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Original research

Train hard, sleep well? Perceived training load, sleep quantity and sleep stage distribution in elite level athletes

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ABSTRACT

Objectives: Sleep is essential for recovery and performance in elite athletes. While it is generally assumed that exercise benefits sleep, high training load may jeopardize sleep and hence limit adequate recovery. To examine this, the current study assessed objective sleep quantity and sleep stage distributions in elite athletes and calculated their association with perceived training load.
Design: Mixed-methods.
Methods: Perceived training load, actigraphy and one-channel EEG recordings were collected among 98 elite athletes during 7 consecutive days of regular training.
Results: Actigraphy revealed total sleep durations of 7:50 ± 1:08 h, sleep onset latencies of 13 ± 15 min, wake after sleep onset of 33 ± 17 min and sleep efficiencies of 88 ± 5%. Distribution of sleep stages indicated 51 ± 9% light sleep, 21 ± 8% deep sleep, and 27 ± 7% REM sleep. On average, perceived training load was 5.40 ± 2.50 (scale 1–10), showing large daily variability. Mixed-effects models revealed no alteration in sleep quantity or sleep stage distributions as a function of day-to-day variation in preceding training load (all p's > .05).
Conclusions: Results indicate healthy sleep durations, but elevated wake after sleep onset, suggesting a potential need for sleep optimization. Large proportions of deep sleep potentially reflect an elevated recovery need. With sleep quantity and sleep stage distributions remaining irresponsive to variations in perceived training load, it is questionable whether athletes' current sleep provides sufficient recovery after strenuous exercise.

1. Introduction

Athletes consider sleep as being essential for their health,[1] recovery and performance.[2] Despite its perceived importance, elite athletes appear to sleep worse compared to gender and age matched, non-exercising controls, which is reflected in shorter sleep duration, elevated wake after sleep onset and lower sleep efficiency.[3] Despite the importance of sleep, systematic research on sleep-wake behaviour in elite athletes is still scarce and much can be gained by improving methodological approaches. Commonly, representative sleep quantity estimates[3,4] are based on default actigraphy settings, whereas—for athletes—higher sensitivity to sleep settings have recently been shown to reflect better agreement with polysomnography (PSG).[5] In this respect, replicating previous studies among elite athletes while using a higher sensitivity to sleep threshold can further contribute to accuracy and validity of sleep-wake estimates.

Besides sleep quantity, a healthy distribution of sleep stages is considered crucial for psychological and physiological functioning.[6] Sleep stage distribution is modified by physical exercise, as sleep adjusts to the body's daily need for recovery,[7,8] but may also be negatively affected by suboptimal sleep-wake behavior (e.g., sleep restriction, fragmentation, overtraining, and (anticipatory) stress).[6,9,10] In general, it is assumed that exercise benefits sleep, as is expressed in shorter sleep onset latencies, fewer occurrences of wake after sleep onset, longer sleep durations, fewer sleep stage changes and more regular REM to non-REM transitions.[11] In particular, and in line with the restoration hypothesis of sleep, pro-

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portions of deep sleep tend to be higher in active versus non-active individuals[7] and have been shown to increase following a day of strenuous exercise.[8] At the same time, however, there is evidence suggesting that in specific cases, athletes' training demands may also jeopardize sleep (for a comprehensive review see: Ref. 12). For example, prolonged periods of extreme exercise intensity[13,14] may worsen sleep quantity and quality, as is reflected in increased wakefulness and decreased proportions of REM sleep.[7]

Despite its relevance for recovery and performance in elite athletes, a representative field-based indication of sleep stage distributions in elite athletes (e.g., proportions of light sleep, deep sleep, REM sleep) is currently not available. Furthermore, no studies have examined the extent to which naturally occurring day-to-day variation in training load is indeed associated with (mal-) adaptive changes in sleep. To address these issues, the current study aimed to target the following research questions. First, what is the objective sleep quantity in elite athletes and how are their sleep stages distributed?; and second, are sleep quantity and sleep stage distributions associated with (day-to-day variation in) preceding perceived training load? To provide a robust answer to these questions, a mixed-method approach was employed in which actigraphy-based sleep quantity, EEG-based sleep staging, and perceived training load were monitored in a large cohort of elite athletes during seven consecutive days of regular training. With respect to objective sleep quantity and sleep stage distributions, it was expected to replicate previously reported sleep insufficiencies (i.e., elevated wake after sleep onset, and relatively low sleep efficiency),[3,4] and—given the activity profile of the sample—to observe relatively high proportions of deep sleep.[7,8] With regard to associations between sleep quantity and sleep stage distributions and day-to-day variation in training load, it was expected that proportions of deep sleep would increase following days with moderate to high training load,[8] but that sleep onset latencies and wake after sleep onset would increase when training load would be more extreme.[14]

