INTRODUCTION

Basic Military Training (BMT), consists of physical training, combat training and general military skill training to prepare Australian Army recruits for military life [1]. During BMT, recruits are exposed to a variety of stressors that combined with physically demanding training sessions, may induce a state of physiological fatigue [2,3]. Monitoring recruits responses to these stressors throughout BMT may therefore be useful to help prevent reductions in performance (e.g. physical and cognitive), along with the costly consequences of injury and illness, such as loss of training time and discharge [4]. However, large platoon sizes (up to 60 recruits), full day training schedules (0600 – 2200 hours) and staff allocations present challenges in implementing objective monitoring techniques, considering expense along with the requirement for mass data download and analyses to inform near real-time recruit management.

Subjective measures, which are relatively simple and inexpensive to implement may offer a practical and feasible alternative to objective measures of workload [5]. One commonly employed tool to monitor training responses is rating of perceived exertion (RPE) expressed relative to training time as a session-RPE (s-RPE) [6]. The construct validity of s-RPE has been established against external workload measures derived from global positioning systems (GPS) and accelerometery, representing the physical work performed (stress), such as distance and PlayerLoad™, and internal load measures, reflecting an individual's physiological response to the given work (strain), such as heart rate [7-9]. During BMT the monitoring of recruit workload should however not be exclusively limited to physical training sessions, as other programmed training activities (e.g. marching, military education, field exercises and drill) also contribute to a recruit's cumulative daily workload [1]. Yet, due to time constraints, along with additional data to cumulate, the collection of RPE at multiple time points throughout a day may be problematic. Good agreement has however been observed between daily heart rate derived training impulse (TRIMP), Edwards TRIMP, and a single daily measure of RPE ($R^2 = 0.57 – 0.77$) within British Army recruits during BMT [10]. Edwards TRIMP multiplies the duration spent in five heart rate zones by a corresponding coefficient, whereby greater coefficients are applied to higher heart rate zones, and sums the results [11]. Smaller associations were also reported between daily RPE and average daily heart rate ($R^2 = 0.37 – 0.40$) and distance derived metrics ($R^2 = 0.20 – 0.38$) [10]. Accordingly, a single daily measure of RPE may present an avenue for practically monitoring recruit's internal workload. However, the regression analyses by O'Leary et al. [10] were performed on group (male or female) daily averages, and whilst simple regression analyses on individual data points were also conducted ($R^2 = 0.16 – 0.28$), these analyses do not account for by-recruit differences in workload and perceived exertion. Accounting for between recruit variations may be particularly important considering the diverse nature of recruit populations, in relation to age, training history and fitness [12]. Furthermore, recent research has suggested that separating global RPE (differential RPE; d-RPE) into its specific psychophysiological mediators may improve workload quantification [13,14]. Yet, no study to date has examined d-RPE, separate scores for breathlessness (RPE-B) and leg muscle exertion (RPE-L), when reported as a daily measure of workload. Further analysis into the suitability of daily RPE and d-RPE measures as a reflection (e.g. proxy measure) of whole day workloads in recruit populations is thus warranted.

In addition to subjective workload ratings, subjective ratings of sleep may also provide a practical tool to monitor recruits' physiological state, considering sleep disturbance has previously been associated with markers of overtraining during BMT [3]. Herein, throughout BMT numerous factors (e.g. stress, sleep environments, altered sleep schedule and prescribed sleep periods) can compromise recruits' sleep [15], which can be problematic as insufficient or inadequate sleep can negatively impact on physical performance [16], wellness [15], the ability to learn complex tasks [17] and may also increase the risk of injury and illness [16,18]. Suitably, the implementation of strategies to identify recruits with compromised sleep during BMT seems warranted [19]. A number of validated subjective sleep questionnaires exist (e.g. Pittsburgh Sleep Quality Index), however these tools are lengthy to administer and are inappropriate or impractical for daily monitoring [20]. Shorter questionnaires have shown strong agreement between self-reported and objective measures of sleep duration in professional rugby players [21] and physical education students [22]. However, the accuracy of subjective, in comparison to objective measures to monitor sleep during BMT is unclear.

A lack of agreement between subjective and objective measures presents a problem to practitioners wishing to implement subjective monitoring strategies. Correspondingly, the aims of this study were two-fold: 1) to assess if daily RPE measures reflect an Australian Army recruits daily workload relative to objective measures of internal and external workload and 2) to determine if self-reported sleep measures reflect objective measures of sleep estimated via activity monitors.

