

3-31-2021

Relationships between internal training load in a taper with elite weightlifting performance calculated using different moving average methods

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[10.1123/IJSP.2020-0002](https://doi.org/10.1123/IJSP.2020-0002)

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Coyne, J. O. C., Newton, R. U., & Haff, G. G. (2021). Relationships between internal training load in a taper with elite weightlifting performance calculated using different moving average methods. *International Journal of Sports Physiology and Performance*, 16(3), 342-352.

<https://doi.org/10.1123/IJSP.2020-0002>

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**Relationships Between Internal Training Load In a Taper
with Elite Weightlifting Performance Calculated Using
Different Moving Average Methods**

Journal:	<i>International Journal of Sports Physiology and Performance</i>
Manuscript ID	IJSPP.2020-0002.R1
Manuscript Type:	Original Investigation
Date Submitted by the Author:	14-Mar-2020
Complete List of Authors:	Coyne, Joseph; Edith Cowan University, Centre for Exercise and Sports Science Research Newton, Robert; Edith Cowan University, Centre for Exercise and Sports Science Research Haff, G.; Edith Cowan University, Centre for Exercise and Sports Science Research; Salford Univeristy, Directorate of Sport, Exercise, and Physiotherapy
Keywords:	Monitoring, Simple Moving Average, Exponentially Weighted Moving Average, Periodization, Acute to Chronic Workload Ratio

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- 1 Relationships Between Internal Training Load In a Taper with Elite Weightlifting
- 2 Performance Calculated Using Different Moving Average Methods

For Peer Review

3 ABSTRACT

4 **Purpose:** A simple and two different exponentially weighted moving average methods
5 were used to investigate the relationships between internal training load (TL) and elite
6 weightlifting performance. **Methods:** Training impulse data (sessional ratings of perceived
7 exertion * training duration) were collected from 21 elite weightlifters (age 26.0 ± 3.2 years,
8 height 162.2 ± 11.3 cm, body mass 72.2 ± 23.8 kg, previous 12 month personal best total
9 $96.3 \pm 2.7\%$ of world record total) during the eight weeks prior to the 2016 Olympic Games
10 qualifying competition. The amount of training modified or cancelled due to injury/illness
11 was also collected. Training stress balance (TSB) and acute to chronic workload ratio
12 (ACWR) were calculated with the three moving average methods. Along with the amount
13 of modified training, TSB and ACWR across the moving average methods were then
14 examined for their relationship to competitive performance. **Results:** There were no
15 consistent associations between performance and TL on the day of competition. The
16 volatility (standard deviation) of the ACWR in the last 21 days preceding competition was
17 moderately correlated with performance across moving average methods ($r=-0.41-0.48$,
18 $p=0.03-0.07$). TSB and ACWR volatility in the last 21 days were also significantly lower
19 for successful performers but only as a simple moving average ($p=0.03$ and 0.03 , $g=1.15$
20 and 1.07 respectively). **Conclusions:** Practitioners should consider restricting change and
21 volatility in an athlete's TSB or ACWR in the last 21 days prior to a major competition.
22 Additionally, a simple moving average seemed to better explain elite weightlifting
23 performance compared to the exponentially weighted moving averages in this investigation.

24
25 KEYWORDS

26 Monitoring, Simple Moving Average, Exponentially Weighted Moving Average,
27 Periodization, Acute to Chronic Workload Ratio

28
29

30 INTRODUCTION

31 Training load (TL) monitoring is an associated extension of periodization theory.¹ In
32 practice, methods of monitoring TL can vary considerably depending on the type of sport
33 or activity.² Despite this, TL models are commonly computed using training impulse
34 data^{2,3}, which is calculated as a product of an intensity factor multiplied by a
35 volume/duration factor.³ An athlete's overall response to training is then modelled as the
36 difference between "fitness" (positive) and "fatigue" (negative) functions.^{2,3} Popular
37 simplified extensions of this model has been the development of training stress balance
38 (TSB) and the acute to chronic workload ratio (ACWR).^{4,5} These have been calculated
39 using the difference (TSB) or ratio (ACWR) between the simple moving (rolling) averages
40 of TL over acute and chronic periods.^{4,5}