2. Method

Participants were recruited via the Netherlands Olympic Committee*Netherlands Sports Federation (NOC*NSF) or via the head coaches of the respective sports federations. A total number of 98 elite athletes (56 female; 42 male), competing at the highest national and international (youth or senior) level, participated in the study. Athletes were aged 18.8 ± 3.0 years (range 15–32), had an average Body Mass Index of 21.3 ± 1.6, had practiced their sport on average for 10.0 ± 3.5 years, and spent on average 19.3 ± 5.1 h per week on training and competition. Athletes competed in different individual and team sports (Road Cycling $n = 26$, Triathlon $n = 8$, Mountain Bike $n = 4$; Handball $n = 13$, Volleyball $n = 30$, Soccer $n = 17$). Ethical approval was obtained from the faculty's ethical committee [ECSW2013-1612-170] and all participants or responsible guardians signed informed consent.

Data were collected as part of a larger project assessing subjective sleep quantity, quality, and sleep hygiene practices among Dutch elite athletes.[15] In the current project, sleep quantity, sleep stage distributions and perceived training load were monitored during 10 consecutive days of regular training, of which the last 7 days were included for further analysis. Sleep quantity and sleep stage distributions were measured using wrist actigraphy and a wireless one-channel EEG sensor, respectively. Perceived training load was assessed by means of an evening diary. All athletes slept in a (training) environment that was highly familiar to them. In all cases, the monitoring period was free from competition, with the exception of exhibition matches. Handball and volleyball players, triathletes and mountain bikers were monitored during a training period at their home-base. Typically, training was performed between 6.00 AM and 7.00 PM and either consisted of 1 or 2 sessions per day. Road cyclists and soccer players were monitored during one of their annual training camps abroad. The female cyclists ($n = 9$) crossed six time-zones in a west-ward inter-meridian travel. For those athletes, data collection started after 6 days to allow for circadian adaptation to the new time-zone.

To assess sleep-wake patterns, an actigraph was continuously worn around the non-dominant wrist and only detached during training or when being in contact with water (Actiwatch 2, Philips Respironics, Murrysville, USA). Activity and photonic light was sampled in 60 s bins. Parameters of interest were time in bed (TIB; h:min), total sleep time (TST; h:min), sleep onset latency (SOL; min), wake after sleep onset (WASO; min), fragmentation index (%) and sleep efficiency (SE; %).

Sleep stages were recorded by means of a wireless, self-logging headband sensor (Wireless System, WS; Zeo Inc., Newton, USA). The wireless system (WS) has been validated for sleep registration in healthy adults and performs an automatic classification of sleep stages based on recordings of a single bi-polar channel, which is located at the forehead (EEG position approximately at Fp1–Fp2 with a ground at Fpz) and integrated into an elastic headband.[16] Based on analysis of 30-s epochs the WS distinguishes between episodes of wakefulness, light sleep (comparable to stages 1 and 2), deep sleep (comparable to stages 3 and 4) and Rapid Eye Movement (REM) sleep. As reported by Shambroom et al.,[16] agreement between WS and PSG is 98.5% for scoring sleep/wakefulness and 83.6% for sleep stage classification. In the current study, WS recordings were used to calculate both absolute (h:min) and relative (% of TST) proportions of light sleep, deep sleep, and REM sleep. The WS was attached before lights-off and removed following lights-on.

To aquire a coherent measure of training load that would capture self-perceived load across an entire day (including one or more training sessions), self-perceived training load was measured every evening, using a single-item question: i.e., "How high was today's training load?".[17] All athletes were familiar with this, or very similar questions. In accordance with the Dutch grading system, a 10-point rating scale (i.e., 1 = 'very low training load'; 10 = 'very high training load') was employed.