MATERIALS AND METHODS

Participants

Fifty-nine recruits (male = 48; female = 11; age: 23 ± 5 years [range: 17 – 44 years]; height: 1.77 ± 0.09 m; mass: 75.7 ± 13.2 kg) undertaking BMT at the Army Recruit Training Centre, Kapooka, volunteered to participate in this study. Twenty-three male and 7 female recruits (*n* = 30) (age: 22 ± 6 years [range: 17 – 44 years]; height: 1.77 ± 0.09 m; mass: 76.3 ± 13.5 kg) from two platoons in separate companies, were included in the assessment of workloads. A different platoon including 25 male and 4 female recruits (*n* = 29) (age: 23 ± 6 years [range: 18 – 30 years]; height: 1.78 ± 0.09 m; mass: 75.6 ± 13.2 kg), were included in the analyses of sleep. Prior to study commencement, written and verbal information about the research and its procedures were provided to all participants, before written informed consent was obtained. The research received ethical approval from the Australian Defence Human Research Ethics Committee (083-18) and DST Low Risk Ethics Panel (LD-20-18) and conformed to the Declaration of Helsinki.

Procedures

Testing was conducted during week 3 of the 12-week Australian Army BMT course. For the assessment of workloads, recruits were monitored from Monday – Saturday (6 days), while for the assessment of sleep, recruits were monitored for 7 nights (Sunday – Saturday). An outline of the study design is provided in Figure 1.

INSERT FIGURE ONE ABOUT HERE

Workload monitoring

Heart rate, global positioning systems and activity monitor

Recruits were fitted with a heart rate monitor (Polar Team 2, Polar Electro Oy, Kempele, Finland), positioned around the chest, a GPS (OptimEye X4, 10 Hz GPS units, Catapult Innovations, Canberra, Australia), containing a 100 Hz triaxial accelerometer, worn in a vest, positioned on the upper thoracic region of the spine and an activity monitor (GT9X Link, ActiGraph, Pensacola, FL, USA), sampling at 100Hz, on the non-dominant wrist. Monitors were fitted each morning between 0600 – 0640 h and worn throughout the day (0640-2100 h). At the end of each day data were downloaded using the proprietary software associated with each device.

For each recruit maximal heart rate was initially predicted using an equation [23], but adjusted if a recruit obtained a higher maximal heart rate during physical training. Recruit average heart rate (absolute) and daily training impulse (TRIMP) using Edwards TRIMP [11], was calculated for each training day. Edwards TRIMP multiplies the training duration accumulated in five heart rate zones (zone 1 = 50-60% HRmax, zone 2 = 60-70%, zone 3 = 70-80%, Zone 4 = 80-90% and zone 5 = 90-100% HR maximum) by a corresponding coefficient for each zone and sums the results [11]. On all testing days recruits were assigned the same GPS units, to avoid inter-unit error [24]. PlayerLoad™, calculated using a customised algorithm within the software provided (Openfield 1.21.1 Software, Catapult Innovations, Melbourne, Australia), was used as a measure of external load. In brief, PlayerLoad™ is derived from tri-axial accelerometers and represents the square root of the sum of squared instantaneous rate of change of acceleration within the three planes divided by 100 (Catapult Innovations, Melbourne, Australia). The accelerometers measuring PlayerLoad™ possess high inter and intra device reliability [25], while PlayerLoad™ has been shown to demonstrate moderate to high reliability and validity [26-28]. Daily step count was calculated by the wrist worn ActiGraph activity monitor.

Subjective workload measurement

Recruits were familiarised with workload-related questions and the modified category ratio (CR)-10 Borg scale [29], which included idiomatic verbal anchors, prior to data collection. At the end of each day (2100-2130 h) recruits were asked to rate "How physically demanding was training today?" (RPE) [10,29]. Additionally, to obtain separate scores (d-RPE) for breathlessness (RPE-B) and leg muscle exertion (RPE-L), recruits were asked "How physically demanding was training today on your breathing" (RPE-B) and "How physically demanding was training today on your legs?" (RPE-L) [13,14]. As each training day during BMT is confined to set training hours (0600-2200h), session duration remains constant, therefore RPE can be compared across days without multiplying by session duration [10].

Sleep monitoring

Recruit time in (hh:mm) (i.e. lights out) and out of bed (hh:mm) (i.e. morning wake up) was provided by platoon staff using a platoon sleep record. If activity monitor or self-reported sleep data were not available for a given night, these data were excluded from the analyses.

