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Ecological momentary assessment of the stress-recovery process through technology mHealth in sports: a scoping review

Joel Guillen Cots^{1,2*} , Lluís Capdevila^{1,2} , Josep-Maria Losilla³ and Eva Parrado^{1,2}

Abstract

Background This scoping review aimed to identify how Ecological Momentary Assessment methodologies using mobile health technologies are applied to monitor training load and the stress-recovery process in athletes. The review focused on mapping the technologies and methodologies employed, examining their use in team and individual sports, and exploring the relationships between external and internal load measures, as well as the extent to which subjective and objective indicators are integrated within monitoring systems.

Method Following PRISMA-ScR guidelines, a systematic search across four databases identified 71 studies published between 2012 and 2025 that met eligibility criteria.

Results Half of studies focused on elite or international athletes (50.68%), with a predominance of male participants (63.4%). Team sports represented the vast majority (87.3%), particularly soccer (42.5%) and basketball (15.1%). A wide range of technologies was reported, from advanced wearable systems to smartphone applications, with external load commonly tracked via GPS and accelerometry, and internal load through heart rate indices, Training Impulse, Rating of Perceived Exertion, and wellness questionnaires. However, only seven studies directly compared subjective and objective measures of internal load, revealing partial convergence and underscoring the value of multimodal monitoring strategies.

Conclusions Ecological Momentary Assessment-based mobile health systems provide valuable insights into athlete load and recovery, but important gaps remain in individual sports, female representation, and recovery-related behaviors. Future research should prioritize methodological transparency, broader inclusion of populations, and the adoption of emerging non-invasive biosensing technologies to achieve a more holistic and ecologically valid model of athlete monitoring.

Keywords Athlete monitoring, EMA, mobile health, fatigue, well-being, training load

*Correspondence:

Joel Guillen Cots
joel.guillen@uab.cat

¹Laboratory of Sport Psychology, Department of Basic Psychology,
Universitat Autònoma de Barcelona, Bellaterra, Spain

²Sport Research Institute, Universitat Autònoma de Barcelona, Bellaterra,
Spain

³Department of Psychobiology and Methodology of Health Sciences,
Faculty of Psychology, Autonomous University of Barcelona, Bellaterra,
Barcelona, Spain



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Background

During physical activity, athletes face situations that can affect their performance. These situations may be related to the demands of the sport itself or to external issues, causing physical or psychological fatigue. Conceptually, fatigue can be understood both as a progressive decrement in performance over time (fatigability) and as the subjective experience of needing rest or perceiving a discrepancy between the effort invested and the performance achieved [1]. The inability to sustain athletic performance, together with inadequate rest and recovery, may constitute a significant source of stress for athletes. To preserve well-being and sustain optimal performance, athletes must therefore prioritize recovery. Effective management of the stress–recovery process can only be achieved by considering all relevant factors, including training characteristics, sleep, nutrition, social environment, and health status, among others, and should consequently be approached as holistically as possible [2–4].

Within sport science, a central objective is to monitor and interpret athletes' status to mitigate injury, illness, and non-functional overreaching [2, 5] and to ensure day-to-day readiness [6]. The work performed in training and competition is typically summarized as training load [7] and comprises both external and internal components [8]. Measuring the external load gives information about the work done by the athletes, while measuring the internal load relates to knowing the stress that the body has been subjected to [9]. There are several parameters used to evaluate both internal and external load. Parameters of time, distance, power output or composite methods derived from acceleration (Player Load) correspond to external load [10, 11], while blood lactate, oxygen uptake, heart rate indices, rating of perceived exertion (RPE) or wellness questionnaires correspond to internal load, among others [9, 10]. Both measures are important; however, the key to determining whether an athlete is fatigued lies in the relationship between external and internal load [6] and in the integration of these measures within a holistic framework of fatigue assessment, thereby enabling a more individualized training process [12]. For example, high internal load levels when the external load is low, may indicate a lack of adaptation to training. Moreover, athletes can be in a state of under-recovery not only due to high stress but also as a result of insufficient recovery [3]. To restore the resources that have been invested, athletes need to engage in recovery strategies, which may be either physical or psychological. Periodization and monitoring of recovery is important for optimal athlete performance [13], as athletes spend more time recovering than training itself [14].

Technological advancements have enabled the creation of comprehensive monitoring systems that offer detailed insights into an athlete's performance and health

[15, 16]. Mobile health (mHealth) is the use of mobile and wireless technologies (e.g., smartphones, apps, and wearable sensors) to deliver health-related services and to collect health data in real time [17]. The combination between these devices and advanced analytics software has become a cornerstone of contemporary training programs. These tools provide real-time data within athletes' natural environments and thereby facilitate Ecological Momentary Assessment (EMA). EMA refers to the repeated, real-time assessment of individuals' behaviors, experiences, and physiological states in their everyday contexts, reducing recall bias and increasing ecological validity [18]. This methodological approach enables coaches and sports scientists to obtain rich, timely information to guide decision-making regarding athletes' status [11, 19]. This is especially important in athlete monitoring, as EMA is well suited to capturing the dynamic nature of stress and recovery, which can fluctuate across days and within the same day in response to training, competition, and contextual demands [3]. Furthermore, with the increasing reliance on objective metrics, recent perspectives emphasize the need to integrate subjective monitoring to achieve a more holistic understanding of athletes' states [20]. Nevertheless, sports staff generally prefer assessment tools that are simple, easy to use, time-efficient, non-invasive, and non-fatiguing for athletes [5, 21]. Given the wide variety of training load measures and monitoring systems available, there is a need-to-know not only which measures and technologies are the most used but also in what context, for which type of sport, and which might be the most suitable.

Previous studies have addressed this need by conducting systematic reviews to classify the measures used to examine the state of athletes [22–25] and the technological devices employed for monitoring [26–28]. In their meta-analysis, McLaren et al. [29] reported associations among wearable-derived variables, including links between heart-rate-based training impulse (TRIMP) and total distance covered. More recently, Helwig et al. [30] summarized wearable-based relationships between external and internal indicators, highlighting the frequently studied pairing of session RPE (sRPE) with accelerometry-derived load. However, both reviews primarily focused on team sports athletes, overlooking individual sports athletes and considered invasive technology for the monitoring of the internal parameters. Notably, female athletes remain underrepresented in the athlete-monitoring literature, potentially limiting the generalizability of existing findings [31]. Accordingly, applying monitoring frameworks derived primarily from male athletes may be problematic, as sex-specific physiology and hormone fluctuations can influence commonly used internal-load and recovery markers such as HRV [32].

For this reason, the objective of this scoping review is (a) to identify EMA methodologies through mHealth technology to monitor the training load or the stress-recovery process in athletes, (b) to classify the methodologies and technology used according to individual or team sports, (c) to describe the relationship between external parameters (distance, accelerations, decelerations, etc.) and internal parameters (physiological, cardiovascular, neuromuscular, subjective, etc.), and (d) to analyze the relationship between subjective and objective parameters of the internal measures.