Data was processed as follows: Actigraphy data were analysed using Respironics Actiware 5 (Philips Respironics, Murrysville, USA). Data were visually inspected and excluded when activity counts and light values indicated detachment of the sensor. In all other cases, rest intervals were manually set when (i) event markers identified bed- and rise time, or—in case event markers were missing—when (ii) light and activity was absent. If light and activity values were ambiguous, (iii) WS data and diary entries were used to set rest intervals. The default setting (10-min immobility parameter) was used to identify sleep onset and sleep offset. Following Sargent et al.,[5] episodes of sleep/wakefulness were identified using a high sleep-wake threshold (i.e., AW >80; epochs are scored as wake if activity counts are above 80). TIB, TST and fragmentation were derived from the "rest" interval. SOL, WASO and SE were derived from "sleep" interval.

Sleep stages were automatically classified by the WS. Consecutively, data were processed as follows: First, to determine lights-off and lights-on times, actigraphy and diary entries were taken as a reference. Second, in order to match TIB values with actigraphy and diary reports, missing epochs were manually added at the beginning and end of a night and classified as "undefined" when necessary. Third, nights with more than 15% "undefined-" epochs were excluded from further analysis, which was the case for 31.5% of all possible recordings (e.g., losing the headband, equipment malfunctioning). Little's MCAR test revealed that data was missing at random (χ^2 (193) = 226.225, $p = .051$), indicating that available data (i.e., 68.5% of all possible recordings) may be taken as representa-

Table 1
Descriptive statistics for all sleep quantity and sleep stage distribution measures.

	M (SD)	*% of nights scored ≥ (cutoff)*
Sleep quantity (actigraphy)		
Time in bed (h:min)	8:32 (01:10)	
Total sleep time (h:min)	7:50 (01:08)	5.25 (≤6 h)
Sleep onset latency (min)	13.92 (15.69)	14.24 (≥30 min)
Wake after sleep onset (min)	33.03 (17.00)	7.35 (≥60 min)
Fragmentation (%)	33.44 (11.07)	–
Sleep efficiency (%)	88.47 (5.46)	22.34 (≤85%)
Sleep stage distribution (WS)		
Light (h:min)	4:02 (0:52)	
Deep (h:min)	1:36 (0:32)	
REM (h:min)	2:10 (0:46)	
Light (%)	51.36 (8.54)	
Deep (%)	20.99 (7.73)	
REM (%)	27.36 (7.39)	

Note: WS—wireless system.

tive. Fourth, sleep onset was operationalized as the first of three consecutive epochs of “light sleep”. Compared to PSG, the WS overestimates REM at the cost of “wake”.[16] Therefore, all “undefined” or “REM” epochs that preceded sleep onset were manually scored as “wake”. Finally, based on the normative range of REM sleep latency (49.5–278.5 min) provided by Mitterling et al.,[18] “REM” epochs within the first 30 min of the night and without succeeding “deep sleep” were also manually scored as “wake”.

To assess objective sleep quantity and sleep stage distributions, descriptive statistics were performed on actigraphy (sleep quantity) and WS (sleep stage distributions) data. To investigate how day-to-day variation in preceding training load affects objectively measured sleep quantity and sleep stage distributions, linear mixed-effects models were employed. Linear mixed-effects models are an extension to linear regression, that take the nested structure of the data into account (i.e., repeated measurements within participants). We used the lmer function of the lme4 package (version 1.1.-1) in R (R Core Team, 2015). All dependent measures (TST, SOL, WASO and SE—obtained from actigraphy; % Light, % Deep, and % REM—obtained from the WS) were analysed in separate models. Each model included a fixed intercept and fixed effects for gender (with contrast set as 1 for male and −1 for female), age, a lag variable for the dependent (sleep-)variable in question as covariates, and training load. To dissociate changes in sleep stage distribution from possible changes in sleep quantity, the statistical models for sleep stage distribution only included the relative (i.e., %) proportions of light sleep, deep sleep and REM sleep. Variables were scaled before entering the model. Following Barr et al.,[19] a maximal random-effects structure was used, by including a per-participant random intercept, as well as per-participant random slope for training load and the lag variable. For convergence reasons, we excluded all possible random correlation terms among the random effects. P-values were determined using the function ‘mixed’ from the package afex, using type 3 tests and the parametric bootstrap method (with 1000 simulations), which in turn calls the function PBmodcomp from the package pbkrtest (version 0.4.6). Confidence intervals were calculated using parametric bootstrapping as implemented in lme4’s bootMer function, with 10,000 simulations and deriving 95% confidence intervals using the function boot.ci of the package boot (version 1.3.17).