41
42 Training load can be described as either internal or external and it is recommended that
43 both these constructs are used to assess the training process.^{6,7} There are a number of
44 external TL measures that are common in weightlifting e.g. volume load.^{8,9} The use of
45 internal TL measures such as sessional ratings of perceived exertion (sRPE) in
46 weightlifting remain contentious despite recommendations as a primary TL measure^{10,11}
47 and its common use in endurance sports.² Theoretically, sRPE accounts for the perception
48 of physiological, biomechanical and mental work an athlete completes and any influence
49 of environmental factors inside and outside of training⁷ and may be a useful complement
50 for external TL in weightlifting. There appears to be relationships with sRPE and
51 performance in both open (Australian Rules football)¹²⁻¹⁴ and closed skill sports (sprinting
52 and distance running).¹⁵⁻¹⁷ However, the evidence for this relationship with performance
53 has been presented with a number of different TL derivatives e.g. ACWR, TSB, strain,
54 monotony. One major difference between these variables is that monotony and strain are
55 products of the TL standard deviation.¹⁸ **Although relationships with performance have
56 not seemed to be examined, previous athlete monitoring research using monotony has
57 suggested relatively less negative training outcomes (i.e. illness) if the TL standard
58 deviation is higher when compared to the weekly TL.^{18,19}** This is notable considering the
59 standard deviation of time series data is considered important in other industries that
60 specialize in forecasting and risk assessment like the financial markets.²⁰ **For instance, in
61 financial analysis, greater volatility of an asset may indicate a greater risk in and higher or
62 lower prices for buying and selling the asset or options for the asset.²⁰** The time series'
63 standard deviation is commonly referred to as volatility in the financial industry²⁰ and this
64 term will be used throughout the remainder of the paper.

65
66 There has been debate about the most appropriate moving average methods used to
67 determine acute and chronic TL.^{21,22} It is theorised that simple moving averages (SMA)
68 may not account for variations in how TL is accumulated by athletes nor best represent the
69 physiological gain or decay of "fitness" and "fatigue".^{21,22} Exponentially weighted moving
70 averages (EWMA) have been recommended as a superior alternative.²¹⁻²³ However, like
71 SMA, there are also conceptual issues with EWMA.⁷ For instance, the set time constants
72 used with EWMA calculations may be problematic as athletes will have individual
73 "fitness" and "fatigue" gain and decay rates.⁷ Additionally, there have also been several
74 different EWMA calculations presented in the scientific literature.^{14,21} All three of the
75 different calculation methods produce different TL values for acute and chronic periods

76 and it is unclear whether one has a superior relationship to performance. Further debate
77 has also been raised over the use of the ACWR with the main criticism being that the ratio
78 produces a spurious correlation due to mathematical coupling i.e. the numerator (acute TL)
79 is contained in the denominator (chronic TL).²⁴ However recent publications suggest that
80 any correlations between acute and chronic TL in the ratio may not necessarily be spurious
81 (i.e. misleading) or may be practically unrelated to ACWR's relationships with other
82 factors e.g. injury risk.^{25,26} **Nevertheless, TSB (as it is the difference rather than the ratio**
83 **between acute and chronic loads) may be preferred over the ACWR for practitioners**
84 **concerned with these issues.**
85

86 In light of the potential benefits of using sRPE as a method for quantifying TL and the low
87 level of current evidence supporting potential relationships between sRPE and performance
88 in closed skilled sports like weightlifting, further investigation in this area is warranted.
89 As such, the first two aims of this study are to: i) examine whether TL variables were
90 correlated to the performance of elite weightlifters; and ii) determine if meaningful
91 differences existed in the TL variables between higher and lower performers. It was
92 hypothesized that there would be a significant correlation in TL variables with performance
93 along with significant differences between higher and lower performers. The third aim of
94 the investigation was to compare if there was any effect of moving average methods on the
95 statistical analysis. The authors hypothesized that TL derivatives calculated using EWMA
96 would have a greater correlation to performance and better separate higher and lower
97 performing groups than a simple moving average.
98

99 METHODS

100 *Subjects*

101 Twenty-eight elite male (n=13) and female (n=15) weightlifters (26.0 ± 3.2 years, $162.2 \pm$
102 11.3 cm, 72.2 ± 23.8 kg, previous 12 month personal best total $96.3 \pm 2.7\%$ of world record
103 total) from the same national team participated in this 8-week study. **The subjects competed**
104 **across the full range of male and female weight classes in the 2016 Olympic Games (54kg-**
105 **+105kg male, 48kg-+75kg female).** Seven subjects were excluded from analysis due to
106 issues with data collection compliance (n=3; all male) or failing to post a competition total
107 i.e. a successful lift in both snatch and clean & jerk (n=4; 3 female and 1 male). The data
108 for this study were initially collected within the athletes' training environment and was
109 released de-identified from the respective National Olympic Committee in this university
110 approved retrospective study. Approval for this investigation was granted by the
111 University Human Ethics Committee (Approval #19521) and conforms to the *Code of*
112 *Ethics of the World Medical Association* (Declaration of Helsinki).
113

114 *Design*

115 This investigation was a retrospective observational study design. Internal TL data (sRPE
116 and training duration) were collected from elite weightlifters during the last 8 weeks prior
117 to a major competition that was critical to selection for the 2016 Olympic Games. Illness
118 or injury incidents that caused an athlete to modify technical training or seek medical
119 attention were noted throughout the 8-week training period.²⁷ The correlations between
120 acute TL, chronic TL, TSB, ACWR, %INJ and competitive performance were examined.

