting head impacts in American football. *Annals of biomedical engineering*, *48*, 2599-2612.

Gallo, T. F., Cormack, S. J., Gabbett, T. J., & Lorenzen, C. H. (2017). Self-reported wellness profiles of professional Australian football players during the competition phase of the season. *The Journal of Strength & Conditioning Research*, *31*(2), 495-502.

Gamble, P. (2006). Periodization of training for team sports athletes. *Strength & Conditioning Journal*, *28*(5), 56-66.

Gasparini, R., & Álvaro, A. (2020). Positional analysis of Brazilian soccer players using GPS data. *Revista Brasileira de Computação Aplicada*, *12*(3), 16-32.

Gastin, P. B., Hunkin, S. L., Fahrner, B., & Robertson, S. (2019). Deceleration, acceleration, and impacts are strong contributors to muscle damage in professional Australian football. *The Journal of Strength & Conditioning Research*, *33*(12), 3374-3383.

Gaudino, P., Iaia, F. M., Strudwick, A. J., Hawkins, R. D., Alberti, G., Atkinson, G., & Gregson, W. (2015). Factors influencing perception of effort (session rating of perceived exertion) during elite soccer training. *International journal of sports physiology and performance*, *10*(7), 860-864.

Geurkink, Y., Boone, J., Verstockt, S., & Bourgois, J. G. (2021). Machine learning-based identification of the strongest predictive variables of winning and losing in Belgian professional soccer. *Applied Sciences*, *11*(5), 2378.

Geurkink, Y., Vandewiele, G., Lievens, M., De Turck, F., Ongenae, F., Matthys, S. P., ... & Bourgois, J. G. (2019). Modeling the prediction of the session rating of perceived exertion in soccer: Unraveling the puzzle of predictive indicators. *International journal of sports physiology and performance*, *14*(6), 841-846.

Giménez, J. V., Jiménez-Linares, L., Leicht, A. S., & Gómez, M. A. (2020). Predictive modelling of the physical demands during training and competition in professional soccer players. *Journal of Science and Medicine in Sport*, *23*(6), 603-608.

Goes, F. R., Kempe, M., Van Norel, J., & Lemmink, K. A. P. M. (2021). Modelling team performance in soccer using tactical features derived from position tracking data. *IMA Journal of Management Mathematics*, *32*(4), 519-533.

Griffin, A., Kenny, I. C., Comyns, T. M., & Lyons, M. (2020). The association between the acute: chronic workload ratio and injury and its application in team sports: a systematic review. *Sports Medicine*, *50*, 561-580.

Guerrero-Calderón, B., Klemp, M., Morcillo, J. A., & Memmert, D. (2021). How does the workload applied during the training week and the contextual factors affect the physical responses of professional soccer players in the match?. *International Journal of Sports Science & Coaching*, *16*(4), 994-1003.

He, K. (2021). Prediction model of juvenile football players' sports injury based on text classification technology of machine learning. *Mobile Information Systems*, *2021*, 1-10.

Héder, M. (2017). From NASA to EU: the evolution of the TRL scale in Public Sector Innovation. *The Innovation Journal*, *22*(2), 1-23.

Hennessy, L., & Jeffreys, I. (2018). The current use of GPS, its potential, and limitations in soccer. *Strength & Conditioning Journal*, *40*(3), 83-94.

Hiploylee, C., Wennberg, R. and Tator, C.H. (2016), "*The financial toll of career-ending concussions in professional hockey*", Concussion, Vol. 1, p. CNC20, doi: 10.2217/cnc-2016-0008.

Horvat, T., & Job, J. (2020). The use of machine learning in sport outcome prediction: A review. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *10*(5), e1380.

Hughes, M. D., & Bartlett, R. M. (2002). The use of performance indicators in performance analysis. *Journal of sports sciences*, *20*(10), 739-754.

Impellizzeri, F. M., Menaspà, P., Coutts, A. J., Kalkhoven, J., & Menaspà, M. J. (2020). Training load and its role in injury prevention, part I: back to the future. *Journal of athletic training*, *55*(9), 885-892.

Jaspers, A., De Beéck, T. O., Brink, M. S., Frencken, W. G., Staes, F., Davis, J. J., & Helsen, W. F. (2018). Relationships between the external and internal training load in professional soccer: what can we learn from machine learning?. *International journal of sports physiology and performance*, *13*(5), 625-630.

Jauhiainen, S., Äyrämö, S., Forsman, H., & Kauppi, J. P. (2019). Talent identification in soccer using a one-class support vector machine. *International Journal of Computer Science in Sport*, *18*(3), 125-136.

Jelinek, H. F., Kelarev, A., Robinson, D. J., Stranieri, A., & Cornforth, D. J. (2014). Using meta-regression data mining to improve predictions of performance based on heart rate dynamics for Australian football. *Applied Soft Computing*, *14*, 81-87.