3. Results

Table 1 provides an overview of actigraphy-based sleep quantity measures over the 7-day monitoring period (means and standard deviations). On average, athletes lay in bed for 8:32 ± 01:10 (M ± SD) hours and had a total sleep time of 7:50 ± 01:08 (M ± SD)

Table 2
Mixed-effects models testing the effect of training load on sleep quantity.

	Time in bed			Total sleep time			Sleep onset latency			Wake after sleep onset			Sleep efficiency		
	B	*CI*	*p*	*B*	*CI*	*p*	*B*	*CI*	*p*	*B*	*CI*	*p*	*B*	*CI*	*p*
Fixed effects															
(Intercept)	514.64	[505.30, 524.10]		471.68	[463.00, 480.40]		14.5	[12.64, 16.33]		33.78	[31.26, 36.32]		88.15	[87.53, 88.77]	
Gender	−13.12	[−22.55, −3.69]	0.01	−15.34	[−24.10, −6.57]	0.003	0.05	[−1.77, 1.84]	0.96	1.78	[−0.79, 4.38]	0.18	−0.74	[−1.36, −0.12]	0.02
Age	9.72	[0.68, 18.82]	0.04	8.06	[−0.22, 16.36]	0.06	−1.36	[−3.09, 0.41]	0.16	1.79	[−0.69, 4.29]	0.17	0.11	[−0.51, 0.71]	0.72
Lag variable	1.32	[−5.35, 8.05]	0.64	3.85	[−2.47, 10.28]	0.29	1.56	[−0.21, 3.31]	0.2	2.25	[0.51, 4.01]	0.03	1.23	[0.65, 1.82]	0.004
Training load	−0.9	[−6.75, 4.95]	0.78	0.83	[−4.73, 6.37]	0.75	−1	[−2.35, 0.36]	0.15	−0.79	[−1.92, 0.32]	0.15	0.3	[−0.12, 0.72]	0.15
Random parts															
Ngrp		96			96			96			96			96	
Observations		495			495			495			495			495	

Table 3
Mixed-effects models testing the effect of training load on sleep stage distributions.

	Light sleep %			Deep sleep %			REM sleep %		
	B	*CI*	*p*	*B*	*CI*	*p*	*B*	*CI*	*p*
Fixed effects									
(Intercept)	52.05	[51.08,53.00]		20.63	[19.81,21.46]		27.64	[26.85,28.44]	
Gender	0.34	[−0.62,1.28]	.56	0.26	[−0.57,1.09]	.49	−0.37	[−1.15,0.42]	.37
Age	1.25	[0.35,2.13]	.01	−1.38	[−2.19,-0.58]	.004	−0.09	[−0.73,0.54]	.75
Lag variable	3.76	[2.67,4.86]	.001	2.75	[1.84,3.66]	.001	3.19	[2.16,4.22]	.001
Training load	0.23	[−0.51,0.97]	.56	−0.10	[−0.84,0.65]	.66	−0.23	[−1.09,0.64]	.62
Random parts									
*N*grp		80			80			80	
Observations		309			309			309	

hours. Sleep onset latency was 13.92 ± 15.69 (M ± SD) minutes. Wake after sleep onset was 33.03 ± 17.00 (M ± SD) minutes, and was distributed over 33.44 ± 11.07 (M ± SD) nocturnal awakenings. Sleep efficiency was 88.47 ± 5.46% (M ± SD). In addition, Table 1 displays the percentage of nights on which athletes slept less than 6 h (5.25%), on which it took them longer than 30 min to fall asleep (14.24%), on which their wake after sleep onset was longer than 60 min (7.35%) and on which their sleep efficiency was below 85% (22.34%).

For reason of comparison, the same analysis was run with sleep estimates derived from the default actigraphy settings (i.e. AW >40 instead of AW > 80).[5] This analysis revealed the same general picture but—primarily due to an increase in wake after sleep onset—caused the incidence of poor sleep among athletes to become more pronounced (i.e. 10.94% of nights with TST ≤6 h; 14.24% of nights with sleep onset latency ≥30 min; 42.28% of nights with wake after sleep onset ≥60 min; and 52.47% of nights with SE ≤85%).

Table 1 also provides an overview of absolute (minutes) and relative (percentages) sleep stage distributions over the 7-day monitoring period. Averaged distribution of sleep stages reflected 4:02 ± 0:52 h:min (51.36 ± 8.54%) light sleep, 1:36 ± 0:32 h:min (20.99 ± 7.73%) deep sleep, and 2:10 ± 0:46 h:min (27.36 ± 7.39%) REM sleep.

