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Relationship between external and internal load indicators and injury using machine learning in professional soccer: a systematic review and meta-analysis

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ABSTRACT

This study verified the relationship between internal load (IL) and external load (EL) and their association on injury risk (IR) prediction considering machine learning (ML) approaches. Studies were included if: (1) participants were male professional soccer players; (2) carried out for at least 2 sessions, exercises, or competitions; (3) correlated training load (TL) with non-contact injuries; (4) applied ML approaches to predict TL and non-contact injuries. TL included: IL indicators (Rating of Perceived Exertion, RPE; Session-RPE, Heart Rate, HR) and EL indicators (Global Positioning System, GPS variables); the relationship between EL and IL through index, ratio, formula; ML indicators included performance measures, predictive performance of ML methods, measure of feature importance, relevant predictors, outcome variable, predictor variable, data pre-processing, features selection, ML methods. Twenty-five studies were included. Eleven addressed the relationship between EL and IL. Five used EL/IL indexes. Five studies predicted IL indicators. Three studies investigated the association between EL and IL with IR. One study predicted IR using ML. Significant positive correlations were found between S-RPE and total distance (TD) ($r = 0.73$; 95% CI (0.64 to 0.82)) as well as between S-RPE and player load (PL) ($r = 0.76$; 95% CI (0.68 to 0.84)). Association between IL and EL and their relationship with injuries were found. RPE, S-RPE, and HR were associated with different EL indicators. A positive relationship between EL and IL indicators and IR was also observed. Moreover, new indexes or ratios

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(integrating EL and IL) to improve knowledge regarding TL and fitness status were also applied. ML can predict IL indicators (HR and RPE), and IR. The present systematic review was registered in PROSPERO (CRD42021245312).

Introduction

Soccer is an intermittent and open skills team sport that requires high physical performance characteristics to support the fundamental technical-tactical aspects of performance (Hader et al., 2019). Training allows to increase athletes' performance minimizing injury risk (IR) through the variation in training stimuli (Viru & Viru, 2000). Inappropriate training stimuli and recovery could negatively affect fitness level or lead to an increase in IR (Gabbett et al., 2014; Jaspers et al., 2017). The high incidence of injuries in professional soccer players could be the result of an inadequate modulation of training workload. Hence, the attention to the players' recovery status during the season should be given more consideration by the medical and technical staff during the training scheduling process (Verstappen et al., 2021).

Training load (TL) is defined as 'a higher-order construct reflecting the amount of physical training that is actually done and experienced by the athletes' (Coutts et al., 2017; Impellizzeri et al., 2019; Jeffries et al., 2021). Two dimensions called internal (IL) and external load (EL) characterize the TL (Impellizzeri et al., 2005, 2019). Commonly, training prescription describes a short to long plan of the EL that allows to organize the exercises/training sessions (Coutts et al., 2017; Impellizzeri et al., 2019). The EL induces internal responses that reflect psychological, physiological, biochemical, metabolic, and biomechanical stress stimuli (Impellizzeri et al., 2005; McLaren et al., 2018; Vanrenterghem et al., 2017).

The acute dose – response paradigm indicates that specific internal responses, which are obtained by HR or RPE, are induced by prescribed external training factors (Bartlett et al., 2017; McLaren et al., 2018). Hence, EL and IL monitoring is essential for athletes' management during both training and competition to maximize athletic performance and minimize IR (Bartlett et al., 2017; Gabbett et al., 2014). Specifically, it is suggested that internal responses to a given EL be considered since different internal responses can be observed as a consequence of the same EL among different athletes (Impellizzeri et al., 2019). Indeed, several studies have examined the relationship between EL and IL to monitor training or competition load in soccer (Akenhead et al., 2016; Akubat et al., 2014; Bartlett et al., 2017; Beato & Drust, 2021; Casamichana et al., 2013; David; Casamichana & Castellano, 2015; Castagna et al., 2019; Castillo et al., 2017; Coppalle et al., 2021; Costa et al., 2013; Giménez et al., 2019; Jaspers et al., 2017; Malone et al., 2015; Martín-López et al., 2021; Miguel et al., 2021; Oliveira et al., 2019, 2019).

Some research has investigated the application of a new index that takes into account both IL and EL to better understand the role of TL and its implications on performance and injury prevention in soccer (Derbidge et al., 2020; Grünbichler et al., 2020; Malone et al., 2018; Suarez-Arrones et al., 2015; Torreño et al., 2016) (Akubat et al., 2018; Clemente et al., 2019; Hadi; Nobari et al., 2020; Rebelo et al., 2012; Reinhardt et al., 2020; Nobari et al., 2020). For example, Suarez-Arrones et al.

(2015) detected lower overall running performance during match play with lower efficiency index scores (mean speed in m·min^{-1}/mean exercise intensity (%HRmax)) (Suarez-Arrones et al., 2015). In recent years, more complex and potentially more efficient analysis methods have been implemented to manage the huge amount of data resulting from the monitoring of TL (Claudino et al., 2019; Van Eetvelde et al., 2021).

Machine learning (ML), which deals with creating systems that learn or improve performance based on multidimensional data, could allow practitioners to understand the complex relationships between phenomena with the aim of predictions (Jaspers et al., 2017). In fact, several studies have used this analytic approach to predict IR and performance in team sports (Rossi et al., 2018; Vallance et al., 2020; Van Eetvelde et al., 2021). ML includes different complex methods for managing a very large database in order to find relationships between multiple features variables. Therefore, it is necessary to apply pre-processing methods (e.g. imputation, standardization, and discretization) and reduce the size of the data by selecting the most relevant features to avoid multicollinarity problem. Finally, well-performing models provide insight into the most important factors, by looking at which of them have the greatest influence in the decision-making process of ML models. In this context, a growing number of studies have focused on the prediction of both injuries and performance through ML approaches (Geurkink et al., 2019; Jaspers et al., 2018; Alessio; Rossi et al., 2019). Although a previous review reported that there is no consensus regarding the best way to predict sports injuries and performance using ML, each method is able to predict a specific variable in different contexts (Kotsiantis et al., 2007) such as the Decision Tree (Rossi et al., 2018) and the Artificial Neural Network (Claudino et al., 2019). For example, in soccer, technical and tactical analysis (Abdullah et al., 2016; Wang, 2014) and match participation (Strnad et al., 2017) were predicted, while TL variables such as those related to GPS (i.e. high-speed running distance and total distance) and previous injuries were applied to predict injuries, while RPE was predicted from training volume value and psychological factors induced by the distance to the matchday (Rossi et al., 2018; Alessio; Rossi et al., 2019).

In recent years, a growing number of investigations have focused on better understanding the relationship between IL and EL in professional soccer players. Hence, new indexes and ML approaches have been implemented with the aim of monitoring TL and injury prediction. Although several reviews have been published regarding the application of ML techniques in sports contexts (e.g. those focusing on ML methods for sports injuries (Sigurdson & Chan, 2021) and sport injury prediction/prevention (Van Eetvelde et al., 2021); those exploring ML in the study of TL and performance in soccer (Rico-Gonzalez et al., 2023); those using ML for soccer player injuries (Nassis et al., 2023)), none of these have focused on summarizing the existing body of knowledge regarding the relationship between TL and injuries.

A comprehensive summary of evidence using a systematic review could help to clarify trends in scientific research, identify main methodological approaches, and highlight gaps that need to be addressed in the coming years. Therefore, the aim of this systematic review and meta-analysis was to investigate the interaction between IL and EL indicators and to determine the relationship between TL indicators (both internal and external) and injuries using ML approaches in professional soccer players.

Materials and methods

This systematic review followed the PRISMA 2020 guidelines (Page et al., 2021).

Protocol and registration

The protocol of this systematic review was registered in PROSPERO (CRD42021245312) at 4 May 2021.

Eligibility criteria

Studies published in peer-reviewed journals, including those with 'in press' or 'ahead-of-print' status, were considered. Publication restrictions between 2010 and 2021 were established as ML studies applied to soccer have increased over the past decade. Language restriction to English was established as used by most of the impact factor journals.

Eligibility criteria were established based on the PECOS approach (population, exposure, comparator, outcome, study design): (I) population: participants were male professional soccer players over the age above 12 years; (II) exposure: players exposed to at least two sessions, exercises, or competitions with an objective evaluation of both IL and EL parameters; (III) comparator: no comparison was planned for this review; (IV) outcome(s): studies that correlated TL (both EL and IL) with non-contact injuries or research that applied ML approaches to predict TL and non-contact injuries; (V) study design: observational studies. As for the outcomes, the main load indicators extracted included internal (RPE, S-RPE, HR) and external (GPS variables related to distance, speed, acceleration, and energy profile thresholds); relationship between EL and IL through index, ratio, and formula; ML indicators included performance measures, predictive performance of ML methods, measure of feature importance, relevant predictors, outcome variable, predictor variable, data pre-processing, features selection, ML classification methods.

Exclusion criteria were: (I) studies that did not report indicators of EL or IL in terms of volume and intensity; (II) studies that did not focus on the relationship between EL and IL, between TL and changes in performance, or between TL and non-contact injuries; (III) studies that investigated the effects of rehabilitation, nutritional strategies, or environmental factors (e.g., heat, altitude); (IV) studies that used biological markers as parameters to measure IL; (V) studies that did not use GPS-provided data to determine EL; (VI) studies that did not integrate both EL and IL to determine TL; (VII) studies in which the monitored training protocols referred to strength training; (VIII) if studies were reviews, meta-analyses, abstracts, statements, opinion pieces, citations from scientific conferences, commentaries, editorials, book reviews, books, letters, and non-peer reviewed journal articles.

Information sources

PubMed, Scopus, and Web of Science databases were used to conduct the searchers. The screening was performed between 30 March 2021 and 15 May 2021. In addition to the

Table 1. Results overview of the included studies.