Jones, C. M., Griffiths, P. C., & Mellalieu, S. D. (2017). Training load and fatigue marker associations with injury and illness: a systematic review of longitudinal studies. *Sports medicine*, *47*, 943-974.

King, D., Brughelli, M., Hume, P., & Gissane, C. (2014). Assessment, management and knowledge of sport-related concussion: systematic review. *Sports medicine*, *44*, 449-471.

Klemp, M., Wunderlich, F., & Memmert, D. (2021). In-play forecasting in football using event and positional data. *Scientific Reports*, *11*(1), 24139.

MEDICA, E. M. (2019). Modeling of relationships between physical and technical activities and match outcome in elite German soccer players. *J Sports Med Phys Fitness*, *59*(5), 752-9.

Maerlender, A., Masterson, C. J., Norris, R., & Hinthorne, A. (2020). Validating tackle mechanics in American football: improving safety and performance. *Annals of biomedical engineering*, *48*(11), 2691-2700.

Malone, S., Hughes, B., Roe, M., Collins, K., & Buchheit, M. (2017). Monitoring player fitness, fatigue status and running performance during an in-season training camp in elite Gaelic football. *Science and Medicine in Football*, *1*(3), 229-236.

Malone, S., Owen, A., Newton, M., Mendes, B., Tiernan, L., Hughes, B., & Collins, K. (2018). Wellbeing perception and the impact on external training output among elite soccer players. *Journal of science and medicine in sport*, *21*(1), 29-34.

Mandorino, M., Figueiredo, A. J., Cima, G., & Tessitore, A. (2021). A data mining approach to predict non-contact injuries in young soccer players. *International Journal of Computer Science in Sport*, *20*(2), 147-163.

Mandorino, M., Figueiredo, A. J., Cima, G., & Tessitore, A. (2022). Predictive analytic techniques to identify hidden relationships between training load, fatigue and muscle strains in young soccer players. *Sports*, *10*(1), 3.

Mason, J., Wellmann, K., Groll, A., Braumann, K. M., Junge, A., Hollander, K., & Zech, A. (2021). Game exposure, player characteristics, and neuromuscular performance influence injury risk in professional and youth field hockey players. *Orthopaedic journal of sports medicine*, *9*(4), 2325967121995167.

Mosey, Tim J., and Lachlan J.G. Mitchell. "Key Performance Indicators in Australian Sub-Elite Rugby Union." *Journal of Science and Medicine in Sport* 23, no. 1 (January 2020): 35–40. https://doi.org/10.1016/j.jsams.2019.08.014.

O'Connor, S., Moran, K., Burke, C., & Whyte, E. (2019). Sports-related concussion in adolescent Gaelic games players. *Sports health*, *11*(6), 498-506.

Oliver, J. L., Ayala, F., Croix, M. B. D. S., Lloyd, R. S., Myer, G. D., & Read, P. J. (2020). Using machine learning to improve our understanding of injury risk and prediction in elite male youth football players. *Journal of science and medicine in sport*, *23*(11), 1044-1048.

Peek, R. J., Middleton, K. J., Gastin, P. B., Carey, D. L., & Clarke, A. C. (2021). Position specific peak impact and running demands of professional rugby union players during game play. *International Journal of Sports Science & Coaching*, *16*(5), 1162-1168.

Perri, E., Simonelli, C., Rossi, A., Trecroci, A., Alberti, G., & Iaia, F. M. (2021). Relationship Between Wellness Index and Internal Training Load in Soccer: Application of a Machine Learning Model. *International Journal of Sports Physiology and Performance*, *16*(5), 695-703.

Philp, F., Al-Shallawi, A., Kyriacou, T., Blana, D., & Pandyan, A. (2020). Improving predictor selection for injury modelling methods in male footballers. *BMJ open sport & exercise medicine*, *6*(1), e000634.

Rao, H. M., Yuditskaya, S., Williamson, J. R., Vian, T. R., Lacirignola, J. J., Shenk, T. E., ... & Quatieri, T. F. (2021). Using oculomotor features to predict changes in optic nerve sheath diameter and impact scores from contact-sport athletes. *Frontiers in neurology*, *12*, 584684.

Rajšp, A., & Fister Jr, I. (2020). A systematic literature review of intelligent data analysis methods for smart sport training. *Applied Sciences*, *10*(9), 3013.

Ratten, V. (2019). Sports technology and innovation. *Cham: Springer Books*, 95-111.

Revie, M., Wilson, K. J., Holdsworth, R., & Yule, S. (2017). On modeling player fitness in training for team sports with application to professional rugby. *International Journal of Sports Science & Coaching*, *12*(2), 183-193.

Reyers, M., & Swartz, T. B. (2021). Quarterback evaluation in the national football league using tracking data. *AStA Advances in Statistical Analysis*, 1-16.