Tables 2 and 3 show an overview of the results of the mixed-effects model analyses that tested the impact of day-to-day variation in perceived training load on sleep quantity and sleep stage distribution, respectively. In both Tables, statistical outcomes (i.e., small point estimates [*B*], confidence intervals [CI] and *p*-values; see Section 2) concerning the impact of training load are reported in the fifth row (labelled: 'Training load'). Outcomes regarding the control variables (i.e., gender, age, and a lag variable of the dependent variable in question; see Section 2) are reported in the first three rows.

On average, training load was experienced as moderate (5.40 ± 2.50; M ± SD; scale 1–10), with large between-subject variability (range = 9) and within-subject variability (mean range of 5.65 ± 1.96). Despite the fact that available data thus covered a wide range of low, moderate and high levels of perceived training load, linear mixed-effects modelling showed that day-to-day variation in training load had no significant effect on sleep quantity (Table 2). That is, variation in perceived training load was not significantly associated with time in bed ($B = -0.90$ (2.96), $p = .78$), total sleep time ($B = 0.83$ (2.86), $p = .75$), sleep onset latency ($B = -1.00$ (0.69), $p = .15$), wake after sleep onset ($B = -0.79$ (0.06), $p = .15$), or sleep efficiency ($B = 0.30$ (0.21), $p = .15$). In addition, mixed-effects modelling also showed that day-to-day variation in training load had no significant effect on sleep stage distribution (Table 3). As such, day-to-day variation in training load was not significantly associated with light sleep ($B = 0.23$ (0.37), $p = .56$), deep sleep ($B = -0.10$ (0.37), $p = .66$) or REM sleep ($B = -0.23$ (0.44), $p = .62$). Confirming the robustness of the results, the confidence intervals displayed in Tables 2 and 3 are narrow, indicating good model precision. Furthermore, regression lines are flat and, in line with the non-significant *p*-values, small point estimates (*B*, comparable to β-values in regression) suggest small effect sizes.

To further indicate the robustness of the findings, post-hoc analyses using the more conservative default actigraphy settings (i.e. AW > 40) were run. Again, none of the analyses reached significance (all *p*'s > .13), thereby confirming that day-to-day variation in perceived training load was not significantly associated with (changes in) sleep quantity and the distribution of sleep stages.

4. Discussion

The present study aimed to shed light on objective sleep quantity and sleep stage distributions in elite athletes and how these sleep measures are associated with day-to-day variation in preceding training load. All measures were assessed during seven consecutive days of regular training.

With regard to sleep quantity, the current study revealed an average sleep duration of almost eight hours. Likely due to the use of more liberal actigraphy settings (i.e., AW >80)[5] athletes' sleep quantity thus turned out to be slightly more favourable than observed in previous reports.[3,4] Nevertheless, the picture of restless sleep in athletes persists, as was for instance reflected in elevated values for wake after sleep onset. Also, the average sleep efficiency of 88% appears to be relatively low when compared to reference values for the current age group (i.e., 92%).[20] More specifically, on 22% of the nights, sleep efficiency was below 85%, which is considered the upper limit for poor sleep.[21] Post-hoc analysis using the default actigraphy settings (i.e. AW >40; as in: Ref. 3,4) revealed a similar picture, but led to a higher estimation of wake after sleep onset and—consequently—a higher percentages of nights (i.e. 53%) on with sleep efficiency was below 85%. All in all, these data indicate that while elite athletes sleep almost eight hours per night, their sleep is fragmented, thereby pointing towards a clear need for sleep optimization strategies.

Assessment of sleep stage distributions indicated that REM sleep and light sleep remained within healthy ranges.[6,20] Yet, in line with the activity level of the current sample (i.e., elite athletes), deep sleep was at the higher end of the optimum (21%),[7] thereby suggesting an elevated need for recovery.