Studies	Correlation between external and internal load	External and Internal Loads integrated approaches: new indexes/ratios.	Predicting Internal Load	Association between EL and IL indicators and injuries	Predicting injuries through EL and IL indicator
Enes et al. (2021)	Yes				
Gaudino et al. (2015)	Yes				
Geurkink et al. (2019)			Yes		
Gomez-Piriz et al. (2011)	Yes				
Grünbichler et al. (2020)		Yes			
Jaspers et al. (2018)			Yes		
Jaspers et al. (2018)				Yes	
Lacome et al. (2018)			Yes		
Malone et al. (2018)				Yes	
Malone et al. (2018)		Yes			
Marynowicz et al. (2020)	Yes				
Maughan et al. (2021)	Yes				
Maughan et al. (2020)	Yes				
Montini and Rocchi (2020)	Yes				
Rago et al. (2019)	Yes				
Rossi et al. (2019)			Yes.		
Scott et al. (2013)	Yes				
Silva et al. (2018)			Yes		
Suarez-Arrones et al. (2015)		Yes			
Torreño et al. (2016)		Yes			
Vallance et al. (2020)					Yes
Wiig et al. (2020)	Yes				
Derbidge et al. (2020)		Yes			
Lu et al. (2017)				Yes	
Alemdaroğlu (2020)	Yes				

automatic search, two authors conducted the manual search from the references list of manuscripts. Moreover, experts were asked to help in the double-check of references.

Literature search strategy

The combinations of two groups of keywords were used. In detail, group 1 included: 'training load', 'rpe', 'gps', 'internal external load'; group 2 included: 'soccer', 'football', 'machine learning', 'injury', 'index'. The terms of group 1 and 2 were combined with AND. The references of the included studies were also checked to ensure to identify of all the relevant articles for this topic (Table 1).

Study selection

To select relevant articles, duplicates were removed. Afterwards, titles, abstracts, and full texts of the studies were independently screened against the inclusion and exclusion criteria by two authors. Any disagreements were discussed between the two authors and were resolved.

Data items

The following information were collected from the included studies.

Main outcomes: session-RPE or RPE (score obtained from the players); total distance (TD), and player load (PL) were adopted for meta-analysis.

The selected articles were classified according to their methodological quality with the aim of understanding the interaction between IL and EL indicators, finding the relationship between TL indicators (both IL and EL) and injuries. Moreover, we searched for the implication of TL for injury prediction using ML approaches.

Information regarding age, country of origin, competitive level, body mass, height, duration of the intervention, number of total observations, number of observations per athlete, and individual observations were the context-related information analysed by the studies.

Information regarding the first author and year of publication; the main load measures included both internal (RPE, S-RPE, HR) and external (GPS variables) parameters; relationship between EL and IL through index, ratio, and formula; ML indicators included performance measures, predictive performance of ML methods, measure of feature importance, relevant predictors, outcome variable, predictor variable, data pre-processing, features selection, and ML classification methods were extracted from the studies.

All data were summarized using descriptive tables and analysed through a narrative synthesis.

Quality assessment

The quality of the included studies was assessed by two reviewers. They resolved any disagreements about each item through deliberation. An adjusted version of the Downs and Blacks checklist (Downs & Black, 1998; Kaur et al., 2016) was applied to evaluate the quality of included studies using the following sub-scale: reporting (items 1, 2, 3, 5, 6, 7 and 10), external validity (items 11 and 12), internal validity-bias (items 15, 16, 18 and 20), internal validity-confounding (items 21 and 25), and power (item 27). The score of the item 27 was modified from 0–5 to 1 or 0 so that a study received 1 if the study had an appropriate power, in other aspect, it was scored 0. Kappa correlation coefficient was used to detect inter-rater reliability for each checklist item between the two reviewers. Studies with scores of 11 or higher (65%) were at a low risk of bias and investigations with scores below 11 were at a high risk of bias.

Meta-analysis

To conduct a meta-analysis the 'metafor' package of the R software (Version 1.4.1103) using the Hunter-Schmidt model on raw correlation coefficients (bias corrected) between S-RPE and TD, as well as between S-RPE and PL was adopted. This approach reduces estimator variance when correlations from each study do not need to be transformed into z-scores (Rosenblad, 2009). Significance was set at $p < 0.05$. The effect size was represented through a forest plot with 95% confidence interval (CI). A funnel plot was also performed to understand publication bias. Heterogeneity was explored using the I^2 statistic, in which values < 50% indicate low heterogeneity, 50–75% moderate heterogeneity, and values > 75% high heterogeneity. Since both models presented heterogeneity below 50%, no moderator analysis was conducted.

Results

A total of 35,310 articles were retrieved through the database searches of which 15,342 were duplicates. Twenty-five studies met the inclusion criteria and were included in the review of which 22 were included after screening the titles, abstracts, and full texts; three were identified through the references screening of all the included studies. The flow diagram (Figure 1) summarizes the screening process. All the included studies used GPS and/or triaxial accelerometers variables to assess EL. Eleven articles addressed the relationship between EL and IL of which nine used RPE and or S-RPE for monitoring IL and two used both HR and S-RPE indicators. Five articles used EL/IL new indexes: four applied HR and one used RPE and S-RPE for IL assessment. Five studies predicted IL indicators. In particular, two predicted HR, while three predicted RPE through EL applying ML approaches. Three studies investigated the association between EL (GPS) and IL (RPE) with IR. Only one study predicted IR (Vallance et al., 2020) implementing ML approaches through IL and EL.

Overview of the studies

Table 2 shows the main characteristics of the included studies. Table 3 shows TL indicators (external and internal) and new-derived indexes or ratios. Table 1 shows the overview of the included studies.

Sample size varied between 10 and 48 athletes for a total of 636 athletes. Participants were male professional soccer players (age 24.3 ± 3.3 years, height 180.8 ± 2.2 cm, weight 75.1 ± 2.9 kg).

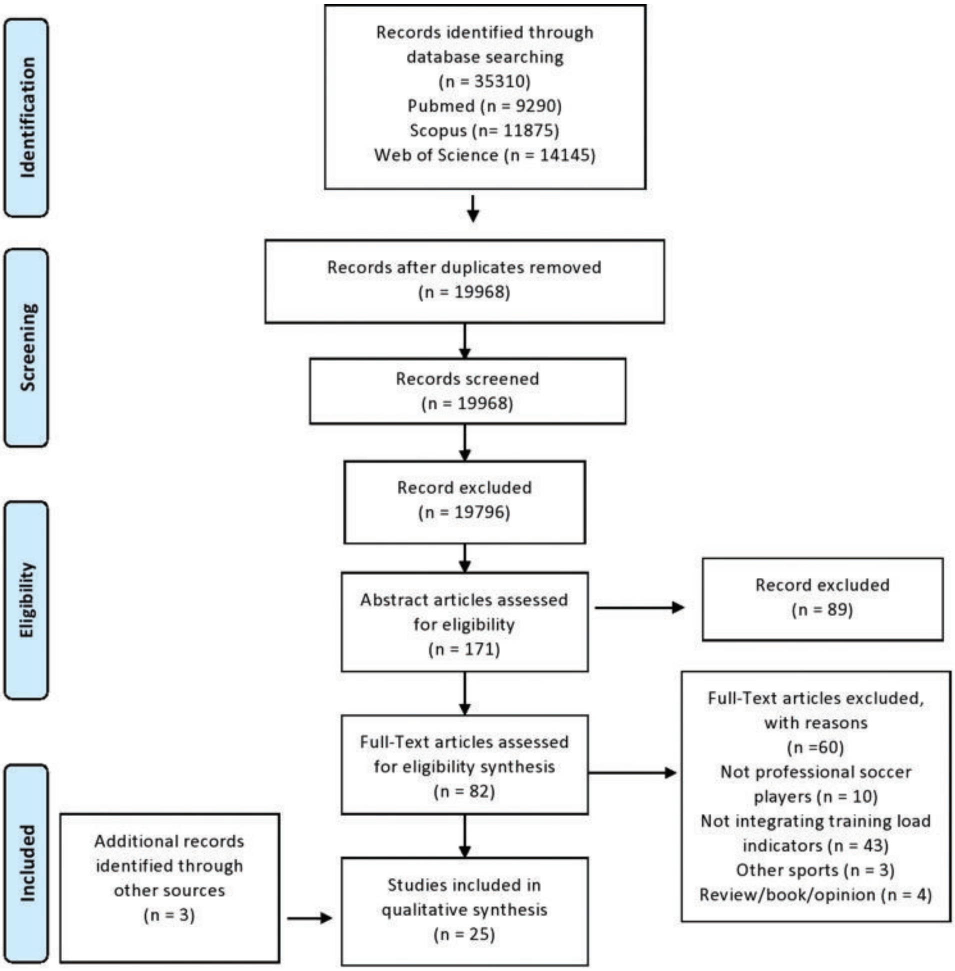

Figure 1. Flow diagram.

Studies were conducted in Australia, Austria, Belgium, Brazil, France, Italy, Netherlands, Norway, Portugal, Russia and Spain.

The studies research protocol duration varies between 6 weeks and 2 seasons.

IL was assessed with RPE proposed by Foster (Foster, 1998; Foster et al., 2021), S-RPE (derived multiplying RPE x duration) (Foster et al., 2017, 2021), and/or HR, while EL using GPS (Rossi et al., 2018) and/or accelerometer indicators. Twenty-one studies (84%) used standard statistical analysis (Alemdaroğlu, 2020; Derbidge et al., 2020; Enes et al., 2021; Gaudino et al., 2015; Gomez-Piriz et al., 2011; Grünbichler et al., 2020; Jaspers et al., 2018; Lacome et al., 2018; Lu et al., 2017; Malone et al., 2018, 2018; Marynowicz et al., 2020; Maughan et al., 2020, 2021; Montini & Rocchi, 2020; Rago et al., 2019; Scott et al., 2013; Silva et al., 2018; Suarez-Arrones et al., 2015; Torreño et al., 2016; Wiig et al., 2020) and only four (16%) (Geurkink et al., 2019; Jaspers et al., 2018; Alessio; Rossi et al., 2019; Vallance et al., 2020) used ML approaches to analyse data. Only four studies regarding injuries were included: three used IL and EL to understand their association with injuries (Jaspers et al.,

Table 2. Main characteristics of the included studies.