Rommers, N., Rössler, R., Verhagen, E., Vandecasteele, F., Verstockt, S., Vaeyens, R., ... & Witvrouw, E. (2020). A machine learning approach to assess injury risk in elite youth football players. *Medicine and science in sports and exercise*, *52*(8), 1745-1751.

Rossi, A., Pappalardo, L., Cintia, P., Iaia, F. M., Fernández, J., & Medina, D. (2018). Effective injury forecasting in soccer with GPS training data and machine learning. *PloS one*, *13*(7), e0201264.

Rossi, A., Perri, E., Pappalardo, L., Cintia, P., & Iaia, F. M. (2019). Relationship between external and internal workloads in elite soccer players: Comparison between rate of perceived exertion and training load. *Applied sciences*, *9*(23), 5174.

Rowson, S., & Duma, S. M. (2013). Brain injury prediction: assessing the combined probability of concussion using linear and rotational head acceleration. *Annals of biomedical engineering*, *41*, 873-882.

Schmid, M., Blauberger, P., & Lames, M. (2021). Simulating defensive trajectories in American football for predicting league average defensive movements. *Frontiers in Sports and Active Living*, *3*, 669845.

Seshadri, D. R., Thom, M. L., Harlow, E. R., Gabbett, T. J., Geletka, B. J., Hsu, J. J., ... & Voos, J. E. (2021). Wearable technology and analytics as a complementary toolkit to optimize workload and to reduce injury burden. *Frontiers in sports and active living*, *2*, 228.

Shim, V. B., Holdsworth, S., Champagne, A. A., Coverdale, N. S., Cook, D. J., Lee, T. R., ... & Fernandez, J. W. (2020). Rapid prediction of brain injury pattern in mTBI by combining FE analysis with a machine-learning based approach. *IEEE Access*, *8*, 179457-179465.

Soligard, T., Schwellnus, M., Alonso, J. M., Bahr, R., Clarsen, B., Dijkstra, H. P., ... & Engebretsen, L. (2016). How much is too much?(Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. *British journal of sports medicine*, *50*(17), 1030-1041.

Staunton, C. A., Abt, G., Weaving, D., & Wundersitz, D. W. T. (2022). Misuse of the term 'load' in sport and exercise science. Journal of science and medicine in sport, 25(5), 439–444.

Thornton, H. R., Delaney, J. A., Duthie, G. M., Scott, B. R., Chivers, W. J., Sanctuary, C. E., & Dascombe, B. J. (2016). Predicting self-reported illness for professional team-sport athletes. *International journal of sports physiology and performance*, *11*(4), 543-550.

Thornton, H. R., Delaney, J. A., Duthie, G. M., & Dascombe, B. J. (2017). Importance of various training-load measures in injury incidence of professional rugby league athletes. *International journal of sports physiology and performance*, *12*(6), 819-824.

Vallance, E., Sutton-Charani, N., Imoussaten, A., Montmain, J., & Perrey, S. (2020). Combining internal-and external-training-loads to predict non-contact injuries in soccer. *Applied Sciences*, *10*(15), 5261.

Wang, C., Vargas, J. T., Stokes, T., Steele, R., & Shrier, I. (2020). Analyzing activity and injury: lessons learned from the acute: chronic workload ratio. *Sports Medicine*, *50*(7), 1243-1254.

Wilkerson, G. B., Gupta, A., Allen, J. R., Keith, C. M., & Colston, M. A. (2016). Utilization of practice session average inertial load to quantify college football injury risk. *Journal of strength and conditioning research*, *30*(9), 2369-2374.

Wilkerson, G. B., Gupta, A., & Colston, M. A. (2018). Mitigating sports injury risks using internet of things and analytics approaches. *Risk analysis*, *38*(7), 1348-1360.

Windt, J., Gabbett, T. J., Ferris, D., & Khan, K. M. (2017). Training load--injury paradox: is greater preseason participation associated with lower in-season injury risk in elite rugby league players?. *British journal of sports medicine*, *51*(8), 645-650.

Wu, L. C., Kuo, C., Loza, J., Kurt, M., Laksari, K., Yanez, L. Z., ... & Camarillo, D. B. (2017). Detection of American football head impacts using biomechanical features and support vector machine classification. *Scientific reports*, *8*(1), 1-14.

Zadeh, A., Taylor, D., Bertsos, M., Tillman, T., Nosoudi, N., & Bruce, S. (2021). Predicting sports injuries with wearable technology and data analysis. *Information Systems Frontiers*, *23*, 1023-1037.

Zumeta-Olaskoaga, L., Weigert, M., Larruskain, J., Bikandi, E., Setuain, I., Lekue, J., ... & Lee, D. J. (2021). Prediction of sports injuries in football: a recurrent time-to-event approach using regularized Cox models. *AStA Advances in Statistical Analysis*, 1-26.