Method

The study was carried out in conformity with the PRISMA Extension for Scoping Reviews (PRISMA-ScR) recommendations [33]. The protocol for this scoping review was previously registered at the International Platform of Registered Systematic Review and Meta-Analysis Protocols (INPLASY) with the registration number: INPLASY202330089 [34]. In accordance with the principles of open science, all datasets and supplementary information referenced in the following sections are publicly available in the CORA repository and can be accessed at <https://doi.org/10.34810/data2613>.

Search strategy

The search for the primary studies was carried through four databases: APA PsycInfo by ProQuest, PubMed by US National Center for Biotechnology Information, Web of Science Core Collection by Clarivate, and SPORTDiscus by EBSCOHost.

The search strategy followed the Peer Review of Electronic Search Strategies (PRESS) [35] and PRISMA for Searching (PRISMA-S) guidelines [36], and consisted of three groups of search terms referring to: (a) sports and physical activity, (b) wireless/wearable technologies and mobile applications, and (c) training load or stress-recovery state. We also added a fourth group of terms preceded by the Boolean operator NOT to improve the specificity of the search strategy and exclude injured athletes.

The generic search expression used was: ("sport\$" OR "athlet*" OR "exercis*" OR "physical activit*") AND ("mobile health" OR "mHealth" OR "eHealth" OR "e-Health" OR "wearable\$" OR "wireless technolog*" OR "microsensor\$" OR "microtechnolog*" OR "GPS" OR "accelerometer" OR "training monitoring" OR "mobile app*" OR "smartphone app*") AND ("stress" OR "fatigue" OR "load" OR "workload" OR "overtraining" OR "under-recovery" OR "staleness" OR "overreaching" OR "rest" OR "recovery" OR "exhaustion" OR "tiredness" OR "readiness") NOT ("Injur*"). The specific syntax adapted to each of the bibliographic databases consulted is available in the supplementary file "Database-specific search syntax".

The search was performed on 6 April 2025 and was restricted to publications from 2012 to 2025. The year 2012 was selected because it marks a turning point in smartphone use (e.g., smartphone adoption in Europe reached approximately 47.6% [37] and in the systematic use of mobile devices to promote physical activity [38]. Only articles published in English or Spanish were included.

Study selection

Eligible studies involved athletes aged 13–65 (youth, amateur, or high-performance) in team or individual sports, using EMA via mHealth to monitor training load or stress–recovery, with experimental, single-case, cohort, or cross-sectional designs. We excluded studies on injured athletes; validation/reliability papers without monitoring; one-off lab/field tests without longitudinal monitoring; and those measuring only internal or only external load or lacking their relationship. Full criteria are detailed in the previously published protocol [34].

References identified by the search strategy were entered into Mendeley bibliographic software, and duplicates were removed by one reviewer (JG). Two reviewers (JG & EP) independently screened the articles in two phases. In the first phase, the inclusion and exclusion criteria were applied to all titles and abstracts. Articles meeting the inclusion criteria were chosen, and in cases where decisions could not be reached based solely on the title and abstract, the complete article was retrieved. In the second phase, the full-text inclusion and exclusion criteria was assessed. A third author (LC) solved discrepancies during the process. Cohen's kappa coefficient was calculated to measure the agreement between the reviewers during the reviewing process.

Data management/data extraction

A data extraction protocol was designed for the selected studies (supplementary file "Data extraction"). The extracted information included:

- General information: title, author, year of publication and journal.
- Research design.
- Characteristics of the target population of the study: number of participants, age, gender, sport level and sport type.
- The monitoring process: technology, stress-recovery variables (based on Bourdon et al. [10], periodicity and the main results.

Since our exploratory review was designed to be exploratory and descriptive, which differs fundamentally from the analytical and evidence-based approach of systematic

reviews, no formal assessment of the quality of the included studies was performed [39].

Data analysis

A narrative synthesis was performed to analyze and present the results. Information extracted from the included studies was organized in tables and complemented by graphical representations to facilitate the identification of patterns and trends. The analysis of the results was carried out taking into account the variability that could be related to the following moderating variables: year of publication, gender, age, analysis approach and geographical origin of the study, type of sport and whether it was classified as an individual or team sport, and the types of portable devices used to monitor the internal or external load variables in each study.

Results

Study selection

The search identified a total of 9175 articles across the four databases. After eliminating duplicate studies and screening by title and abstract, 435 studies were selected for review based on their full text. Ultimately, 71 studies met the eligibility criteria and were included in the review (see Fig. 1). A very good agreement between the reviewers was shown, as the Cohen's kappa coefficient was 1 in the first phase and 0.836 (I.C 95%: 0.746–0.925) in the second phase.

Characteristics of the selected studies

Figure 2 shows the number of papers published every year since 2012. The years with more publications of studies included were 2021 ($n=16$) and 2019 ($n=10$).

Regarding participant characteristics, most studies included only male athletes ($n=1120$), and only 21 (29.57%) focused on female athletes ($n=323$). Additionally, four studies included mixed-gender participants. As for the number of participants, most studies included between 11 and 30, and only 11 studies (15.49%) had more than 30 participants. Regarding age distribution, according to the available data (with seven articles not providing this information), the reported mean ages range from 14.14 to 38.85 (with corresponding standard deviations ranging from 0.40 to 8.88). Regarding competitive level [40], approximately half of the athletes were classified as elite or international, most of the remaining participants competed at a highly trained national level, and only a small proportion were considered trained or developmental. As for analytical approaches, most studies employed conventional methods (descriptive, correlational, or regression analyses), and only a quarter used advanced techniques such as principal component analysis, machine learning, or mixed models. In terms of location, the United States and Australia were the most

represented countries, followed by Spain and Portugal, with the remaining studies distributed across Europe, Africa, and Asia (see Table 1). The included studies generally reported evidence of device validity and/or reliability for objective measures of external load and internal load, whereas greater heterogeneity was observed in the assessment of subjective internal load. Reporting of missing data also varied across studies: some attributed missingness to injury or playing role/position, and several did not report reasons for missing data. Importantly, all studies described the procedures followed during data collection, with protocols tailored to the specific sport context, the monitoring technologies employed, and the variables assessed.

Sports participation

In relation to the sports included in the studies, soccer was the most present ($n=31$, 42.46%), followed by basketball ($n=11$, 15.06%) and rugby ($n=4$, 5.47%). Figure 3 displays all the sports included, split by the type of sport, individual (blue, $n=9$, 12.67%) or team (yellow, $n=62$, 87.32%) sports.

The monitoring process of the included studies are summarized in Table 2, involving the training load measures employed and the duration of data collection. Three studies (4.22%) monitored athletes for less than one week, 14 studies (19.71%) for periods between two weeks and one month, and 16 studies (22.53%) for one to three months. Half of the studies ($n=36$, 50.70%) collected data over periods longer than three months, whereas two studies did not report the duration of monitoring.