Studies Author, year	Sample number/level/ age (years)/mass (kg)/height (cm)	Duration	Obs. sample: Obs. per athlete/tot. individual obs.	Findings
Enes et al. (2021)	23/First division 26.7 ± 3.9/78.0 ± 5.0/178.0 ± 5.2	38 weeks		Physical measures and EL influenced-on match-based IL and can be used for IL prediction.
Gaudino et al. (2015)	22/Professional 26 ± 6/79 ± 7/182 ± 7	38 weeks	Median observation per players was 86 ± 28 (range 25–120) 1892 individual training observation mean duration of 57 ± 16	RPE of TL was correlated with HSR distance and the number of impacts.
Geurkink et al. (2019)	46/elite 25.6 ± 4.2	June 2015 and March 2017	913 individual training observations/61 training sessions	ELIs are the strongest predictors of the S-RPE.
Gomez-Piriz et al. (2011)	22/first division 26.74 ± 4.2/179.74 ± 4.0/73.7 ± 3.3	February to March 2008	124 data were obtained and analysed	TBL is a valid tool to determine specific-soccer TL.
Grünbichler et al. (2020)	14/Austrian Second League/ 22.6 ± 4.3/181.5 ± 5.7/75.7 ± 5.8	13-week period (competitive season) 2017/2018 from March 2018 until June 2018	514 individuals training and 180 match observations/44 training sessions and 16 competitive matches	TL recorded during the days before a match can predict match workload efficiency.
Jaspers et al. (2018)	38/highest league in the Netherlands/ 22.7 ± 3.4/1.83 ± 0.06/77.0 ± 6.7	two seasons (2014/2015 and 2015/2016)	23 players: (35 to 160) mean and st. dev. of 125 ± 34 sess. 28 players: (51 to 163) mean and st. dev. of 109 ± 33 sess.	ML can predict RPE based on a large set of ELIs.
Jaspers et al. (2018)	35/first team at the highest level (Eredivisie)/23.2 ± 3.7/77.5 ± 7.4/1.82 ± 0.06 m,	two seasons (2014/2015 and 2015/2016)	external load data for field training sessions and matches was 870 of 8103 (11%)	ELIs are associated with increased or decreased IR. Cumulative weekly loads for TD DECeff is recommended. A high ACWR for THSR should be avoided. Protective effects were found with medium ACWR for ACCeff, DECeff, and S-RPE
Lacome et al. (2018)	10/elite French football team/26 ± 5/ 76 ± 5/182 ± 6	one season (2016/2017)		Large associations between the HR responses to SSGs and some SSGs.
Malone et al. (2018)	37/(Liga Nos, Portugal) /25 ± 3/183 ± 7/72 ± 7	48 weeks 2015/2016	22080 individual pitch-based training sessions/460 training sessions	Workload measures were associated with measures and IR. Cumulative HSR and SR workloads or large week-to-week changes in these workloads increased IR. Players exposed to large and rapid increases in HSR and SR distances were more likely to sustain a lower limb injury.

(*Continued*)

Table 2. (Continued).

Studies Author, year	Sample number/level/ age (years)/mass (kg)/height (cm)	Duration	Obs. sample Obs. per athlete/tot. individual obs.	Findings
Malone et al. (2018)	48/(Liga NOS and Champions league)/ 25.3 ± 3.1/183 ± 7/72 ± 7	2014/2015 season	22080 individual pitch-based training sessions/460 training sessions	Wellbeing measures were related with reduction in training measures.
Marynowicz et al. (2020)	18/youth national teams/17.81 ± 0.96/ 179.47 ± 4.77/70.94 ± 4.72	2018/2019 in-season competition (18 weeks)		S-RPE and related to many EL factors, allows the monitoring of both acute load and cumulative load.
Maughan et al. (2021)	20/17.4 ± 1.3/178.0 ± 8.1/71.8 ± 7.2	46-week (6-week pre-season and 2 competitive phases) (20-weeks and 19-weeks) split by a 2-week break	total of 3221 sets of observations	There are strong correlations between S-RPE, S-RPE-L, S-RPE-B, and EL variables.
Maughan et al. (2020)	20/17.4 ± 1.3/178.0 ± 8.1/71.8 ± 7.2	2018/2019 season	2827 individual recordings comprising of 696 MD recordings and 2131 training session	TD, PL and LI.Running showed large to very-large correlations with S-RPE. HSR showed small to large correlations, SD showed trivial to moderate correlations. ACC showed moderate correlations, whilst DEC showed small to large correlations with S-RPE.
Montini and Rocchi (2020)	20/Italian (Serie A) 25.8 ± 4.1/76.8 ± 4.3/184 ± 4.6	October 2016 to August 2017	In-season period (34 training sessions and matches (October 2016 and December 2016); the pre-season (30 training sessions and matches (July and August 2017)	S-RPE and kJ as the most effective TL indicators in soccer.
Rago et al. (2019)	13/Italy (Serie Bwin.it)/25.8 ± 3.5/ 181.5 ± 5.6/78.3 ± 5.9	2016/2017 season	256 individual observations/a median of 20 training sessions per player (range: 15–25 sess.)	The magnitude of the relationships between EL and RPE parameters appear to slightly strengthen when EL are adjusted to individual fitness capacities, with special emphasis on cardiorespiratory fitness.
Rossi et al. (2019)	22/Italian championship/21.9 ± 4.5/ 180.6 ± 5.2/72.3 ± 4.1	2016/2017 season	1674 individual sessions/195 collective sessions	ML approach permits to reveal the IL based on external and contextual features. RPE is affected by the workload performed in the previous training week, while S-RPE reflects the workload performed in the current training session.
Scott et al. (2013)	15/Australian A-League/24.9 ± 5.4/ 77.6 ± 7.5/181.1 ± 6.9	2010/2011	97 individual sessions	TD, LSA volume, and PL are adequate indicators of EL during field-based compared with measures of IL. HSR and VHSR volume are somewhat related to IL.

(*Continued*)

Table 2. (Continued).

Studies Author, year	Sample number/level/ age (years)/mass (kg)/height (cm)	Duration	Obs. sample: Obs. per athlete/tot. individual obs.	Findings
Silva et al. (2018)	20/Russian Premier League and in the UEFA Champions League/26.53 ± 3.92/ 182.88 ± 5.52/76.69 ± 6.14	2015–2016 second pre-season period	270 individual training obs.	TRIMP method and EL and time HR 80% (tHR80%) as the best HR indices of TL and intensity, respectively. ACC and HIRE (high intensity bursts) were the physical activities that were most impacting in HR responses.
Suarez-Arrones et al. (2015)	30/Champions League or UEFA Europa League	two seasons	(n = 348)/4–15 times on each player over a period of two seasons	Physical and physiological demands of professional soccer players showed several differences among playing positions.
Torreño et al. (2016)	26/national league, national cup, national super cup and UEFA Europa League/27.3 ± 3.4/180.4 ± 3.6/76.2 ± 6.8	two seasons	(n = 223 match files)/3–15 times on each player over a period of two seasons	The relationship between EL and IL measures among position-specific confirms that players with more overall running performance during the full-match (W-MD and 2ndS) presented the higher values in Effindex.
Vallance et al. (2020)	40/French Ligue 2/29.4 ± 5.8/175.3 ± 5.2/76.5 ± 8.2	one full-season (2017/2018) June 2017 to May 2018	245 training sessions	The subjective variables (i.e., IL) of the pre-session questionnaire (such as sleep quality, fatigue, shape, mood) as well as post-session questionnaire (satisfaction and pleasure) and RPE are found to be determining factors in the occurrence of injuries.
Wiig et al. (2020)	18/Norwegian Premier league 26/183/80	In-season March to November (32 weeks)	207 individual training obs/21 training sess. median of 10 (4) obs. per player (range 7–18)	The EL variables with no threshold or low intensity-threshold had the strongest relationships with S-RPE.
Derbidge et al. (2020)	10/professional development league/ 19.6 ± 1.4/74.4 ± 8.7/180.5 ± 5.3	2018/2019 8-week period during the in-season competitive phase	7 training sessions	The significant effect observed between PW and TD:HRe, PL:HRe and ED:HRe during the SSG's allow scope for external:internal (E:I) ratio's to be used as a 'invisible' fatigue detection tool. E:I ratios is not an appropriate method to determine neuromuscular fatigue.

(*Continued*)

Table 2. (Continued).

Studies Author, year	Sample number/level/ age (years)/mass (kg)/height (cm)	Duration	Obs. sample Obs. per athlete/tot. individual obs.	Findings
Lu et al. (2017)	45/Australian A-League and Asian Champions League/26.4 ± 5.1/181.3 ± 7.1/74.5 ± 12.1	2013/2014 (14 weeks preseason and 32 weeks in season) and 2014/2015 (14 weeks preseason and 31 weeks in season)	211 ± 55 sessions per participant	High absolute and relative load of both exposure and S-RPE workload sustained determined injuries. The absence of any 'spike' in workload prior to injury occurrence was reflected in the lack of week-to-week changes and monotonous profile. Exposure and S-RPE workload ACWR tended to be the highest in comparison to the other load variables.
Alemdaroğlu (2020)	20/professional soccer team/27.6/ 177.6 ± 7.1/69 ± 8.3	10-week soccer season	761 individual field-based training	S-RPE and both HR-based TL models show strong correlations with the number of ACC and DEC actions and with TD, correlations with distances covered in high-speed zones are less convincing.

Legend: EL, external load; IL, internal load; RPE, rating of perceived exertion; TL, Training Load; HSR, High Speed Running; ELIs, External Load indicators S-RPE, Session-Rate of Perceived Exertion; TBL, Total Body Load; ML, Machine learning; IR, injury risk; TD, Total Distance; DECeff, Deceleration Effort; ACWR, Acute Chronic Workload Ratio; THSR, total high-speed running; ACCeff, Acceleration Effort; HR, heart rate; SSG, Small Side Games; GPS, global positioning system; HRΔ, delta heart rate; HSR, high speed running; SR, sprint running; S-RPE-L, Session-Rate of Perceived Exertion-leg muscle exertion; S-RPE-B, Session-Rate of Perceived Exertion-breathlessness; PL, PlayerLoad and LI.Running, low intensity running; SD, sprint distance; LSA, low speed activity; VHSR, very high speed running; HIRE, high intensity repeated efforts; 2ndS, second strikers; PW, perceived wellness; HRe, HR extertion; ED, equivalent distance; ACC, accelerations; DEC, decelerations.