Activity monitors

Actigraphy measures were recorded in 1 min epochs via an activity monitor (GT9X Link, ActiGraph, Pensacola, FL, USA), sampling at 30 Hz, on the non-dominant wrist and analysed using the Cole-Kripke algorithm within the ActiGraph software (ActiLife v6.13.4 ActiGraph, Florida, USA). ActiGraph devices have been shown to be a valid alternative to polysomnography for measuring sleep duration and efficiency [30]. Recruits wore the same monitor throughout the study period, fitted on the Sunday and returned the following Sunday morning. All non-wearing times were excluded from analyses while in and out of bed-time were manually assigned according to the platoon sleep record. All remaining epochs were used to determine sleep efficiency (percentage of time in bed that was spent asleep) and sleep duration (total sleep minutes obtained during a sleep period) [31].

Subjective sleep measurement

Recruits were familiarised with the custom designed sleep questionnaire prior to data collection. Each morning recruits were asked one question “How did you sleep last night?” requiring a Likert scale response, whereby 1 indicated *‘terrible sleep’*, to 10 *‘excellent sleep’*; and three questions “How long did it take you to fall asleep last night?”, “How long were you awake before the bugle this morning?” and “How long were you awake for in total during the night?”, requiring pre-defined category responses; 0-10, 10-20, 20-30, 30-60 minutes or 60+ minutes.

Data analyses

A total of 180 individual days were included in the analyses of daily RPE, while 194 comparisons were obtained for the sleep analyses. For responses to subjective sleep questions, the maximal value in the range was selected (e.g. 10 for 0-10 minutes). Recruits reporting ‘greater than 60 minutes’ were allocated 61 minutes. Perceived sleep duration was calculated as total time in bed as provided by platoon staff - (time to fall asleep + time awake before bugle + time awake during the night).

Statistical analyses

All statistical analyses were performed using *R* (version 4.0.0, R Foundation for Statistical Computing, Vienna, Austria). To assess the association between objective (TRIMP, average heart rate, PlayerLoad™ and step-count) and subjective (RPE, RPE-B and RPE-L) measures of workload, linear mixed-models were performed using the *lme4* package [32]. In each model the objective workload measure (i.e. TRIMP) was entered as the fixed effect predictor variable and intercepts for each recruit as well as by-recruit random slopes were included as random effects. Where the inclusion of random slope analyses did not improve model fit (as assessed by the conditional R^2), a random intercept only model was conducted. To assess if the inclusion of d-RPE measures explained a greater proportion of the variance in each objective workload measure, linear mixed-models were constructed whereby the objective measure was modelled as a function of RPE, RPE and RPE-B, RPE and RPE-L, and all RPE measures. Within each model, intercepts for each recruit were included as random effects. Models were compared using Akaike Information Criterion (AIC), with a lower AIC score indicative of a more parsimonious model. Qualitative terms for the relative AIC difference (ΔAIC) from the estimated best model (i.e. model with the lowest AIC value; ΔAIC = 0) were assigned according to the following scale: 0-2, essentially equivalent; 2-7, plausible alternative; 7-14, weak support; >14, no empirical support [33]. The association between sleep efficiency (objective) and perceived sleep quality (subjective) was assessed using a linear mixed-model with sleep efficiency entered as the fixed effect and intercepts and slopes for each recruit entered as random effects. Model estimates are presented with 95% confidence limits along with slope significance. Marginal (variance explained by the fixed effect alone) and conditional (proportion of variance explained by both the fixed and random effects) R^2 values are presented to indicate the association between objective and subjective measures [34]. Agreement between subjective and objective measures of sleep duration was investigated by determining mean bias and the typical error of the estimate (TEE). A repeated measures correlation examined the relationship between subjective and objective measures of sleep duration, with the correlation coefficient reported with 95% confidence limits. Heteroscedasticity was initially assessed via Pearson correlations on the absolute deviations between self-reported and activity monitor sleep duration (r = -0.12). For all analyses statistical significance was set at $p < 0.05$. Descriptive statistics are presented as mean ± standard deviation (SD).

RESULTS

Average daily workload data are presented in Table 1. Slope estimates along with marginal and conditional R^2 values for associations between objective workload measures and daily RPE measures are presented in Table 2.

INSERT TABLE ONE ABOUT HERE

INSERT TABLE TWO ABOUT HERE

Linear mixed-model estimates for associations between daily RPE, along with the inclusion of d-RPE measures, and objective workload measures are presented in Table 3.