External and internal load variables and technologies

The most frequently reported external load variables were distance ($n=44$, 24.86%), Player Load ($n=41$, 23.16%), speed ($n=36$, 20.34%), and acceleration/deceleration ($n=24$, 13.56%). These metrics were commonly monitored using branded systems such as Catapult ($n=26$, 36.62% of studies, e.g., [36, 56, 78]), Polar Team ($n=9$, 12.68%, e.g., [73, 80, 81]), SPI ($n=9$, 12.68%, e.g., [49, 96, 100]), STATSports ($n=8$, 11.27%, e.g., [39, 41, 97]). Other technologies such as WIMU [61, 67, 90], Zephyr Bioharness [65, 94] and PlayerTek [55] were used less frequently. Regarding the integration of technology trademarks and external load variables (Fig. 4A), distance was mainly assessed with Catapult ($n=14$) and SPI ($n=8$); Player Load almost exclusively with Catapult ($n=22$); speed with Catapult ($n=12$) and STATSports or SPI ($n=7$); and acceleration/deceleration with Catapult or Polar Team ($n=7$). When stratified by sport type, Player Load ($n=19$) and distance and speed (both $n=12$) were the most frequently reported variables in team sports (Fig. 4B), whereas in individual sports (Fig. 4C) time, distance, and Player Load (each $n=5$) were reported most frequently.

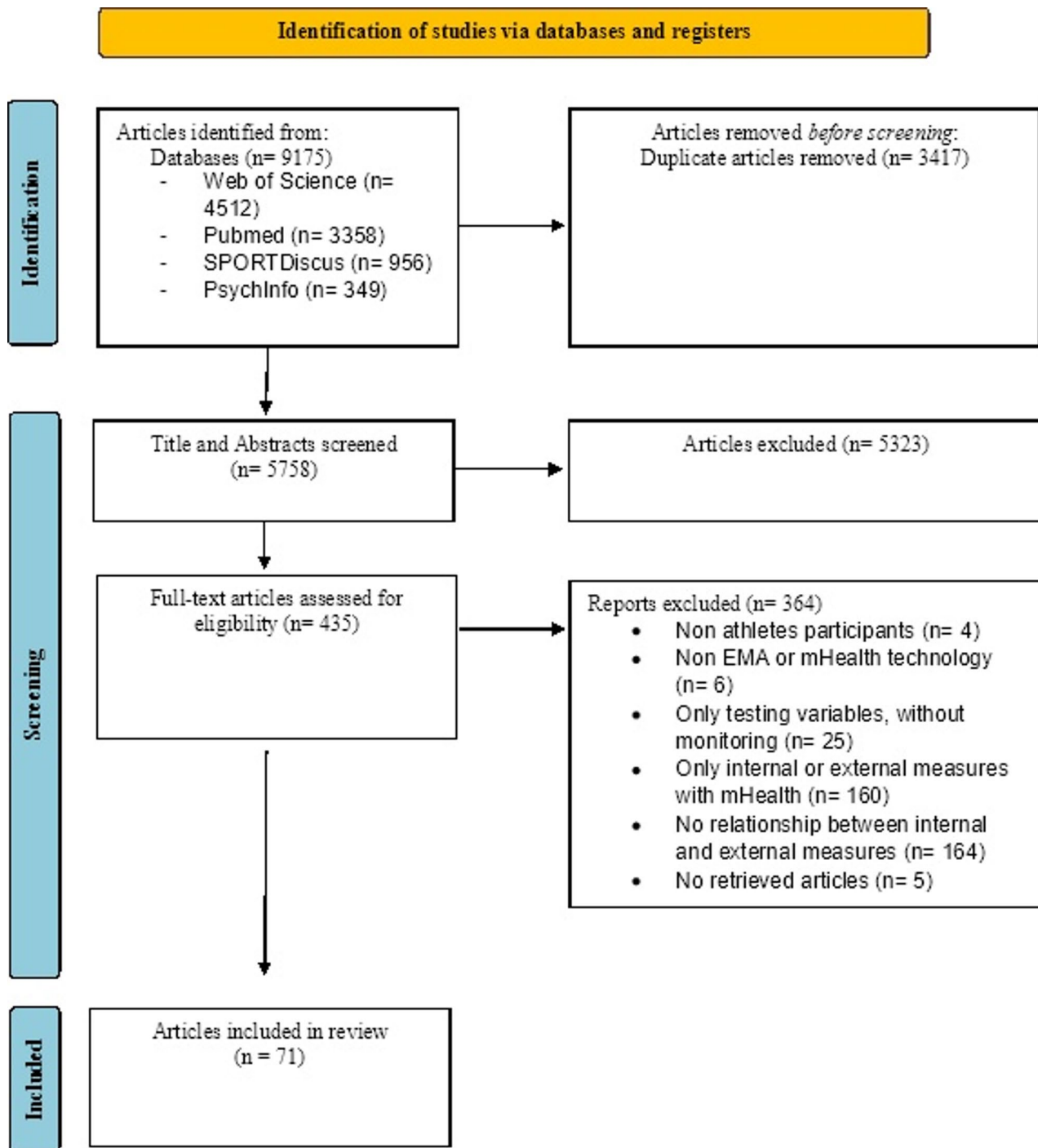


Fig. 1 PRISMA flowchart of the scientific literature search and the selection of studies

As shown in Fig. 5, the most used objective internal load variables included heart rate indices ($n = 39$, 32.77%) and TRIMP scores ($n = 19$, 15.96%). The most commonly used technology trademarks to collect objective measures were Polar ($n = 34$, 69.39% of studies, e.g., [35, 92, 95, 99]) and FirstBeat ($n = 4$, 8.16%, e.g., [44, 63, 86, 88]).

The most frequently reported subjective internal load variables were Wellness ($n = 24$, 20.17%), RPE ($n = 23$, 19.33%), and sRPE ($n = 13$, 10.42%). Wellness measures commonly included self-reported perceptions of fatigue, stress, muscle soreness, and sleep quality, and were assessed using different Likert scales (e.g., 1–5, 0–10,