2018; Lu et al., 2017; Malone et al., 2018) and one used ML approach to predict IR (Vallance et al., 2020).

ML studies characteristics and results are presented in Table 4 and Table 5, respectively.

Quality assessment

The methodological quality of the included studies was assessed according to the Downs and Black checklist, reported in the supplementary section. 11 out of the 25 studies (44%) were selected as high-quality, while 14 (56%) as low-quality. K inter-rater reliability agreement was 0.659 between the two reviewers.

Meta-analysis

The meta-analysis was carried out on the correlation between S-RPE and TD, as well as between S-RPE and PL. Funnel plot did not indicate any publication bias (Figures 2 and 3). Regarding the correlation between S-RPE and TD (Figure 4), a significant positive effect was observed (k = 10; $r = 0.73$ [0.64–0.82]; $p < 0.001$; $I^2 = 46\%$), indicating that greater TD relates to greater S-RPE. Moreover, regarding the correlation between S-RPE and PL (Figure 5), a strong significant positive effect was observed (k = 9; $r = 0.76$ [0.68–0.84]; $p < 0.001$; $I^2 = 38\%$), indicating that greater PL relates to greater S-RPE.

Relationship between external and internal load indicators

The relationship between EL and IL indicators has been examined by 11 studies (Alemdaroğlu, 2020; Enes et al., 2021; Gaudino et al., 2015; Gomez-Piriz et al., 2011; Marynowicz et al., 2020; Maughan et al., 2020, 2021; Montini & Rocchi, 2020; Rago et al., 2019; Scott et al., 2013; Wiig et al., 2020). A strong correlation between IL and EL was found throughout these studies. In particular, positive correlations between S-RPE and EL variables were highlighted in nine studies (Enes et al., 2021; Gaudino et al., 2015; Gomez-Piriz et al., 2011; Marynowicz et al., 2020; Maughan et al., 2020, 2021; Montini & Rocchi, 2020; Rago et al., 2019; Wiig et al., 2020). EL variables were grouped into three main categories: distance, acceleration/deceleration, and number of impacts, as reported in Table 3. It is also important to underline that the studies showed that S-RPE was more associated with volume indicators (e.g., TD, LRI) than with intensity indicators. In particular, the correlation between S-RPE and EL indicators was lower when high-intensity thresholds were considered (HSR and VHSR distance, HIE >2.5 $m{*}s^{-1}$, and HIE >3.5 $m{*}s^{-1}$) (Alemdaroğlu, 2020; Gaudino et al., 2015; Maughan et al., 2021; Rago et al., 2019; Scott et al., 2013; Wiig et al., 2020). Moreover, to monitor different trainings, a combination of EL indicators is more related to S-RPE than assessing this relationship one parameter per time (Gaudino et al., 2015; Marynowicz et al., 2020; Maughan et al., 2020). Thus, some authors combined the variables to create new indexes aiming to better represent TL.

External and internal loads integrated approaches: new indexes/ratios

Five studies used different approaches to create a new index or ratio for IL and EL (Derbidge et al., 2020; Grünbichler et al., 2020; Malone et al., 2018; Suarez-Arrones et al., 2015; Torreño et al., 2016). Indices/ratios list is shown in Table 3. Grünbichler et al. (2020)

Table 3. Main features of the measures of load of the included studies.

Studies Author, year	Measures of load Internal Device/parameters	External Device/parameters	Relationship/index External/internal load ratio
Enes et al. (2021)	Session-RPE Borg CR-10 scale were multiplied by the time (in minutes) and expressed in arbitrary units (a.u.)	GPS device (OPTIMEYE S5, Catapult®, Melbourne, Australia) Player Load (au), Player Load min − 1 (au), Total Distance (m), Relative Distance (m.min −1), Distance >20 km.h − 1 (m), Quantity of Stimuli >20 km.h − 1 (frequency), Maximal speed (km.h − 1).	No
Gaudino et al. (2015)	RPE training load (RPE-TL) Borg CR-10 scale were multiplied by the time (in minutes)	10-Hz GPS integrated with a 100-Hz 3-dimensional accelerometer, a 3-dimensional gyroscope, and a 3-dimensional digital compass (STATSports Viper, Northern Ireland). Total distance (m), high-speed distance (m), very-high-speed distance (m), very-high-speed runs (n), impacts (n), dynamic-stress load (AU), accelerations (n), decelerations (n), energy expenditure (kcal), high-metabolic-power dist.(m)	No
Geurkink et al. (2019)	RPE scale Borg CR-10 20 Hz portable HR monitors (Polar Team Pro, Kempele, Finland 10) HR-zones relative to their maximum HR (50% − 60%, 60% − 70%, 70% − 80%, 80% − 90%, 90% − 100%) Time spent in each HR-zone relative to the total time spent in the 5 HR-zones EDW TRIMP	GPS 10 Hz (Polar Team Pro, Kempele, Finland 10 with incorporated accelerometers of 100 Hz Total distance (m), Total time (s), Total number of sprints (n), Deviation of total distance, Diff. in total dist. between players during a training sess., Deviation of total sprints, Diff. in the total number of sprints between players during a training sess. Average speed, distance covered in 5 speed zones (km/h) (3.00–6.99, 7.00–10.99, 11.00–14.99, 15.00–18.99, > 19.00), normalized proportion of distance covered in each speed zone, number of acc. in each zone (m/s2) (0.50–0.99, 1.00–1.99, 2.00–2.99, 3.00–50.00), number of dec. (m/s2) (0.50–0.99, 1.00–1.99, 2.00–2.99, 3.00–50.00), normalized proportion of number of acc. and dec. in each zone, differences in training duration between players during a training sess.	No

(*Continued*)

Table 3. (Continued).

Studies	Measures of load		Relationship/index
Author, year	Internal Device/parameters	External Device/parameters	External/internal load ratio
Gomez-Piriz et al. (2011)	session-RPE (21-point scale)	GPS tracking device (SPI Elite; GPSports Systems) 1 Hz Body load: Computation of player body load during exercise involved the use of the next acceleration zone forces provided in "g" force by the accelerometer of the GPS[a]:	No
Grünbichler et al. (2020)	Polar Team Pro System (Polar Electro Oy, Kempele, Finland). 200 Hz movement sensors as well as heart rate sensors duration (min), Polar Modified training impulse (TRIMPMOD)	Polar Team Pro System (Polar Electro Oy, Kempele, Finland) 10 Hz global positioning (GPS) Duration (min), total distance (m), equivalent distance (m), high speed running (>14.4 km/h) dist. (m), very high speed (>19.8 km/h) running dist. (m), sprinting (>25.2 km/h) dist. (m), number of medium (2.00–2.99 m/s^2) and high (>3.0 m/s^2) acc. number of medium (−2.00 to −2.99 m/s^2) and high (< −3.0 m/s^2) dec.	new index= workload efficiency (ratio of external and internal load in a match,): ED/TRIMPMOD
Jaspers et al. (2018)	RPE (modified Borg CR-10 scale)	10 Hz GPS and 100 Hz accelerometer technology (Optimeye S5, Catapult Sports, Melbourne). Speed (8 ELIs), Acc. and dec. (18 ELIs), PlayerLoad (10 ELIs), RHIE (13 ELIs)	
Jaspers et al. (2018)	RPE Borg CR-10 scale. The load arbitrary units (AU): RPE x training or match duration.	10 Hz GPS technology (Minimax S4 and Optimeye S5, Catapult Sports, Melbourne, Australia). Total distance covered (TD), distance covered at high speed (THSR; >20 km h − 1), N° (ACCeff) >1 m s − 2, N° (DECeff) <−1 m s − 2	ACWR[b]
Lacome et al. (2018)	Heart rate: Polar H1 units (Polar, Kempele, Finland)	5-Hz GPS and 100 Hz accelerometers (SPI-Pro, Team AMS R1 2016.8, GPSport, Canberra, Australia) Total distance (TD, m), high-speed distance (HS, above 14.4 km.h-1, m), very-high speed distance (VHS, above 19.8 km.h-1, m), velocity and force load (vL and fL, respectively, a.u) mechanical work (MechW, a.u)	HRΔ (i.e, the difference between the predicted and actual HR)
Malone et al. (2018)	Borg CR-10 rate of perceived exertion (RPE) scale. RPE was multiplied by the session duration to generate an RPE-load	10-Hz GPS unit (STATSports Viper, Northern Ireland). High-speed (>14.4 km·h-1), sprint (>19.8 km·h-1) running distances	Chronic training loads[c] acute:chronic workload ratio[d]

(*Continued*)

Table 3. (Continued).