121 Differences in these TL variables between higher and lower performers and top five and
122 bottom five performers were also investigated.

123

124 *Methodology*

125 After athlete instruction and familiarisation, sRPE were recorded with the 10-point
126 category ratio scale (CR10) 30-120 minutes after each session^{28,29} for the total training
127 session (i.e. technical and non-technical exercises). The sRPE were then multiplied by the
128 total session duration to give training impulse. The following variables were calculated
129 daily from the training impulse data: i) acute TL (7 day average); ii) chronic TL (21 day
130 average); iii) TSB (chronic - acute TL); and iv) ACWR (acute/chronic TL) using
131 established methods². These variables were calculated with SMA, EWMA as per Williams
132 et al (EWMA-W)²¹ and EWMA as per Lazarus et al (EWMA-L)¹⁴ to establish if there was
133 any effect of moving average method on the statistical analysis. These three moving
134 average methods were chosen for analysis as, at least to the author's knowledge, they have
135 been the prevalent methods presented or suggested in literature on TL monitoring.^{2,14,21} In
136 regard to the differences between the two EWMA calculations used in this study, the
137 primary difference is the time constant component in the calculation. EWMA-W uses
138 $2/N+1$ as the time constant whereas EWMA-L uses $1/N$ with N representing the number
139 of days.^{14,21} EWMA-L has been suggested to be a superior alternative to EWMA-W as it
140 gives a weighted average that has the highest correlation with the SMA of time constant
141 days.¹⁴ For example, the 10-day EWMA-L would have the highest correlation with a 10-
142 day SMA and lower correlations with 7 and 14 days. **However, to the best of the author's
143 knowledge, the two EWMA methods have not been compared with one another with a
144 variable of interest (i.e. performance) and it is debatable as to which one is most appropriate
145 for calculating TL.**

146

147 The acute and chronic periods were set at 7:21 days respectively. The determination of
148 period lengths were based on an average fitness time decay constant of 23.2 days in
149 previous research on elite weightlifters.³⁰ **The period length determination was also based
150 on the typical training micro-mesocycle combination used by the weightlifting athletes in
151 this investigation.⁷ This was typically a three-week mesocycle with a "moderate, "hard",
152 "easy" loading pattern; although there were differences in how technical coaches applied
153 this with individual athletes. Microcycles were generally comprised of two training
154 sessions/day alternated with one training session/day for the first 6 days of the microcycle
155 and a complete rest day on the 7th day. Commonly athletes would perform weightlifting
156 technical exercises (e.g. snatch, clean, jerk) followed by strength exercises (e.g. squat,
157 deadlift) and assistance or hypertrophy exercises (e.g. pull ups, lower back exercises) in
158 each training session. Based on exploratory data analysis, acute TL, chronic TL, TSB and
159 the ACWR were then assessed as: i) absolute values, which represented the value on the
160 day of the competition; ii) the value 21 days prior to competition subtracted from the value
161 on the day of the competition (CHANGE21); and iii) the volatility (calculated as the
162 standard deviation) of values in the last 21 days prior to competition (VOL21).**

163

164 The last 21 days prior to competition was chosen for the time period of interest based on
165 the results of existing performance modelling research, tapering research **and typical taper
166 length of the weightlifting athletes in this investigation.^{30,31} The percentage of modified**

167 training due to injury/illness compared to total training time was also considered in the last
168 6 weeks before competition.²⁷ This percentage of training was based on any injury or
169 illness that affected an athlete's training (e.g. a shoulder injury may have limited exercise
170 choice or volume for coaches) or required medical intervention. TL and injury/illness
171 variables were then compared against competition performance results. **Performance was**
172 **defined as the competition results expressed as a percentage of previous 12-month personal**
173 **best and of the current world record at time of competition from the weightlifters that**
174 **successfully completed a repetition in both lifts.** Athletes were then divided into successful
175 and non-successful groups (n=10 and 8 respectively) and top five and bottom five
176 performance groups. The allocation into either the successful or non-successful groups
177 was determined by whether the athlete produced a competition performance result as
178 percentage of previous 12-month personal best greater or lesser than the smallest
179 worthwhile change threshold. The smallest worthwhile change threshold was defined as
180 0.2 x standard deviation of complete cohort competition results.³² **Meanwhile, the top 5**
181 **competition performance results as percentage of previous 12-month personal best were**
182 **allocated to the top five performance group and the bottom 5 competition performance**
183 **results were allocated to the bottom 5 performance group.** There were 3 athletes from the
184 cohort who were not allocated to either group as their competitive results fell inside this
185 threshold.