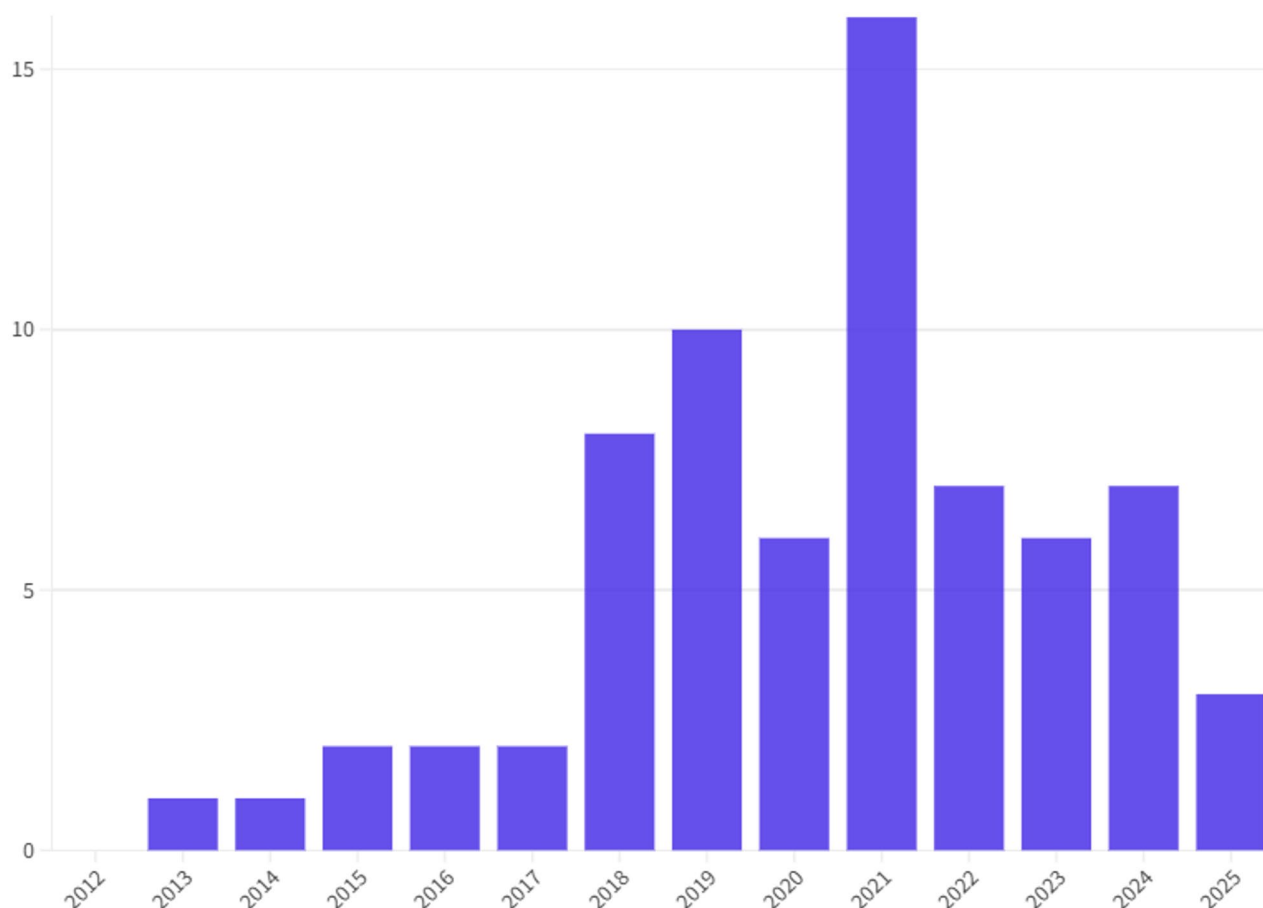


Fig. 2 Number of included studies by publication year since 2012

or 1–7), whereas RPE was consistently reported using a 0–10 Likert scale. These were mostly collected through smartphone apps ($n=25$, 73.53% of studies, e.g., [36, 46, 51]) like TeamBuildr or online forms ($n=8$, 23.53%, e.g., [60, 74, 75]). Regarding the integration between technology trademarks and variables (Fig. 5A), Polar was mainly used to capture heart rate indices ($n=26$) and TRIMP ($n=15$). Smartphone apps were most frequently used for RPE ($n=20$), sRPE ($n=11$), and Wellness ($n=16$). When analyzed by sport type, heart rate indices were the most frequently reported variables in both team (Fig. 5B) and individual sports (Fig. 5C).

Associations between external and internal load

Moderate to very strong correlations between external and internal load were reported in 28 studies, with representative examples including several investigations (e.g., [35, 49, 52, 56, 59, 66, 90, 95, 105]). Variables such as total distance, Player Load, and acceleration volume were frequently associated with TRIMP, %HRmax, or HR zone-based metrics. For example, TRIMP based parameters correlated strongly with total distance ($r = .79$ – 0.84) and Player Load ($r = .81$ – 0.85) [59], while

Player Load alone explained up to 87% of the variance in HR response during intermittent field hockey training [66]. Other approaches employed ratio-based indices to relate external and internal load [103, 107, 111]. These indices confirmed differences according to playing role and exposure time, with HR-derived indicators (e.g., HRmax, cardiovascular capacity) varying by position and match progression, and efficiency indexes (effindex: mean speed/%HRmax) differentiating positions and match halves. Similar comparisons of average heart rate, external intensity, and performance index were also used to examine external–internal load relationships [91].

In contrast, heart rate variability (HRV) indicators such as lnRMSSD showed trivial to small associations with external load in several studies [39, 44, 55, 67, 86]. For instance, external load decreased significantly during a two-week preseason, yet HRV remained unchanged [62], while non-significant correlations ($r < .20$) were observed between HRV and training volume or distance [74]. An exception was reported by Sánchez-Sánchez et al. [93], who found negative associations between pre-match HRV parameters (e.g., LF/HF ratio) and in-match external load metrics such as sprint distance and sprint count.

Table 1 Frequency distribution of general characteristics

Variable	Category	Frequency	
		n	%
Gender	Female	21	29.57
	Male	45	63.38
	Mixed	4	5.63
	Not specified	1	1.40
Participants	1–10	17	23.94
	11–30	42	59.15
	> 30	11	15.49
	Not specified	1	1.41
Level*	Elite/International	37	50.68
	Highly trained/National	32	43.83
	Trained/Developmental	4	5.47
Analysist	Advanced	19	26.76
	Conventional	52	73.24
Country	United States of America	15	21.12
	Australia	13	18.30
	Spain	9	12.67
	Portugal	6	8.45
	France	2	2.81
	Lithuania	2	2.81
	Sweden	2	2.81
	Canada	2	2.81
	United Kingdom	2	2.81
	Italy	2	2.81
	Ireland	2	2.81
	South Africa	2	2.81
	Other countries†	12	16.90
Sport§	Soccer	31	42.46
	Basketball	11	15.06
	Rugby	4	5.47
	Hockey	3	4.10
	American Football	3	4.10
	Badminton	2	2.73
	Gaelic football	2	2.73
	Ice Hockey	2	2.73
	Lacrosse	2	2.73
	Other sports¶	13	17.80

* Level classification based on McKay et al. [40] framework

† Analysis advanced includes principal component analysis, machine learning and mixed models. Conventional includes descriptive, correlational and regression analyses

‡ Other countries (n=1): Chile, Malaysia, Belgium, Germany, Russia, Brazil, Norway, Denmark, Qatar, Iran, Singapore, Mexico

§ The total number of sports included is 73, since Campbell et al. [41] studies three sports

¶ Other sports (n=1): Surf, Cycling, Handball, Cross-Country, Squash, Netball, Volleyball, Beach Volleyball, Trail-Running, Cricket, Tennis, Biathlon, Waterpolo

Session RPE (sRPE) consistently showed moderate to strong correlations with external load (e.g., [36, 45, 48, 56, 89, 99]). For example, a one-unit increase in RPE predicted an additional 106 m of high-speed running and 49 AU of Player Load [52], while sRPE explained up to 65% of the variance in TRIMP [106]. Data were commonly

collected via smartphone applications [43, 96] or standardized post-session scales [63, 106].