Studies	Measures of load		
Author, year	Internal Device/parameters	External Device/parameters	Relationship/index External/internal load ratio
Malone et al. (2018)	Borg CR-10 rate of perceived exertion (RPE) scale. RPE was multiplied by the session duration to generate an RPE-load	Global positioning technology device, with tri-axial accelerometers (MinimaxX, Team 2.5, Catapult Innovations, Australia). Tot. dist. (m), Tot. high-speed dist. (≥19.8–25.2 km·h-1), sprint dist. (≥ 25.2 km·h-1), max vel. (km·h-1), max vel. Dist. (m), max vel. exposures (n), player load (AU), player load slow (AU)	Total Distance: RPE (m·min^{-1}) Total High Speed Distance: RPE (m·min^{-1}) Player Load: RPE (AU·min-1) PlayerLoadslow: RPE (AU·min^{-1})
Marynowicz et al. (2020)	RPE: CR-10 Borg scale The sRPE was calculated by multiplying training duration (minutes)	10 Hz GPS, integrated with a 400 Hz triaxial accelerometer, and a 10 Hz triaxial magnetometer (PLAYERTEK, Catapult Innovations, Melbourne, Australia) Duration (min), Distance (m), PlayerLoad (a.u), High-speed running dist. (m), Impacts (n), Dist. in dec. (m), Dist. in acc. (m), Acc. (n), Dec. (n), Dist. (m) per min., PlayerLoad (a.u) per min., Impacts (n) per min., High-speed running dist. (m) per min., Dist. in dec. (m) per min., Dist. in acc. (m) per min., Acc. (n) per min., Dec. (n) per min.	
Maughan et al. (2021)	RPE: (Borg CR10). Each RPE score was multiplied by session duration to calculate session loads	10 Hz GPS units (Optimeye X4, Catapult Sports, Melbourne, Australia, Firmware version 7.27)/triaxial accelerometer 100 Hz Tot. dist. (TD, m), PlayerLoadTM (PL, au), low intensity running (LIR, < 14. 4 km.h-1, m), running (HIR, 19.8 24. 98 km.h-1, m), sprint (SPR, > 24. 98 km.h-1, m), acc. (>2 m.s-2 count), dec. (<-2 m. s 2, count) expressed in their absolute units and per min..	
Maughan et al. (2020)	RPE: RPE score was multiplied by session duration to obtain subjective training load	10 Hz GPS units (Optimeye X4, Catapult Sports, Melbourne, Australia, Firmware version 7.27)/triaxial accelerometer 100 Hz Tot. dist. (m), PlayerLoad (au), low intensity running (<14.4 km.h-1, m), running (19.8–24.98 km.h-1, m), sprinting (>24.98 km.h-1, m), acc. (>2 m.s-2 count); and dec. (<-2 m.s-2, count)	
Montini and Rocchi (2020)	RPE: CR-10 scale Session rating of perceived exertion values were obtained by multiplying the value of the 10-point Borg scale and the training duration in minutes	GPS device (20 Hz GPS system; GPEXE, Exelio Srl, Udine, Italy) operating at a sampling frequency of 18.18 Hz. Total energy expenditure was expressed in kJ·kg21. Such parameter represents the total external training load	Individual index between ITL and ETL parameters.

(*Continued*)

Table 3. (Continued).

Studies	Measures of load		
Author, year	Internal Device/parameters	External Device/parameters	Relationship/index External/internal load ratio
Rago et al. (2019)	RPE using Borg's category ratio scale (CR10) The overall training load was calculated by using session-RPE (s-RPE), that is calculated multiplying the RPE score (in arbitrary units) by the individual training duration (in min)	10-Hz GPS units (BT-Q1000 Ex, QStarz, Taipei, Taiwan). moderate-speed running (MSR), high-speed running (HSR), sprinting, Total high-intensity activity (THIA) was given by the sum of MSR, HSR and sprinting.	
Rossi et al. (2019)	RPE: CR-10 Borg scale. The RPE is multiplied to the duration of the training session to obtain the training load (S-RPE).	10 Hz global position system (GPS) (Playertek, Dundalk, Ireland) that is also characterized by a 400 Hz Tri-Axial Accelerometer and 10 Hz Tri-Axial magnetometers 21 kinematic velocity, 37 metabolic metabolic power, 30 mechanicals	ACWR, (EWMA)[e], Monotony Week[f], Monotony Month[g], StrainWeek[h], Strain Month[i], RPEPrevPlayer[j], RPEPrevTeam[k], RPEPrevRole[l], ID training[m]
Scott et al. (2013)	Polar Team2 Pro (Polar Electro, Kempele, Finland) (HRmax), (HRrest), Banister's TRIMP, Edwards' TRIMP Borg's Category Ratio-10 RPE scale sRPE score provided by players was multiplied by training duration (min)	MinimaxX 2.0 GPS device (Firmware version 6.59, Catapult Innovations, Scoresby, Australia) and triaxial accelerometer (Kionix: KXP94) Average speed (m/min), TD covered (m), Volume of low-speed activity (LSA; <14.4 km/h), high-speed running (HSR; >14.4 km/h), very-high-speed running (VHSR; >19.8 km/h) were recorded in metres and seconds, Player-load	
Silva et al. (2018)	A heart rate monitor (Polar Electro Inc., Lake success, NY, USA) Hrmax VO2max tHR70 time spent HR above 70% of max tHR80 time spent HR above 80% of max tHR85 time spent HR above 85% of max HRE Heart rate exertion ETL (Edwards training load) TRIMP	10 Hz GPS integrated with a 100-Hz 3-dimensional accelerometer, a 3-dimensional gyroscope, a 3-dimensional digital compass and a heart rate receiver (Viper Pod, 50 gr, 88 × 33 mm, STATSports Viper, Northern Ireland). Acc. >2 m/s2 (n), Acc. >2.5 m/s2 (n), Acc. >3 m/s2 (n), Dec. >2 m/s2 (n), Dec. >2.5 m/s2 (n) Dec. >3 m/s2 (n), Tot. dist. (m), Dist. >14.4 Km/h (m), Dist. 14.4–19.8 Km/h (m), Dist. >19.8 Km/h (m), Impacts (n), Dynamic stress load (AU), Total loading (AU), High intensity bursts (n), High metabolic load dist. (m)	

(*Continued*)

Table 3. (Continued).

Studies Author, year	Measures of load: Internal Device/parameters	Measures of load: External Device/parameters	Relationship/index External/internal load ratio
Suarez-Arrones et al. (2015)	Short--range telemetry (SPI--Pro--X, GPSports, Australia) (HRmax)	GPS unit (SPI Pro X; GPSports Systems, Canberra, Australia)5 Hz and accelerometer data at 100 Hz respectively N° of Sprints, Average time of sprint (s), Average minutes between sprint, Average Sprint Distance, Maximal Sprint Distance, Maximal Speed, RSS (Repeated-Sprint Sequence), Relative total distance (RD) (m··min--1)[n] , Work--to--rest ratio (RD >7.0 km··h--1/RD ≤7.0 km··h--1)	The performance efficiency (Effindex)[o]
Torreño et al. (2016)	HR: HR belts (Polar®, Finland) The data stored includes HR, time, speed, and distance.	GPS unit (SPI Pro X; GPSports Systems, Canberra, Australia) GPS 5 Hz frequency and accelerometer data to 100 Hz Tot. dist. covered (TD), distance covered running above moderate-speed (>13.0 km·h-1), above high-speed (>18.0 km·h-1).	The performance efficiency (Effindex)
Vallance et al. (2020)	RPE (VAS10) rating of perceived exertion of the session	10 Hz GPS system (Optimeye S5, Catapult Innovations, Melbourne, Australia) integrated with a 100 Hz triaxial accelerometer and a gyroscope. tot_dur., tot dist., total Player Load, vel[p], max_vel maximum speed in m/s	
Wiig et al. (2020)	Borg CR- 10 scale sRPE-TL was calculated by multiplying the sRPE by the session duration in minutes	GPS: 10-Hz (OptimEye S5, Firmware 7.18; Catapult Sports, Melbourne, Australia) 100 Hz. 3-dimensional accelerometer, magnetometer, and gyroscope PlayerLoad, PlayerLoad2D, Total distance (m), (high intensity events) HIE > 1.5, HSRD(>14.4 m/s), andVHSRD (>19.8 m/s), HIE > 2.5, and HIE > 3.5	
Derbidge et al. (2020)	HR monitors (T31, Polar, Finland) A novel measure of HR exertion (HRe)[q] HR max	10 Hz GPS unit integrated with a 100 Hz accelerometer (Viperpod, Statsports, Ireland) TD (m), PlayerLoadTM(PL) (au) and Explosive distance (ED) (is the cumulative distance an individual has spent accelerating and decelerating >2 m/s) (m)	E:I Ratio (au) = external load/internal load TD: HRe, PL: HRe ED: HRe

(*Continued*)

Table 3. (Continued).

Studies Author, year	Measures of load: Internal Device/parameters	Measures of load: External Device/parameters	Relationship/index External/internal load ratio
Lu et al. (2017)	s-RPE (Borg's CR-10)	5 Hz GPS unit (10 Hz interpolated to 15 Hz) with a 100 Hz, 16 G triaxial accelerometer (SPI HPU GPSports, Canberra, Australia) Total distance (m), distance by speed zones (m), mean speed (m.s-1), and body load (Arbitrary units; AU), low speed running (<14. 4 km.h-1 high speed running (>14. 5 km.h-1), and very high-speed running (>20 km.h-1)	Acute: Chronic Workload Ratio
Alemdaroğlu (2020)	RPE (CR-10 scale, Table 2) by multiplying the training duration (in minutes) by the RPE Two HR-based methods: PLR TRIMP EDW TRIMP[s]	GPS (Polar electro, Kemple, Finland). Total distance (TD) was measured, with the players' activities divided into five speed thresholds[r] , Dec. and acc. (actions thresholds were set for low-intensity, moderate-intensity and high-intensity ACC actions at 1–2, 2–3, and >3 m.sn-2; DEC actions at −1–2, −2–3, and >-3 m.sn-2)	