186
187

188 *Statistical Analysis*

189 Statistical analyses were performed using statistical software (R statistics package,
190 <https://www.r-project.org>) or purposefully designed Excel spreadsheets (Microsoft
191 Corporation, Washington, U.S.). All data were analysed as mean \pm standard deviation
192 (SD). Pearson's correlation analyses with 95% confidence intervals were used to
193 determine if there were any linear relationships between **the TL variables calculated with**
194 **the different moving average methods and competition performance and also between**
195 **percentage of total training modified due to injury and illness and competition**
196 **performance.** R-z transformations were also applied to determine if there were any
197 significant differences between correlations with performance amongst the various moving
198 average methods. Differences between groups were expressed relative to the total cohort
199 as a beta percentage (e.g. successful group – non-successful group / total cohort) to account
200 for subjects within the smallest worthwhile change thresholds and the national team's
201 normal training practice. If the different groups' TL and injury/illness variables were
202 normally distributed, an independent student's t-test or Welch's t-test was used based on
203 F-test results. If the different groups' TL and injury/illness variables were not normally
204 distributed, log transformation of the particular variable³² and visual inspection of log-
205 transformed QQ plots were applied before using the appropriate t-test based on variance
206 testing. **Outliers were inspected and were excluded only if they were results of errors in**
207 **data collection.** The alpha level for significance was defined as $p \leq 0.05$. For normally
208 distributed variable comparison, effect sizes (Hedge's g) were also calculated and
209 interpreted. If variable data were non-normal, the difference between the two log-
210 transformed values were converted to Hedge's g for comparison.³³ **These effect sizes were**
211 **then interpreted as per the recommendations of Hopkins et al with g <0.19 defined as**
212 **trivial, 0.2-0.59 as small, 0.6-1.19 as moderate, 1.2-1.99 as large and >2 as very large.**³²

213 Cumming estimation plots were also applied to help visualize differences between
214 groups.³⁴ In these plots, the raw data is plotted on the upper axes and each mean difference
215 is plotted on the lower axes as a bootstrap sampling distribution. Mean differences are
216 depicted as dots and 95% confidence intervals are indicated by the ends of vertical error
217 bars.

218

219 RESULTS

220 A total of 1278 training sessions were included in the present analysis. **The subject's**
221 **competition results as percentages of previous 12-month personal best and of the current**
222 **world record at time of competition along with percentage of total training modified due**
223 **to injury and illness are presented in Table 1.**

224

225

226

TABLE 1 ABOUT HERE

227 The average TSB and ACWR were 20.1 ± 82.1 and 0.93 ± 0.26 (SMA), -40.6 ± 78.8 and
228 1.25 ± 0.49 (EWMA-W), and -80.1 ± 69.0 and 1.57 ± 0.57 (EWMA-L) over the eight
229 weeks. There were significant differences in performance between both successful and
230 non-successful as well as top 5 and bottom 5 groups. In the last 6 weeks preceding
231 competition, the successful and top five performance groups had a lower amount of training
232 modifications due to injury and illness when compared to the non-successful (18%) and
233 bottom five performance groups (22%). However, there were no significant differences
234 and only small effect sizes for the differences in percentage of total training modified due
235 to injury and illness. The three moving average methods for TSB and ACWR were all
236 significantly different from one another ($p < 0.001$, $g = 0.07-0.3$).

237

238 Correlations between performance and the different acute and chronic internal TL variables
239 are presented in Table 2. The correlations between performance and the percentage of
240 training modified due to injury and illness were also small and non-significant. The
241 correlations between the SMA and the two EWMA methods variables were very large
242 ($r = 0.73-0.77$, $p < 0.001$). The correlation between the two EWMA methods for chronic –
243 acute TL and ACWR were very large to nearly perfect ($r = 0.87$ and 0.98 respectively,
244 $p < 0.001$).