Wellness measures such as the perception of fatigue, soreness, sleep quality, and stress were assessed in 24 studies (e.g., [41, 53, 74, 82, 102]). High external loads, particularly accelerations and match load, were negatively associated with subsequent wellness measures (perception of fatigue, soreness, sleep quality, and stress), especially on the first (MD + 1) and second (MD + 2) day after the match. Strong associations were observed between total distance and both muscle soreness ($r = -.67$) and perceived stress ($r = -.70$) [89]. Conversely, other studies found no significant associations between wellness ratings and load metrics [44, 50, 67, 68]. For instance, pre-match wellness scores showed only trivial relationships with match load outcomes [44]. Sleep quality and perceived energy emerged as the most consistent predictors, with significant associations reported in several studies [53, 82, 109]. Notably, athletes with good sleep quality covered ~300 m more per training day compared with those reporting poor sleep [53].

Relationship between subjective and objective internal load measures

Seven studies directly compared subjective (sRPE, RPE, wellness) and objective (HR, TRIMP) internal load measures. A moderate correlation ($r = .45$) between sRPE and Summated Heart Rate Zones (SHRZ) was reported [94]. Shared variances between sRPE, TRIMP, and SHRZ ranged from 14% to 38%, indicating partial overlap between perceptual and physiological load markers [96]. sRPE-TL predicted TRIMP with high accuracy ($R^2 = 0.65$), and model fit improved by an additional 11% when total distance was included [106]. Comparisons between RPE and HR-derived indices also revealed statistically significant associations [51], while perceived exertion ratings were moderately aligned with SHRZ and %HRmax metrics in elite football contexts [63]. Studies on wellness-based load perception demonstrated weak or inconsistent correlations with HR and TRIMP [50], although others noted stronger alignment between wellness indicators and HR zones [80].

Contextual and individual modifiers

Contextual factors influenced load-response relationships across multiple studies. Changes in both external and internal load were associated with different competition phases, such as pre-season versus international tournaments [64, 108]. During high-density match periods, training loads were reduced while game loads remained high [85]. Position-specific differences in workload and physiological response indicated that player role modifies both external load exposure and internal responses (physiological and perceptual) [91, 101]. For instance,

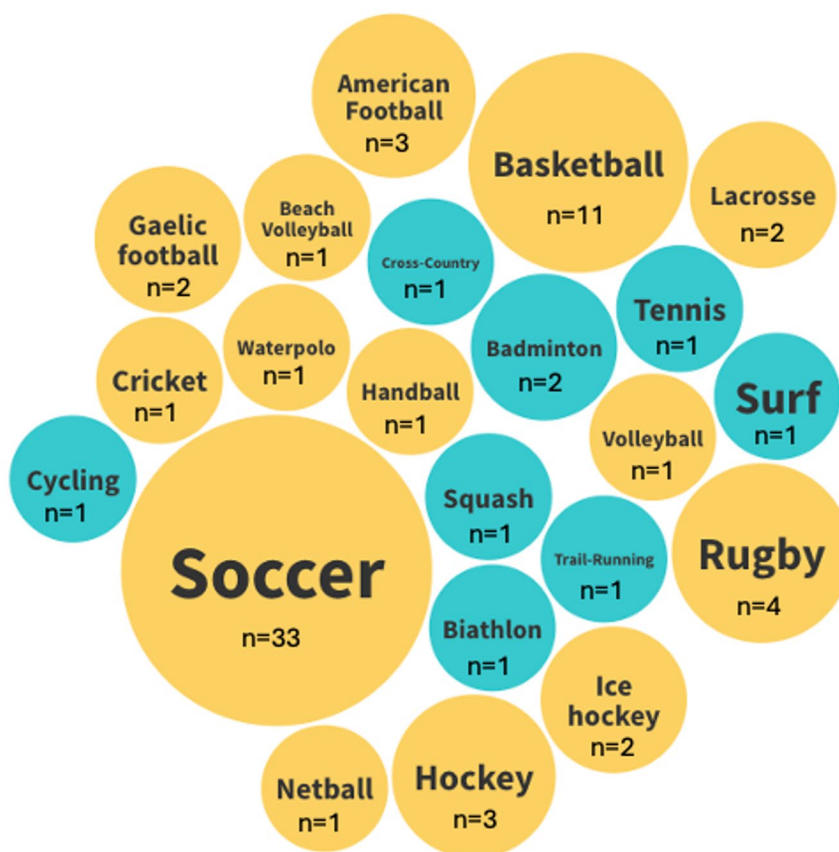


Fig. 3 Sports and type of sports (individual - team) of the included studies. Individual sports in blue color and team sports in yellow

players in more physically demanding positions may accumulate greater high-intensity efforts and exhibit stronger cardiovascular responses than those in lower demanding roles, thereby influencing their subjective perception of effort.

Discussion

The primary objective of this scoping review was to identify EMA methodologies using mHealth technologies for monitoring training load or the stress-recovery process in athletes. Specifically, the review aimed to classify the methodologies and technologies used according to individual or team sports, to describe the relationship between external parameters (e.g., distance, accelerations) and internal parameters (e.g., physiological, cardiovascular, neuromuscular, subjective), and to analyze the relationship between subjective and objective internal load measures.

The findings align in part with previous systematic reviews [29, 30]. Like those works, this review confirms moderate to very strong associations between heart rate-derived internal load (e.g., TRIMP, %HRmax) and external load variables (e.g., total distance, Player Load) across sports and contexts [42, 59, 66, 97, 102]. However, this

review extends prior findings by incorporating a wider range of internal load constructs and exploring differences by sport type, competitive context, and data acquisition methodology.

An important contribution of this review is the identification of advanced analytical approaches. For instance, Campbell et al. [41] applied machine learning models to predict training load from wellness scores, although these models showed limited predictive power. In addition, Rago et al. [88] used unsupervised machine learning to reveal strong associations between internal and external load measures and to identify parameters that distinguished between player groups and temporal patterns. Others studies used canonical correlations [42], stepwise regression [78], or multilinear models [99] to explore multidimensional interactions. While still underused, these approaches point toward a more sophisticated, data-informed future in athlete monitoring.