INSERT TABLE THREE ABOUT HERE

Marginal and conditional R^2 values for the association between activity monitor measures of sleep efficiency (mean = 78.71 ± 6.04%) and perceived sleep quality (mean = 7 ± 2) were 0.005 and 0.697, respectively. The slope estimate for this model was not significantly different from zero (p = 0.29; slope estimate = 0.02; CI -0.02, 0.06). Average sleep duration estimated from subjective sleep questionnaires and activity monitors were 06:49 ± 00:48 and 06:24 ± 00:29, respectively. Sleep duration mean bias revealed that self-reported measures overestimated sleep by an average of 25 minutes compared to activity monitors, while a *trivial* relationship (r = 0.12; CI -0.03, 0.27, p = 0.12) was observed between activity monitor and self-reported sleep duration, with a TEE of 41 minutes.

DISCUSSION

In this study, associations between objective measures of workload and daily RPE measures improved when accounting for by-recruit differences, with strong associations observed between heart rate and PlayerLoad™ derived measures of workload and daily RPE measures. The inclusion of d-RPE, in addition to daily RPE, improved the models, resulting in a lower AIC and accounted for more variance in objective workload measures. The association between measures of objective sleep efficiency and subjective sleep quality was improved when accounting for by-recruit differences, however, perceived sleep duration did not accurately reflect activity monitored sleep duration.

The associations between heart rate and PlayerLoad™ derived objective measures of workload and daily RPE observed in the current study were similar to associations between daily RPE and objective measures of workload observed in British Army recruits [10]. Although, it should be noted that these associations are not directly comparable due to differences in how marginal R^2 and R^2 values are calculated [34]. However, in the current study, considering individual recruit intercepts and slopes (conditional R^2) improved the strength of all associations which was expected considering the diverse nature of recruit populations [12] and intra-recruit dependent variables such as fitness, training history, gender and psychological state [10,35], that can impact responses to perceptions of workload.

Daily TRIMP explained the greatest proportion of variance in daily RPE when considering individual recruit intercepts and slopes. Indeed, TRIMP may be more sensitive to variations in recruit workload as unlike average heart rate, TRIMP accounts for time spent in different exercise intensity thresholds, along with applying weighting factors. This finding is similar to the results of O'Leary et al. [10], who also reported that TRIMP explained a greater proportion of the variance in daily RPE in comparison to average heart rate and daily distance. However, as distance derived metrics require satellite connection to be calculated and BMT activities occur both indoors and outdoors, daily distance may not be the most useful measure of external load in recruit populations. Herein, PlayerLoad™ was used as a measure of external load within the present study given its suitability for encompassing both indoor and outdoor training, and its capacity to capture physical demands of recruit training independent of distance. For example, recruits can cover minimal distance but perform a high number of movements (e.g.

prop and drop). Consistent with reports from team sports [9], a strong association between PlayerLoad™ and daily RPE was observed within the current cohort. In contrast, lower associations were observed between step count and daily RPE, although, the accuracy of wrist worn activity monitors for calculating step count potentially impacted upon this finding [36]. In comparison to external measures of workload, stronger associations were seen between internal measures and daily RPE. Considering RPE is primarily used as a measure of internal workload [35] this finding is not surprising, whilst the strong association between PlayerLoad™ and daily RPE is in keeping with training theory, whereby internal workload is a product of an individual's external workload [37]. Although external workload represents an important contributor to internal workload, internal responses can be impacted by numerous other factors, such as training status, fatigue and genetics, along with other environmental stressors (e.g. hot training conditions), emphasising the importance of monitoring internal loads [37]. Based on the strength of associations between internal load measures and daily RPE within the present study, daily RPE which represents a recruit's own perception of training induced strain, can be used to provide practitioners with a simple yet valuable proxy measure of recruit global internal workload.

Due to their potential to further enhance internal workload quantification [13], d-RPE measures were also considered within the present study. Associations between objective and subjective daily measures of workload were generally stronger for RPE in comparison to d-RPE measures. Previous work within team-sports, has indicated that d-RPE measures make a unique contribution to overall RPE [14]. Differences in associations may therefore signify the ability of recruits to distinguish between different dimensions of effort, whilst indicating that daily RPE provides a global measure of recruit workload. That said, a stronger association was seen between PlayerLoad™ and RPE-B, in comparison to RPE. Higher RPE-B values are associated with increased heart rate and oxygen consumption [13] therefore recruits may have more readily associated RPE-B with the physical work performed that day. For model comparisons, models including d-RPE measures presented with a lower AIC, indicating a better balance between model complexity and explanatory power [38]. Therefore, in comparison to RPE only models, models including d-RPE measures were beneficial for explaining the data within the present study. Yet, practitioners should consider their intended use for d-RPE measures and how it may impact upon decision making [14], along with the extent of information gained, due to the associated time cost and questionnaire fatigue with collecting and analysing the additional questions daily.