Legend: a: 5–6 g: light impact, hard acc., dec., or change of direction, 6–6.5 g: light to moderate impact (player collision, contact with the ground), 6.5–7 g: moderate to heavy impact. (tackle), 7–8 g: heavy impact (tackle), 8–10 g: very heavy impact (scrum engagement, tackle); and 10+g: severe impact, tackle, or collision. b: Acute Chronic Workload Ratio (calculated weekly by dividing the 1-week load of the most recent week by the 4-week rolling average weekly load). These load variables were calculated for selected external and internal load indicators. c: averaged 21-day load, the absolute change in load from the previous week; d: comprised of a 3-day acute load period and a 21-day chronic load period; e: with span = 6/EWMA with span = 28) of the 88 daily features (i.e., 21 kinematic, 37 metabolic, and 30 mechanical); f: Reflection of training variation across a week (6 days). It is the ratio between training loads (i.e., product between duration and rate of perceived exertion (RPE)) mean performed in one week and its standard deviation; g: Reflection of training variation across a month (28 days). It is the ratio between training loads mean performed in one month and its standard deviation; h: Reflection of overall training stress from the week. It is the product between the training loads mean and the Monotony Week; i: Reflection of overall training stress from the week. It is the product between the training loads mean and the Monotony Month; j: Mean of the RPE provided by a player in the previous week (6 days) Win-Draw-Loss Results of previous match; k: Mean of the RPE provided by the team in the previous day; l: Mean of the RPE provided by the players with the same role in the previous day; m: Seven Boolean features reflect the day of the week when players perform a training was performed; n: RD: 0.1 -- 7.0 km··h--1 (m··min--1), RD: 7.1 -- 13.0 km··h--1 (m··min--1), RD:13.1 -- 18.0 km··h--1 (m··min--1), RD:18.1 -- 21.0 km··h--1 (m··min--1), RD: >21.0 km··h--1 (m··min--1), RD: >13 km··h--1 (m··min--1), RD: >18 km··h--1 (m··min--1); o: was calculated as [mean speed in m··min--1/mean exercise intensity (%HRmax)]; p: B1 distance covered between 0 and 1 km/h, B2 distance covered between 0 and 6 km/h, B3 distance covered between 6 and 15 km/h, B4 distance covered between 15 and 20 km/h, B5 distance covered between 20 and 25 km/h, B6 distance covered at more than 25 km/h, acc_B2 number of accelerations above 2 m/s2, acc_B3 number of decelerations above 2 m/s2; q: HRe represents the total volume of cardiovascular exertion an individual will experience relative to time; r: walking (.1–7.1 km.h-1); jogging (jog) (7.2–14.3 km.h-1); running (run) (14.4–19.7 km.h- 1); high-speed running (HSR) (19.8–25.1 km.h-1); sprinting (>25.1 km.h-1); s: method, which determines TL by calculating the product of the accumulated training duration (minutes) in 5 HR zones applying a coefficient relative to each zone (50–60% of HRmax = 1; 60–70% of HRmax = 2; 70–80% of HRmax = 3; 80–90% of HRmax = 4; 90–100% of HRmax = 5) and then summing the result.

created a workload index (Effindex) as the ratio between equivalent distance and TRIMPmod (modified training impulse that describes time spent in certain HR zones multiplied by a weighting factor) (Grünbichler et al., 2020). This index, analysed during matches, was influenced by sprinting distance, TD, Polar training load (PTL), and training duration (Grünbichler et al., 2020). Additionally, Suarez-Arrones et al. (2015) and Torreño et al. (2016) used Effindex to quantify the match stimuli dose-response (Suarez-Arrones et al., 2015; Torreño et al., 2016). These authors defined Effindex as the ratio between mean speed in m·min^{-1} divided mean exercise intensity (%HRmax) for every entire first half of the match (Suarez-Arrones et al., 2015; Torreño et al., 2016). These authors detected that the higher the overall running performance during the full match was the higher Effindex was (Suarez-Arrones et al., 2015; Torreño et al., 2016). Additionally, Derbidge et al. (2020) proposed three different ratios to assess the players' loads: TD/HRe, PL/HRe, and ED/HRe (Derbidge et al., 2020). Moreover, Malone et al. (2018) used EL/IL ratios founding that, during trainings, players with a Z-score of −1 reduced both high-speed and maximal running (Malone et al., 2018).

Predicting internal load

Five studies aimed to predict IL using EL indicators (Geurkink et al., 2019; Jaspers et al., 2018; Lacome et al., 2018; Alessio; Rossi et al., 2019; Silva et al., 2018). Two studies predicted HR with standard statistical analysis (Lacome et al., 2018; Silva et al., 2018) and three studies predicted RPE from EL variables using ML (Geurkink et al., 2019; Jaspers et al., 2018; Alessio; Rossi et al., 2019). The first two studies used GPS indicators for HR and related measures prediction (TRIMP) (Lacome et al., 2018; Silva et al., 2018). Lacome et al. (2018) found a large correlation between HR and GPS variables detecting that the greatest predictors were the force load and the mechanical work (Lacome et al., 2018). Moreover, another study showed that total number of accelerations (>2.5 m*s^{-2}) and high-intensity repeated efforts are predictor of TRIMP and %tHR80 (Silva et al., 2018). The remaining three studies applied ML approaches.

Association between external and Internal Load indicators and injuries

Three studies investigated EL and IL associations with non-contact muscular injuries (i.e., acute and overuse) (Jaspers et al., 2018; Lu et al., 2017; Malone et al., 2018). They found that IL and EL indicators were positively related to injuries (Jaspers et al., 2018; Lu et al., 2017; Malone et al., 2018). High Acute Chronic Workload Ratio (ACWR) for S-RPE (Jaspers et al., 2018; Lu et al., 2017), total high speed running (THSR) distance >20 km*h^{-1} (Jaspers et al., 2018), large and rapid weekly changes in HSR and SR distances (Malone et al., 2018), and higher cumulative HSR and SR workloads (Malone et al., 2018) were found to be related to an increased IR. Conversely, medium levels of ACWR for acceleration effort (ACCeff, >1 m*s^{-2}), DECeff, S-RPE (Jaspers et al., 2018), moderate HSR, and sprint running (SR) distances (Malone et al., 2018) were found to be related to a decreased IR. Moreover, it was found that high physical fitness levels were related to a lower IR (Malone et al., 2018). Furthermore, Lu et al. (2017) found that S-RPE was high in all 3 weeks prior the injury week (Lu et al., 2017). Despite promising results through correlations were presented,

Table 4. Machine learning: data analysis characteristics.

Authors, year	Outcome Variable	Predictor Variable	Analysis procedures	Data pre-processing	Features selection	Machine Learning Classification Methods
Geurkink et al. (2019)	Session Rate of Perceived Exertion (S-RPE)	GPS data: N° 70 External Load Indicators (ELIs) Internal Load Indicators (ILIs) Individual Characteristics (ICs) Supplementary Variables (SVs)	5-fold cross-validation, on average 50 and 13 training sessions were used in respectively the training and test set in each fold.	No	Gradient Boosting Machines, One-hot encoding, Loose accuracy approach	Generalized Additive Models, Multivariate Adaptive Regression Splines, Decision Tree, Random Forest, Linear Regression, Support Vector Regression
Jaspers et al. (2018)	RPE	GPS data: N° 67 External Load Indicators (ELIs)	Experiment 1: data from the first season served as the learning set and the data from the second season as the testing set; Experiment 2: Each season's data was subdivided temporally such that the first 75% served as the learning set and the last 25% served as the testing set	No	Least absolute shrinkage and selection operator (LASSO)	Artificial neural networks (ANN), (LASSO), Baseline
Rossi et al. (2019)	RPE and Session Rate of Perceived Exertion (S-RPE) (observed and the predicted)	GPS data: N° 182 individual features and 11 contextual	The dataset was divided into 3 folds. For each fold, 90% of the dataset was used as a training set and 10% of it as a test set. Classifiers were validated on the remaining 80% of the dataset with a 3-fold stratified v cross-validation strategy, stratified by player identification (ID) Each sample in the dataset was tested once, using a model that was not fitted with that sample.	No	Recursive Feature Elimination with Cross-Validation (RFECV)	Decision Tree Regression (DT), Random Forest Regression (RF), Epsilon-Support Vector Regression (SVR), Logistic Regression (logit), K-Nearest Neighbors (KNN), Linear Decision Tree

(*Continued*)

Table 4. (Continued).

Authors, year	Outcome Variable	Predictor Variable	Analysis procedures	Data pre-processing	Features selection	Machine Learning Classification Methods
Vallance et al. (2020)	Injury at 1 week Injury at 1 month.	Personal Features (n°5) GPS device: (n° 12) Pre-Session Questionnaire (n° 7) Post-Session Questionnaire (n° 3)	Hyperparameters were tuned using a Bayesian optimization procedure according to the different evaluation metrics. 10-fold cross-validations using 4 measures of predictive performance according to the two predictive horizons previously mentioned (1 week and 1-month). This process was repeated 10 times to check the stability of the model's performances.	Data imputation: imputation by mean (for numerical variables) and frequency (for categorical variables) was performed upstream the model comparison was made.	No	K-Nearest Neighbours (KNN), Linear Discriminant Analysis (LDA), Logistic Regression (logit), Ridge classifier (Ridge), Gaussian Naive Bayes classifier (GNB), Classification tree (tree), Random forest (forest), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), eXtreme Gradient Boosting (XGB)

a predictive complex model (such as ML) could be a better approach to determine predictions about IR and other training components.

Predicting injuries through external and internal load indicators

Only a study, conducted by Vallance et al. (2020), investigated the use of ML predictive models for IR considering both IL and EL over both 1-week and 1-month period (Vallance et al., 2020). Considering 1-week injury prediction, results as satisfaction, pleasure, and RPE were the most relevant for precision (i.e., how many of those injuries predicted really happen) and recall (i.e., of all injury examples, how many of those we correctly predicted) (Vallance et al., 2020). As concern 1-month injury prediction, author detected that current pain was the most relevant variable for IR prediction, while average pain in the last 2–3 weeks was the most accurate (i.e., how many examples we correctly predicted) predictor (Vallance et al., 2020). Also, age, weight, and shape-related features were as much relevant for IR accuracy, while worries, fatigue sensations, and EL variables were the most relevant IR precision (Vallance et al., 2020). Summarily, for determining IR factors pre-session questionnaires (to assess sleep quality, fatigue, shape, and mood) and post-session questionnaires (to evaluate satisfaction and pleasure) and RPE were the most suitable indicators to predict IR (Vallance et al., 2020).

Discussion

The first aim of the current systematic review and meta-analysis was to investigate the interaction between internal and external training load indicators, and, consequently, to find the relationship between training load (TL) indicators (both EL and IL) and injuries in professional soccer players.

In general, studies demonstrated a positive correlation between IL and EL indicators. In detail, RPE, S-RPE, and HR were associated with different EL indicators. New indexes or ratios (integrating EL and IL) to enhance knowledge regarding TL and fitness status were also implemented. Moreover, a positive relationship between EL and IL indicators and IR was also observed in only three studies (Jaspers et al., 2018; Lu et al., 2017; Malone et al., 2018). Furthermore, efficient prediction of HR (using traditional statistical methods) (Lacome et al., 2018; Silva et al., 2018) and RPE/S-RPE (using ML) were found (Geurkink et al., 2019; Jaspers et al., 2018; Alessio; Rossi et al., 2019). Only one study was found that successfully predicted IR through ML approaches (Vallance et al., 2020). The results showed that ML approaches are poorly used in professional soccer to predict the effect of training (IL responses to a given EL) and IR.