An important distinction that emerged from this review relates to sport type and gender. Studies mainly focused on team sports ($n = 62$), especially soccer ($n = 33$), while individual sports ($n = 9$) were notably under-represented. Given that individual athletes often follow highly personalized training and recovery patterns,

Table 2 Checklist of the monitoring process of the included studies

Study	Sports	Monitoring process																	
		Training load measures†																	
		Internal					External					Duration							
		Objective			Subjective		Distance	PL	Speed	Acc/Dec	MRC	Time	PO	MP	Ac	<1w.	<1m.	1-3m.	>3m.
TRIMP	HRI	OA	RPE	sRPE	Wellness														
Abdullahi et al. (2019) [42]	Badminton	X					X	X				X							X
Askow et al. (2021) [43]	Soccer	X	X	X	X			X	X			X			X				X
Bellinger et al. (2020) [44]	Soccer					X	X	X	X										X
Bisschoff et al. (2016) [45]	Badminton	X					X	X	X			X	X						X
Campbell et al. (2021) [41]	Cricket, Rugby & Soccer		X	X	X	X	X	X										X	
Chrismas et al. (2019) [46]	Soccer	X				X		X	X					X				X	
Clemente (2018) [47]	Soccer	X				X	X	X							X				
Clements et al. (2025) [48]	Soccer					X	X	X	X								X		
Conte et al. (2021)[49]	Soccer	X		X	X	X	X	X							X				
Conte et al. (2021) [50]	Rugby					X	X	X				X	X						
Costa et al. (2019) [51]	Soccer	X	X	X	X	X	X	X							X				
Croteau et al. (2023) [52]	Water polo		X	X	X		X		X			X							X
Crouch et al. (2021) [53]	Lacrosse	X				X	X	X											X
Cullen et al. (2021) [54]	Soccer		X	X	X	X	X	X	X					X					X
de Dios-Alvarez et al. (2023)[55]	Soccer		X	X	X	X	X	X	X					X					X
Delaney et al. (2018)[56]	Rugby					X	X		X				X				X		
Douchet et al. (2021) [57]	Soccer	X		X	X	X			X	X		X				X			
Draper et al. (2021) [58]	Soccer		X	X	X	X	X	X	X				X						X
Ellis et al. (2021) [59]	Soccer					X	X	X	X						X				
Evans et al. (2022)[60]	Soccer				X	X	X	X	X				X						X
Fernandez et al. (2021) [61]	Hockey		X	X	X	X	X	X	X				X						X
Fields et al. (2021) [62]	Soccer	X				X	X	X	X							X			
Fox et al. (2020)[63]	Basketball	X					X		X	X		X							X
Fox et al. (2018) [64]	Basketball	X				X	X		X								X		
Gielen et al. (2022) [65]	Volleyball	X														X	O		
Gonzalez-Fimbres et al. (2019) [66]	Hockey						X												X
González-García & Romero-Moraleda (2024) [67]	Soccer				X	X	X	X	X							X			
Govus et al. (2018) [68]	American football				X		X		X									X	
Grace et al. (2023) [69]	Lacrosse	X			X	X		X	X									X	

Table 2 (continued)

Table 2 (continued)

Study	Sports	Monitoring process																			
		Training load measures†																			
		Internal								External											
		Objective				Subjective				Distance	PL	Speed	Acc/Dec	MRC	Time	PO	MP	Ac	Duration		
		TRIMP	HRI	OA	RPE	sRPE	Wellness														
Simpson et al. (2020) [101]	Netball	X					X	X		X	X									X	
Sobolewski (2020) [102]	American football	X		X	X		X		X	X	X									X	
Suarez-Arrones et al. (2015) [103]	Soccer	X							X												X
Teixeira et al. (2023) [104]	Soccer	X				X		X		X	X					X					
Tendero-Ortiz et al. (2024) [105]	Tennis	X				X	X	X	X	X	X		X								
Tometz et al. (2022) [106]	Beach volleyball	X		X	X		X														X
Torreno et al. (2016) [107]	Soccer	X				X			X		X										X
Villaseca-Vicuña et al. (2023) [108]	Soccer		X	X	X	X	X	X	X	X	X		X				O				
Wellman et al. (2019) [109]	American football					X	X	X		X	X										X
Wiig et al. (2020) [110]	Soccer			X	X					X											X
Zafar et al. (2024) [111]	Soccer	X									X										X

†Based on Bourdon et al. [10]. X: Indicates that the variable appears in the study, or the duration of data collection. O: Indicates that the duration of the data collection is not reported

TRIMP Training Impulse, HRI Heart rate indices, OA Other assessments, RPE Rating of Perceived Exertion, sRPE session Rating of Perceived Exertion, PL Player Load, Acc/Dec Acceleration/Deceleration, MRC Movement repetition counts, PO Power Output, MP Metabolic Power, Ac Accelerometry, w week, m. months