Similar to associations between objective and subjective measures of workload, there was an improved association between activity monitor recorded sleep efficiency and subjective sleep quality when accounting for by-recruit differences. The slope estimate for this model was however not significant. Accordingly, for a one unit increase in sleep efficiency, confidence intervals for model estimates suggest that subjective sleep quality may increase or decrease. Although subjective sleep quality measures are commonly used to monitor an individual's sleep [39], poor relationships between objective measures and subjective sleep quality have previously been reported [21]. Indeed, whilst activity monitor recorded sleep efficiency represents the percentage of time in bed that was spent sleeping, there is a lack of a consensus related to the definition of subjective sleep quality [39]. Consequently, numerous sleep characteristics (e.g. awakenings) may impact upon subjective sleep quality whilst individual interpretation of sleep quality may explain the vast difference between marginal and conditional R^2 values reported within the present study.

Although validated sleep questionnaires exist [20], the methods used to assess sleep in the present study were adopted given the limited time available for recruits to complete the questionnaire along with the requirement for the questionnaire to be completed daily. Moreover, questions were designed to eliminate the requirement for recruits to have access to a clock or knowledge of exact bed and wake times, while categorical responses were implemented to aid in data analyses. The mean bias between subjective sleep duration and activity monitor sleep duration in the present study is similar to reports in rugby players [21] and physically active university students [22]. However, in contrast to the *very large* relationships between subjective and activity monitor sleep duration (*r* ranging from 0.82 – 0.86) reported by Caia et al. [21] and Kölling et al. [22], a *trivial* relationship [40], was reported within the present study. This may have resulted from the response time categories lacking sensitivity, while the open ended 60+ min category, which was included in perceived sleep duration calculations on 26 instances (13%), made it difficult to calculate exact sleep duration. Exploratory data analyses with these data (61+ min) removed did not result in improved reliability. Additionally, time awake during the night was estimated by summing time to fall asleep, time awake before the bugle and total time awake during the night. Although informed on how to complete the questionnaire recruits may have misinterpreted total time awake during the night as encompassing time to fall asleep and awake before the bugle. The current methods used to assess sleep should therefore be considered as a limitation and not suitable for determining recruit sleep duration. Future research may therefore wish to consider assessing subjective sleep duration using more reliable methods where individuals specify exact timings (hh:mm) for bed, wake times or sleep duration [21,22]. Yet, considering scheduling, specifically in relation to morning routine, along with recruits' knowledge of time, a valid daily measure of subjective sleep duration may be difficult to obtain in a BMT environment.

Limitations

In addition to the limitations associated with the methods used for collecting subjective sleep data, a number of additional limitations should be recognised. Firstly, workloads and sleep were only assessed over a single week. Accordingly, outcomes may not be consistently reflected across BMT and the daily variation in workloads are likely more diverse than that reported in the current study (Table 1) [10,12]. Future studies should therefore assess the sensitivity of daily RPE measures to variations in workload by assessing responses over an entire BMT course. Additionally, only 30 recruits were involved in the assessment of workload and 29 in the assessment of sleep, as such these results may not be representative of all recruits. Further, it should be acknowledged that recruit characteristics such as gender, entry fitness levels, previous training experience and injury status were not considered in the present study but may have impacted upon the results reported. The method used to obtain maximal heart rate may also have resulted in possible error around the regression line and correspondingly some inaccuracy in estimating maximal heart rates [23]. However, a maximal cardiorespiratory fitness test (e.g. multi-stage shuttle run test) was not scheduled during the data collection week and it was not possible to modify the training schedule. Training disruption was also considered when fitting and removing monitors, consequently, the first 40 minutes of each day were excluded from analyses due to variations in when monitors were fitted. Workloads that occurred during this time, which may have impacted upon subjective daily RPE measures, were therefore not captured by objective measures.

CONCLUSIONS

In this study, objective measures of workload were strongly associated with daily RPE when accounting for by-recruit variation in workload measures, with the strongest associations seen between internal measures of workload. Furthermore, the inclusion of d-RPE measures, helped explain the variance in each objective workload measure. The current findings therefore provide support for the use of daily RPE as a proxy measure of internal workload in Australian Army recruits, however, attention should be focused to individual responses. In contrast subjective sleep measures did not reflect objective measures of sleep, therefore the use of the current subjective sleep questionnaire as a proxy measure of objective sleep measures is not recommended.

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FIGURE AND TABLE DESCRIPTIONS

Figure 1. Schematic of study design.

Table 1. Average daily workload measures (mean ± SD)

Table 2. Slope estimates and associations between objective workload and daily RPE measures

Table 3. RPE and differential RPE model comparisons