Contradicting expectations, sleep quantity and sleep stage distributions were not associated with day-to-day variation in perceived training load. That is, high training load was not associated with longer sleep onset latencies and wake after sleep onset (e.g., Ref. 14) and did not lead to increases in the proportion of deep sleep.[7,8] Re-running theses analyses with data obtained from the default actigraphy settings (i.e., AW >40) did not lead to different conclusions. The absence of an adverse sleep quantity effect may be explained by an underrepresentation of extremely high val-

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ues of training load (e.g., perceived training load ≥9). Furthermore, the fact that in all cases, training sessions were finalized at least 3 h before bedtime may have limited potential sleep-disturbing effects of elevated core body temperature,[22] high (physiological) arousal,[23] or increased metabolism.[24] The absence of an association between training load and the proportion of deep sleep is perhaps more surprising. Deep sleep is known to adapt to the body's daily need for recovery and the proportion of deep sleep has been shown to increase following strenuous exercise[8] and to decrease following a sedentary day.[25] Potentially, the high mean value for deep sleep (21%) that we observed in the current sample indicates a ceiling effect, which would explain why the proportion of deep sleep could not increase any further with increases in training load. In this case, it is also plausible that subtle adaptations to training load were not manifested in the macro structure of sleep, but appeared in the micro structure of sleep (slow-wave-activity).[25] To make such adaptation visible, future research should employ measures that capture more fine-grained cortical activity (slow-wave activity, sleep spindles) as well as the temporal distribution of sleep stages.[24] Alternatively, and given that the current study was performed in a field setting, it is also plausible that sleep hygiene aspects such as circadian timing of activity and sleep,[26] (sun-) light exposure, lifestyle practises, daily hassles, but also physiological aspects such as fitness had a profound impact on athletes' sleep and confounded a potential impact of training load on the proportion of deep sleep.[27] If general sleep hygiene factors indeed intervene with the natural adaptation of sleep to increased or decreased recovery need,[8,25,28] optimizing conditions and practices that promote continuous and effective sleep in elite athletes, is strongly recommended (e.g., Refs. 4,15).

Finally, a number of important limitations need to be considered. Measuring elite athletes' perceived training load, sleep quantity and sleep stage distributions in a field setting provides a representative image of actual sleep-wake behaviour, but—at the same time—comes at the cost of small losses in measurement sensitivity. For example, in the current study, field measurements of sleep stage distributions were based on a one-channel EEG device instead of multichannel EEG or PSG, which are preferred in lab settings. For the current device, agreement with PSG has been reported to be 98.5% and 83.6% for scoring sleep/wakefulness and sleep stage classification, respectively (also see Section 2[16]). As such, while some caution is warranted in comparing absolute values to (lab-based) PSG estimates, we believe that the current study does give representative (and unprecedented) insight in general sleep stage distributions in elite athletes in the field. Furthermore, given the consistency of the measurement bias, results with regard to the association between perceived training load and sleep stage distributions should not be affected. Another methodological issue that should be mentioned concerns our measurement of perceived training load. While 1-item measures of daily load have high face-validity, show fair correlations with objective indicators of training load (e.g., heart rate[29]), and have successfully been correlated with sleep in previous studies,[30] distinguishing between intensity, duration, frequency and timing of training sessions would arguably give more precise results. In this respect, future research should assess the robustness of the current results by utilizing more precise and potentially also objective measures of training load.

5. Conclusion

In conclusion, the current study provides a detailed overview of objective sleep quantity, sleep stage distributions and their association with perceived training load in a large cohort of elite athletes. While athletes appear to sleep an average of almost eight hours per night, their sleep is fragmented,[3,4] thereby suggesting a potential need for sleep optimization. Furthermore, observed proportions of deep sleep suggests a high need for recovery. With respect to training load, the current study found no evidence for adaptations in sleep quantity and sleep stage distribution following day-to-day variation in perceived training load. While on the one hand, this suggests that sleep is not jeopardized by high training load, the fact that increases in training load are not accompanied by noticeable increases in the proportion of deep sleep (i.e., restoration hypothesis of sleep)[7,8] suggests that elite athletes may recover insufficiently. Optimizing the conditions and practices that promote continuous and effective sleep (i.e., sleep hygiene) may help to maintain naturally adaptive responses of sleep to fluctuations in physical activity, and thus facilitate adequate recovery.

Practical implications

- Relatively high levels of sleep fragmentation indicate that strategies to optimize sleep in elite athletes should focus on reducing wake after sleep onset and promoting continuous sleep rather than solely focussing on sleep extension.
- Field-based monitoring of sleep quantity and sleep stage distributions may not reflect effects of (changes in) perceived training load.
- Optimizing the conditions and practices that promote continuous and effective sleep (i.e. sleep hygiene) may help to maintain naturally adaptive responses of sleep to fluctuations in physical activity.

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