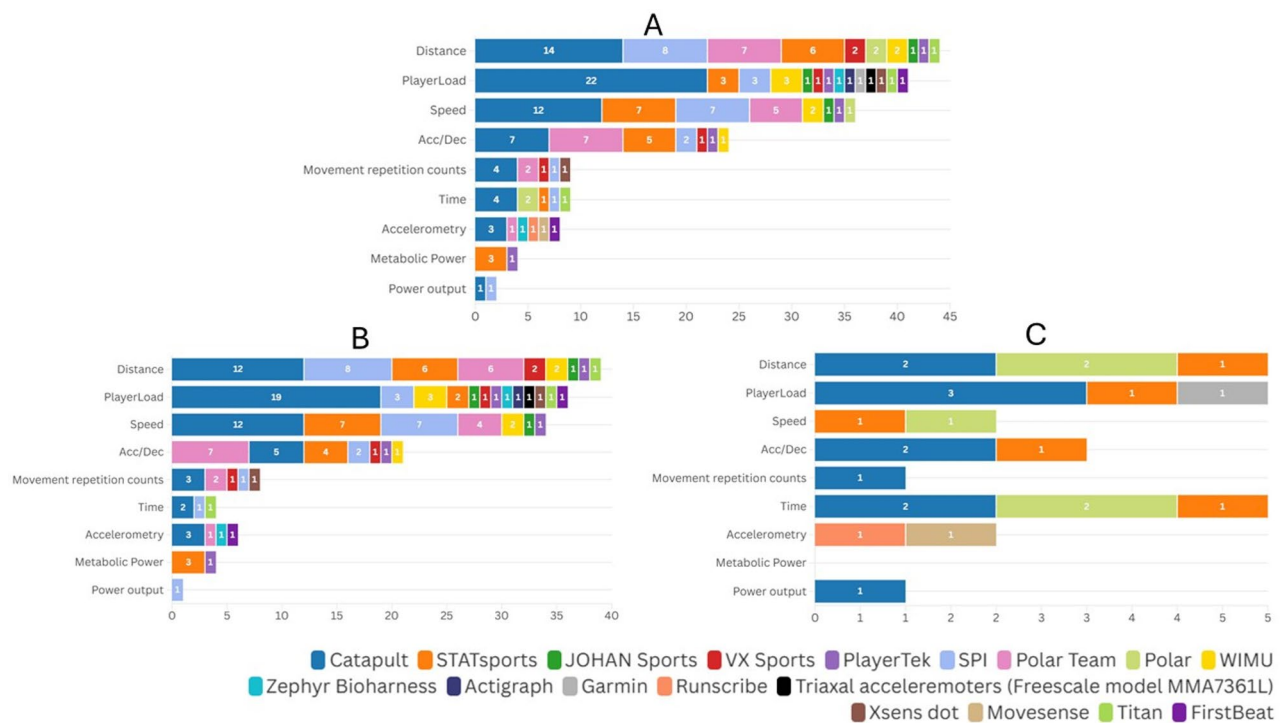


Fig. 4 External load variables and technology trademark used in the included studies. **A** shows total values across all included studies, **B** shows team-sport studies, and **C** shows individual-sport studies. n: indicates the number of occurrences across all studies, not the number of studies. Acc/Dec: Acceleration/Deceleration. Example measurement units reported across studies include: distance (meters), Player Load (arbitrary units), speed (meters per second or kilometers per hour), accelerations/decelerations (meters per second squared), movement repetition counts (e.g., changes of direction, jumps), time (seconds or minutes), accelerometry (x-, y-, and z-axis g-force), metabolic power (watts per kilogram), and power output (joules)

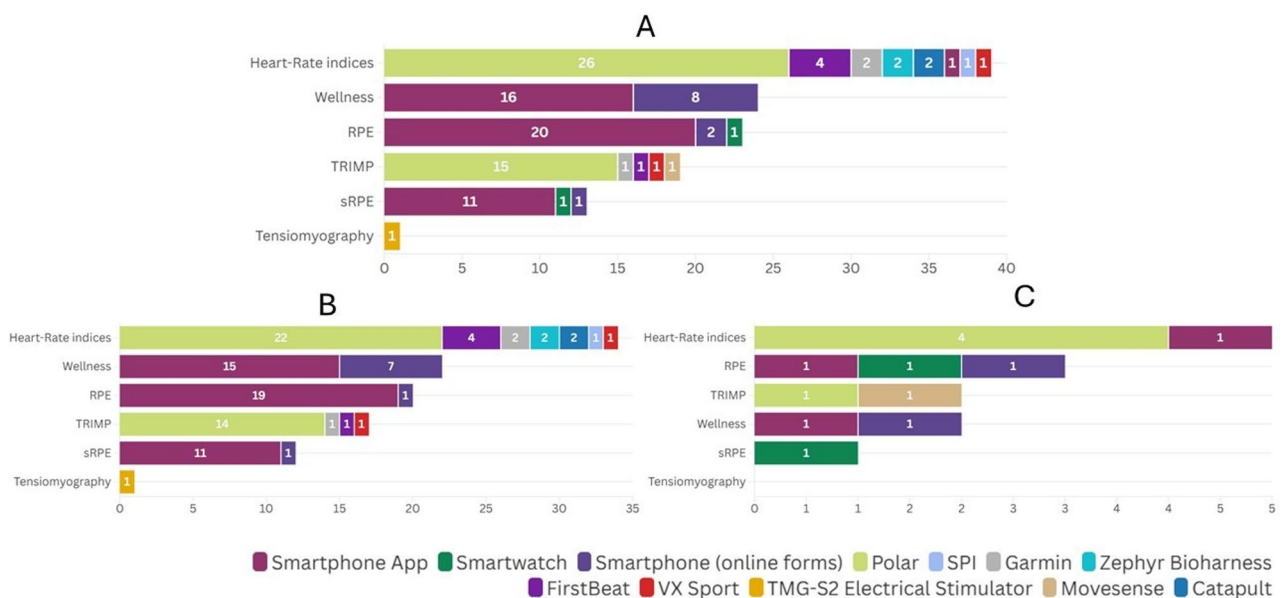


Fig. 5 Internal load variables and technology trademarks used in the included studies. **A** shows total values across all included studies, **B** shows team-sport studies, and **C** shows individual-sport studies. n: indicates the number of occurrences across all studies, not the number of studies. TRIMP: Training Impulse. HR indices: Heart rate indices. RPE: Rating of Perceived Exertion. sRPE: session Rating of Perceived Exertion. Example measurement units reported across studies include: RPE (0–10 Likert scale), sRPE (arbitrary units; calculated as RPE × session duration in minutes), wellness (arbitrary units from Likert scales; e.g., 1–5 or 1–7), heart-rate indices (beats per minute for HRmean/HRmax; percentage of HRmax; and milliseconds for HRV metrics such as RMSSD or SDNN), TRIMP (arbitrary units), and tensiomyography (milliseconds for contraction time)

this imbalance reveals a clear gap in the literature and highlights the need for future research exploring EMA-based monitoring strategies tailored to individual sport contexts. In terms of gender, 45 studies included exclusively male athletes ($n=1120$), whereas only 21 focused on female participants ($n=323$). This gender disparity further underscores the need to expand research efforts to better represent female athletes and their specific training and recovery profiles. Although four studies recruited mixed-gender samples, none reported separate analyses for male and female athletes in the relationship between internal and external loads. In addition, the review revealed important differences in technological accessibility. While elite-level environments frequently employed advanced systems such as Catapult, STATSports, or Polar Team Pro, these tools are often cost-prohibitive for clubs, individual athletes, or teams with limited budgets. However, several studies demonstrated that simpler, low-cost alternatives such as mobile apps or basic subjective scales can still deliver valid and useful data [43, 96]. These findings emphasize the potential of accessible monitoring solutions to extend best practices beyond high-performance environments and into more resource-limited or amateur settings, supporting more equitable athlete care and decision-making.

Regarding the relationship between external and internal load, most studies confirmed robust associations ($r=.79-0.85$). In addition to classic correlations, some adopted derived indices to evaluate internal-to-external load ratios [91, 103, 107], while others related HR-derived cardiovascular capacity to positional demands [111]. These indices offered deeper insights into athlete adaptation and performance economy. By contrast, HRV metrics such as $\ln\text{RMSSD}$ showed limited responsiveness to training load in many studies [46, 62, 74], supporting previous claims that HRV is more effective for long-term recovery monitoring than short-term load assessment. Nevertheless, recent advancements in wearable biosensing technologies [112] now enable the non-invasive and continuous monitoring of internal load parameters like lactate or glucose, via sweat. These parameters were previously restricted to invasive blood-based methods, and their integration into mHealth systems represents a promising step toward more comprehensive and real-time internal load monitoring in the field.

Subjective measures, particularly sRPE, proved reliable and were moderately to strongly correlated with external load [40, 49, 52, 93, 103]. Components of wellness like sleep quality and perceived energy were among the most predictive variables [53, 109], though others like stress or soreness yielded inconsistent results [44, 67, 68]. However, this review revealed that many studies did not report how subjective variables were collected, and several still used non-digital tools, despite the demonstrated

benefits of mobile-based EMA approaches in improving data quality and ecological validity [21]. This lack of methodological transparency and technological integration has also been highlighted in practice-focused studies [113], showing that subjective measures are widely used but often inconsistently applied, with limited feedback to athletes and little standardization. Our findings complement this by showing that while subjective metrics are valuable and commonly used, their implementation often lacks the rigor and integration found in objective monitoring.