Relationship between external and internal load indicators

A general positive correlation between IL and EL indicators were detected in previous studies (Miguel et al., 2021; Rago et al., 2020). Casamichana et al. (2013) reported that PL and TD were significantly correlated with HR and derived measures (e.g., EDW TRIMP) in elite soccer players, and with S-RPE in semi-professional soccer players (Casamichana et al., 2013). Only one included study found a small positive correlation using total body load (TBL, derived by acceleration zone forces provided in 'g' force) and S-RPE (Gomez-

Table 5. Machine learning: study results.

Author, Year	Performance Measures	Predictive Performance of ML Methods	Measure of Feature Importance	Relevant Predictors
Geurkink et al. (2019)	Accuracy: the mean absolute error (MAE) and Root Mean Squared Error (RMSE).	ELIs, since total distance, total time and number sprints are among the strongest predictors. Total duration and the number of sprints were also strong predictors	No	ELIs, since total distance, total time and number sprints are among the strongest predictors.
Jaspers et al. (2018)	Mean Absolute Error (MAE) was used to assess a model's predictive performance.	The LASSO model made more accurate predictions than the ANN model. The group models resulted in equivalent or even more accurate predictions of the reported RPE values than the individual models.	LASSO only selects a subset of the ELIs, those with a non-zero coefficient, to be included in the model.	Machine learning techniques are able to predict RPE based on a large set of ELIs. These techniques can be applied to support expert knowledge for the selection of key ELIs such as decelerations.
Rossi et al. (2019)	Root Mean Squared Error (RMSE) Mean of Absolute Difference (MAD) Bland – Altman analysis	Decision Tree The ordinal regressor is the best classifier in describing both the players' RPE and S-RPE.	No	Predicted RPE and S-RPE are higher than the observed ones when players perceived low RPE while it is lower when the players perceived a high RPE. External loads reflect RPE and S-RPE. Inconsistent relationship between extreme values of RPE and training workload. The distance to the matchday affect the players 'perceived exertion. RPE and S-RPE are strongly affected by the volume of the total training and weakly affected by the training intensity.

(*Continued*)

Table 5. (Continued).

Author, Year	Performance Measures	Predictive Performance of ML Methods	Measure of Feature Importance	Relevant Predictors
Vallance et al. (2020)	Accuracy Precision Recall Area Under the ROC Curve (AUC)	The best performances were obtained with the KNN, tree, forest and XGB classifiers. It is also noticeable that higher performance can be obtained for 1 month predictions with maximum values around 97% for all metrics. The different features related to satisfaction, pleasure and RPE appear to be the most important in terms of precision and recall for 1-week injury prediction. Overall, pain and shape related features as well as personal features (age and weights) appear to be the most important features for accurate injury risk detection (i.e., to get high recall values) and pain; worry as well as fatigue and external load variables are important to get reliable 1-month injury prediction (i.e., with high precision values).	The features importance weights are calculated with two different approaches: CART impurity decrease which is available only for tree-based classifiers and features permutation scrambling sensitivity which can be computed on any predictive model.	For 1-week injury prediction, internal load features data were more accurate than external load features while for 1-month injury prediction, the best performances of classifiers were reached by combining internal and external load features.

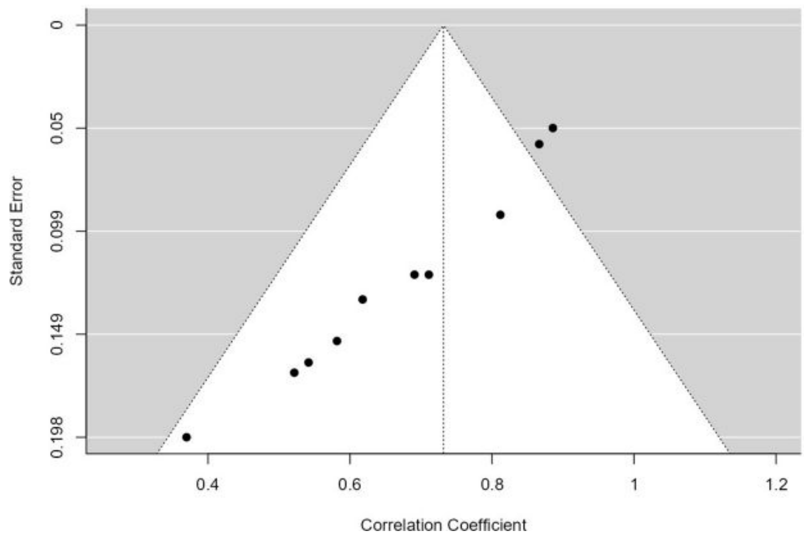

Figure 2. Funnel plot TD and S-RPE.

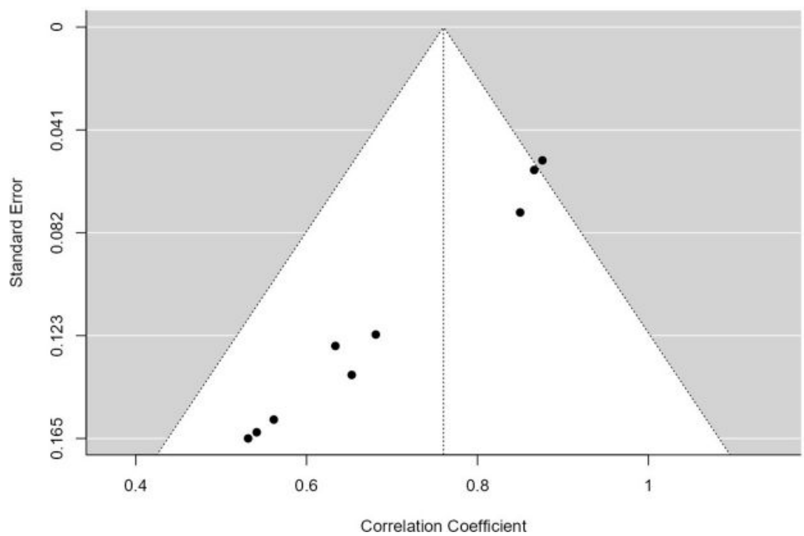

Figure 3. Funnel plot PL and S-RPE.

Piriz et al., 2011). This result could be due to TBL, in their computation, does not consider motion mode and influence of specific actions on energy expenditure (Gomez-Piriz et al., 2011).

Three studies detected a positive correlation between different additional indicators and EL and IL such as the Hooper Index (HI) score (using a scale that includes fatigue, stress, muscle soreness, and quality of sleep) (Oliveira et al., 2019, 2020) and creatine kinase (CK) levels (Oliveira et al., 2019) with new specific S-RPE indexes relative to limbs effort (S-RPE-L) and breathlessness (S-RPE-B).

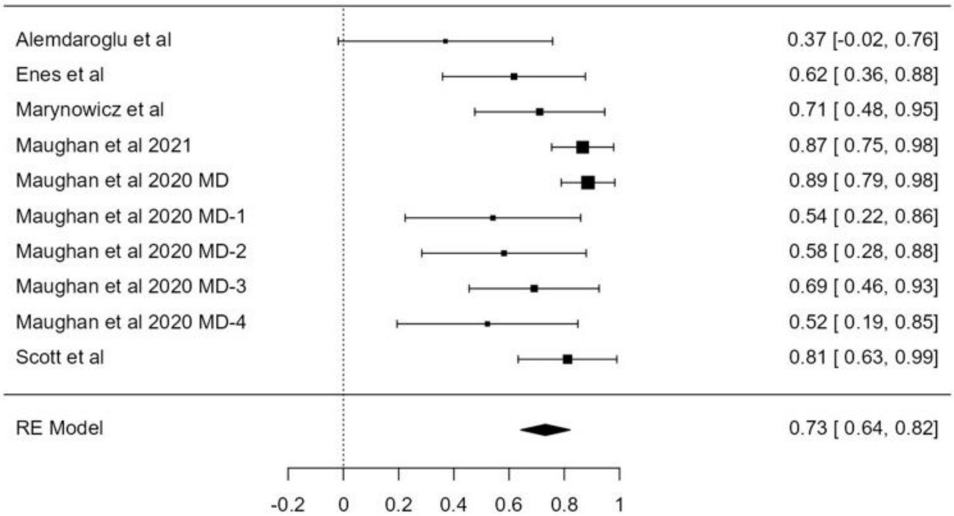

Figure 4. Correlation between S-RPE and TD.

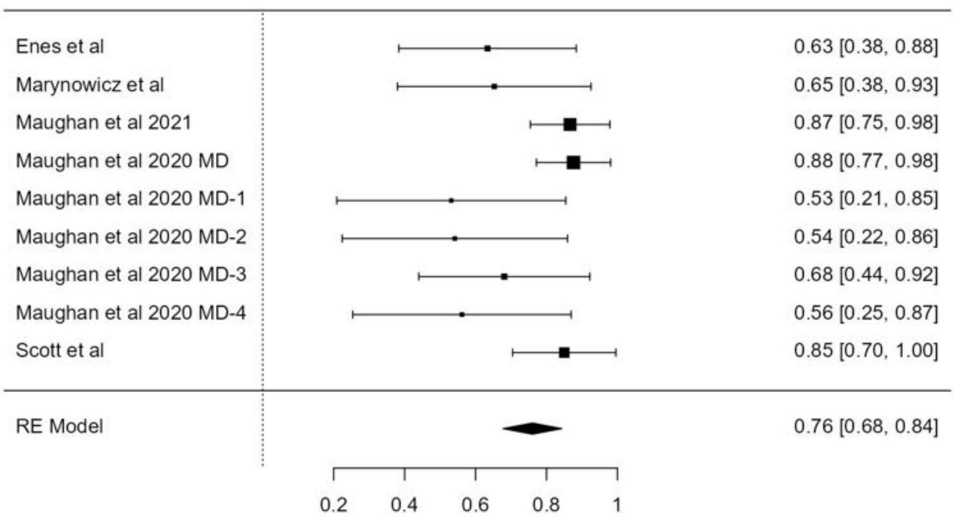

Figure 5. Correlation between S-RPE and PL.