Moreover, only 7 studies compared subjective and objective internal load. These studies compared physiological metrics such as TRIMP, %HRmax, or SHRZ with perceptual indicators like sRPE or wellness scores. Results revealed a partial convergence between these two domains: although correlations were generally significant, the shared variance between sRPE and TRIMP-type models ranged from 14% to 38% [94, 96, 106]. This indicates that while sRPE captures a meaningful portion of physiological load, it also reflects additional psychological, contextual, or perceptual dimensions not accounted for by objective measures. Beyond this, sRPE has become one of the most widely adopted subjective indicators, by conveying a more global sense of effort relative to a given external load [114]. However, the substantial variance not shared with physiological markers such as TRIMP suggests that other aspects of cognitive exertion may play an important role. Incorporating such cognitive measures, particularly when collected in ecological settings through mHealth solutions, may offer a complementary perspective that is less invasive, more affordable, and broadly feasible across sporting environments. This approach aligns with the need for multimodal monitoring strategies, especially in field-based contexts where physiological data may not always be accessible. They also reinforce the notion that subjective data—far from being secondary—provide unique insights into how athletes perceive and integrate training stimuli, including stress, fatigue, and readiness perception. Subjective and objective measures should not be treated as interchangeable, but rather as synergistic components of athlete monitoring. Furthermore, these align with recent views that athlete monitoring must be framed within a complex systems perspective [20]. In this view, perception, recovery behaviors, and environmental context are not peripheral but central to understanding load adaptation. By analyzing both types of internal load and their relationship to external demands, this review contributes to a more integrated and ecologically valid model of athlete monitoring. The potential impact lies in promoting multimodal, ecologically valid approaches that incorporate not only physiological and perceptual load, but also recovery behaviors and emerging biosensing technologies. In

Table 3 Checklist to ensure consistent use of subjective measures

Scale specification	CR-10, 0–100 for RPE; number and type of items for wellness questionnaires
Timing of administration	Pre-session for wellness, post-session for RPE
Mode of administration	App, online forms, verbal
Contextual factors	Individual vs. group setting, environmental conditions
Aggregation & interpretation	Derived summary scores, decision thresholds, missing-data handling, and dashboard-style visualization.

RPE Rating of Perceived Exertion

applied practice, such frameworks can guide coaches and clinicians in tailoring interventions, preventing injury, and optimizing adaptation, while stimulating the development of future sport-specific guidelines.

This scoping review is subject to several limitations. First, although the search strategy was comprehensive, relevant studies may have been missed due to database indexing limitations, language restrictions, or the exclusion of grey literature. Second, the evidence base identified within the selected timeframe (2012–2025) was skewed toward team sports, particularly soccer, and toward elite/international male athletes. Importantly, the comparatively lower number of included studies in individual sports should be interpreted cautiously, as it may reflect the post-2012 expansion and uptake of mHealth/EMA tools in intermittent team-sport settings rather than a definitive lack of monitoring research in individual disciplines. In contrast, the under-representation of female cohorts constitutes a more substantive evidence gap and limits the generalizability of current findings. Third, the heterogeneity of methodologies, technologies, and measurement tools used across studies made direct comparisons difficult. In particular, the lack of standardization in the collection and reporting of subjective internal load measures, such as RPE or wellness scores was notable, as many studies did not specify the format or timing of data collection. Future research would benefit from the adoption of more standardised protocols. Table 3 provides an example checklist to support consistent implementation and reporting of these measures, including: (1) scale specification (2) timing of administration in relation to training or competition (3) mode of administration, (4) contextual factors, and (5) reporting procedures for data aggregation and interpretation.

Moreover, there were substantial differences in the periodicity of data collection (e.g., daily, weekly, post-session) and in the characteristics of the participants, which ranged widely in age, competitive level, and sport discipline. Additionally, even within the same technology brands as Catapult, STATSports or Polar, different models and device generations were used across studies,

potentially affecting the consistency and comparability of the collected data. This variability may limit the comparability and transferability of findings across contexts.

Conclusions

This scoping review provides an updated and comprehensive overview of Ecological Momentary Assessment methodologies using mHealth technologies to monitor training load and the stress-recovery process in athletes. The findings confirm well-established relationships between external load variables and heart rate-based internal measures, while highlighting the growing role of subjective metrics such as sRPE and wellness scores. However, only seven studies directly compared subjective and objective internal load, revealing partial convergence and underscoring the need for multimodal monitoring strategies that combine both types of data to better capture athletes’ psychophysiological responses. This review thus reinforces recent perspectives that advocate for a complex systems approach, where perception, recovery behaviour, and environmental context are integral to understanding training adaptation.

Moreover, the emergence of non-invasive, continuous biosensing technologies capable of capturing internal load markers such as lactate and glucose opens new avenues for real-time, field-based monitoring that complements traditional methods. In parallel, this review identified a notable lack of attention to recovery-related behaviours, which remain insufficiently monitored despite their crucial role in performance and injury prevention. From a practical standpoint, coaches and practitioners seeking to implement EMA and mHealth-based monitoring systems should prioritize simplicity, consistency, and athlete engagement. The choice of tools ought to be guided not only by technological sophistication but also by ease of use, low burden, and compatibility with existing routines.

Future research should prioritize greater methodological transparency, particularly in the collection of subjective data, extend monitoring strategies to individual sports, and incorporate behavioural recovery markers into EMA-based systems. Doing so will bring the field closer to a truly integrated and ecologically valid model of athlete monitoring. A key agenda is the development of personalized models of monitoring, in which individual stress-recovery profiles, thresholds, and early-warning signals of maladaptation can be identified. In addition, more sophisticated quantification of recovery is needed, integrating physiological, psychological, and behavioral markers into coherent indices that can inform real-time adjustments to training prescription. Finally, advances in machine learning and AI-driven analytics offer promising opportunities to handle the complexity of multimodal data, identify non-linear interactions among training loads and performance, and generate individualized recommendations.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s13102-026-01634-8>.

Supplementary Material 1.

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Authors' contributions

J.G, L.C, J-M. L and E.P contributed to the study conception and design. J.G and E.P conducted the literature search and screening. Data extraction was performed by J.G. Methodological quality and consistency were evaluated by J-M.L. J.G analyzed and synthesized the results with feedback from E.P, L.C and J-M.L. J.G drafted the initial manuscript, and E.P, L.C, and J-M.L provided critical revisions to subsequent versions. All authors read and approved the final manuscript.

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Data availability

The data supporting the findings of this study are openly available in the Catalan Open Research Area repository at [<https://doi.org/10.34810/data2613>] (<https://doi.org/10.34810/data2613>).

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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