The findings of the review showed that S-RPE and HR-derived measures were more associated with volume indicators (i.e., TD, LRI) than intensity indicators. In particular, it was found that the correlation is lower between IL and training volume when intensity thresholds increase (Rago et al., 2019; Wiig et al., 2020). Moreover, Scott et al. (2013) reported that cardiac response is more associated with distance covered at low speeds compared to high speeds distance (Scott et al., 2013; T. J.; Scott et al., 2013). This could be due to the role of anaerobic metabolism, mostly involved during short high-intensity activities, which in turn can lead to HR underestimation (Scott et al., 2013; T. J.; Scott et al., 2013). Similarly, other authors referred to the intermittent nature of soccer to justify the lower association between S-RPE and intensity, whereby it can result in the underestimation of RPE and S-RPE (Gaudino et al., 2015; Scott et al., 2013). Moreover, despite it is widely used, it has been speculated that RPE could not be specific to assess IL in soccer training tasks. In addition, RPE could be underestimated in specific-ball drills, and it seems to be more related to non-specific metabolic activities in which HR has a linear response (Gaudino et al., 2015; Scott et al., 2013).

The exclusive use of speed-derived indicators to assess intermittent activities should be limited. In fact, only one of the included studies reported that HSR distance, distance per minute, and decelerations distance per minute were significantly associated with RPE (Marynowicz et al., 2020).

According to our results, PL (derived from accelerations) is largely associated with S-RPE (Abbott et al., 2019; Alemdaroğlu, 2020; Gallo et al., 2015; Gaudino et al., 2015; Lovell et al., 2013; Scott et al., 2013; T. J.; Scott et al., 2013). As well, Gaudino et al. (2015) reported that metabolic power (derived by speed and accelerations) is more appropriated than only speed to assess performance demands, emphasizing again the role of accelerations (Gaudino et al., 2015).

The use of a combination of EL indicators is better related to S-RPE than using only one parameter per time to monitor the different types of training in soccer (Gaudino et al., 2015; Marynowicz et al., 2020; Maughan et al., 2020). Nevertheless, integrated approaches considering both EL and IL indicators were used to better assess TL in professional soccer.

External and internal load new indexes

The results of the current review showed that in professional soccer new indexes or ratios that integrated IL and EL were adopted to assess performance. As a matter of fact, one study used ratios between only EL parameters to monitor players' performance (training/match ratio = weekly load/match demands) (Clemente et al., 2019), while other studies integrated both EL and IL indicators (Akubat et al., 2014, 2018; Delaney et al., 2018; González-Fimbres et al., 2019; Lazarus et al., 2017; Malone et al., 2016; Reinhardt et al., 2020; Taylor et al., 2020). Although these studies allowed an integrated approach (using both EL and IL), they could not globally assess the TL. Indexes only explain the individual internal response to a given EL. Moreover, none of these indexes were used to predict IR.

Predicting internal load (HR) through external load

Five of the included studies investigated the possibility of predicting IL through EL indicators (Geurkink et al., 2019; Jaspers et al., 2018; Lacome et al., 2018; Alessio; Rossi et al., 2019; Silva et al., 2018). Specifically, the prediction of HR through EL was investigated using traditional statistical analysis to assess players' fitness and readiness (Lacome et al., 2018). HR values are more reliable to monitor continuous running activities (on long distances) than soccer performance. Indeed, HR slowly adjusts to stimuli during repeated short bouts of high-intensity activity (general and sport-specific with and without ball) causing an inappropriate underestimation (Scott et al., 2013). Hence, monitoring or predicting HR is not enough to determine players' efforts (i.e., TL). As highlighted in the literature, traditional statistical analysis is less applicable to achieve appropriate prediction. ML approaches are probably more useful, although they are still underutilized in professional soccer (Geurkink et al., 2019; Jaspers et al., 2018; Alessio; Rossi et al., 2019; Vallance et al., 2020).

Association between external and Internal Load and injuries

Our results showed that a relationship between EL and IL with non-contact IR could exist. In fact, the association between IR and TL was largely investigated in soccer (Abbott et al., 2019; Arazi et al., 2020; Bowen et al., 2020; Laura; Bowen et al., 2017; Coppalle et al., 2021; Delecroix et al., 2018; Fuller, 2018; Griffin et al., 2020; Howle et al., 2020; Jaspers et al., 2018; Lu et al., 2017; Malone et al., 2018, 2017; McCall et al., 2018, 2018; Nobari et al., 2020; Raya-González et al., 2019; Sedeaud et al., 2020; Suarez-Arrones et al., 2020). However, Impellizzeri et al. (2020) reported that the use of TL data in injury prevention is not widely supported by evidence because no author has yet established 'the causal link between training/match load and injuries' (Impellizzeri et al., 2020). Indeed, answers to the 'injury problem' are difficult to find considering only the TL measures (or a specific EL or IL variable). Despite these important considerations, the TL could play an important role in the occurrence of injuries because they occur when players are exposed to a specific load (Buchheit & Laursen, 2013).

Machine learning approach for predictions

Only one study, conducted in professional soccer, integrated EL and IL to predict injury (Vallance et al., 2020), while three studies predicted IL considering EL indicators (Geurkink et al., 2019; Jaspers et al., 2018; Alessio; Rossi et al., 2019). Due to the large and multi-dimensional dataset nowadays available in sports, ML approaches are suggested for events' prediction (Oliver et al., 2020). We noted different ML methods used, as reported in Table 4 and Table 5. However, the most used method was the Decision Tree classifier (Van Eetvelde et al., 2021). Claudino et al. (2019) also reported that the other ML models for IR prediction frequently used in team sports were artificial neural networks, support vector machine, and Markov process (Claudino et al., 2019).

Machine learning, training load, and RPE/S-RPE prediction

The scientific literature showed that RPE/S-RPE prediction is feasible by assessing EL using different ML approaches (Geurkink et al., 2019; Jaspers et al., 2018; Alessio; Rossi et al., 2019). Actually, Wiig et al. (2020) stated that EL high-intensity variables have been better used in multiple regression analysis to predict RPE and S-RPE (Wiig et al., 2020). Similarly, two other studies found an accurate prediction ability to assess IL by EL using ML models (Bartlett et al., 2017; Gaudino et al., 2015). Consistently to our results, ML analysis revealed that session distance, HSR, and distance run each minute were the other most predictive variables for RPE prediction (Bartlett et al., 2017).

The prediction can be a useful tool to manage players' training because IL may be affected also by psychological aspects (Abbott et al., 2019; Foster et al., 2017; Rago et al., 2020; Vallance et al., 2020). Specifically, it is known that RPE is affected by the workload performed in the previous training weeks, while S-RPE reflects the workload of the current training sessions (Alessio Rossi et al., 2019). Thus, the psychological tensions (e.g., the distance to the official games) could be fundamental aspects affecting both the RPE and S-RPE (Alessio Rossi et al., 2019).

Machine learning, training load, and injury prediction

The ability to predict injuries in professional soccer through TL indicators was investigated by few articles (Bacon & Mauger, 2017; Rossi et al., 2018; Vallance et al., 2020). Only a study that predicted IR using both EL and IL through ML was found (Vallance et al., 2020). Authors detected that for 1-week IR prediction, IL features were more accurate, while for 1-month IR prediction, the best performance was reached combining IL and EL (Vallance et al., 2020). Another study found that, using linear regression, the distance covered in training and matches can impact on the incidence of overuse injury (Bacon & Mauger, 2017). Similarly, Venturelli et al. (2011), using Cox regression, showed that previous injuries, ΔJH (jump index), and height were negatively correlated to thigh-strain occurrence (Venturelli et al., 2011). Other studies investigated IR prediction using ML. In this vein, Rossi et al. (2018) predicted injuries in soccer players via a multi-dimensional analysis in which only GPS measurements were applied (Rossi et al., 2018). Promising results were also found in elite youth football players, applying anthropometric, motor coordination, and physical performance measures in ML analysis (Rommers et al., 2020). Moreover, another study conducted in elite soccer players examined whether the use of ML can improve the capability of different neuromuscular tests to identify IR (Oliver et al., 2020). The ML model was very sensitive to asymmetry, knee valgus angle, and body size in youth football players (Oliver et al., 2020). Therefore, it was suggested by those studies that implement ML for injury prevention in sports that it should be developed with a high methodological quality (Raya-González et al., 2019; Van Eetvelde et al., 2021).

Conclusion

Our systematic review showed that EL and IL are widely employed for monitoring TL in professional soccer players. We observed that associations between IL and EL and their relationship with injuries could exist. In detail, RPE, S-RPE, and HR were associated with different EL indicators. A positive relationship between EL and IL indicators and IR was also observed. Moreover, new indexes or ratios (integrating EL and IL) to enhance knowledge regarding TL and fitness status were also implemented.

Comparing statistical analysis approaches, ML seems to be the most suitable for IR prediction even if only one study used ML approach to predict injury risk considering both EL and IL indicators. However, determining the cause-effect mechanism of multifactorial phenomena seems not feasible. Important aspects are missing, including the cognitive and emotional load, load due to the use of the ball, and all neuroendocrine factors. Moreover, although the RPE is widely used in both scientific and practice field to monitor the IL, we think that is not sufficient for soccer.

Further studies using ML approaches are recommended to better understand the unclearly established relationship between loads and injuries in professional soccer, also by developing a formula that included both IL and EL to predict injuries with ML.

There are some methodological issues for the current systematic review for which the findings of this study should be considered. First, most of the included studies used observational approaches. Additionally, a complete overview of the different ML approaches is difficult due to the complexity and variety of the methods used (Claudino et al., 2019; Kotsiantis et al., 2007; Van Eetvelde et al., 2021).

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