245

246

247

TABLE 2 ABOUT HERE

248 Following the correlation analysis, the cohort was divided into successful and non-
249 successful along with top five and bottom five performance groups. Acute, chronic, TSB
250 and ACWR as SMA for successful and non-successful performance groups are presented
251 in Figure 1A-C. These same variables for the top five and bottom five performance groups
252 are displayed in Figure 2A-C.

253

254

255

256

FIGURE 1A-C ABOUT HERE

FIGURE 2A-C ABOUT HERE

257 The differences between higher and lower performing groups and top five and bottom five
258 performance groups are presented in Table 3 and Table 4 respectively. Between the high

259 and lower performing group, there was a significant difference between VOL21 TSB and
260 ACWR variables as SMA. Between the top five and bottom five performance groups, there
261 were also significant differences between CHANGE21 TSB and ACWR variables as SMA.
262 The mean differences between successful and non-successful groups in TSB and ACWR
263 as SMA are also shown in Cumming estimation plots (Figures 3A-B). There were no
264 significant differences between groups when using the two EWMA methods.

265
266 TABLE 3 AND TABLE 4 ABOUT HERE
267 FIGURE 3A-B ABOUT HERE
268

269 DISCUSSION

270 Our first hypothesis was that there would be significant correlations between sRPE TL and
271 performance in addition to significant differences in the same variables between higher and
272 lower performers. Several sRPE TL variables were moderately correlated to performance
273 and differentiated between higher and lower performers. These correlations were present
274 even when analysing the data with different moving average methods. In particular,
275 performance was significantly correlated with TSB and ACWR CHANGE21 as SMA ($r=-$
276 0.49 and 0.43 , $p=0.02$ and 0.05). Competitive performance was also significantly
277 correlated with ACWR VOL21 in the two EWMA methods ($r=-0.48$ and -0.43 $p=0.03$ and
278 0.05 ; for interest SMA ACWR VOL21 $r=-0.41$ and $p=0.07$). There were no significant
279 differences between the moving average methods for correlations with performance when
280 examined with r-z transformation. As such, a lower magnitude of change and volatility in
281 the ACWR preceding competition seem to be moderately correlated to increased
282 competitive performance.

283
284 Examining the differences between higher and lower performing groups, CHANGE21 and
285 VOL21 TSB and the ACWR as SMA appeared to distinguish between higher and lower
286 performing groups. The TSB and ACWR VOL21 as SMA were significantly lower in the
287 successful group ($p=0.03$ and 0.03 , $g=0.32$ and 1.07). Although these VOL21 differences
288 were not significant when comparing the top five and bottom five performances
289 (potentially due to sample size), there was a moderate effect size for both ($g=0.91$ and
290 1.16). Further, the TSB and ACWR CHANGE21 as SMA were significantly lower in the
291 top five versus bottom five performances ($p=0.04$ and 0.05 , $g=1.43$ and 1.33). It is notable
292 that the two EWMA methods did not demonstrate any significant differences between
293 groups. This is in opposition to our second hypothesis that TL variables calculated using
294 EWMA would better separate higher and lower performing groups than a SMA.

295
296 There were no consistent relationships between performance and absolute TL variables on
297 the day of competition. This raises the consideration that planning training around having
298 an optimal level of internal TL at competition (e.g. TSB of 90 arbitrary units or an ACWR
299 of 0.6) may not be as important as minimizing change and/or volatility of these measures
300 in the competition taper. However, it should be mentioned that the subjects in this study
301 were from the same national team who all trained together at the same set times with very
302 similar training methods. Absolute values for TL measures may have a performance
303 relationship when comparing groups that are not from the same team or do not train in a
304 similar fashion. Based upon this, more research is warranted in different sports and

305 different teams on the relationship between levels of TL variables on the day of competition
306 and performance.

307

308 The comparison of the different moving average methods was designed to improve our
309 understanding of the most suitable methods for TL calculation. There were significant
310 differences between TSB and the ACWR calculated using the SMA, EWMA-W and
311 EWMA-L. The very large correlations between SMA and both EWMA-W and EWMA-L
312 ($r=0.73-0.77$) were greater than those presented in contemporary research on the topic²³.
313 The nearly perfect linear correlations and low magnitudes of effect between the two
314 EWMA methods show that these methods may be interchangeable provided practitioners
315 understand how to interpret any differences. Although all calculation methods showed
316 some significant correlation with performance, the SMA was also the only method that
317 demonstrated significant differences ($p<0.05$) between successful and non-successful
318 groups. This finding is interesting when compared to previous research that determined
319 the sensitivity of EWMA-W to likelihoods of injury was superior to SMA.²³ A potential
320 explanation for this difference may be previous research examined likelihood of injury
321 instead of performance and used external TL measures instead of internal TL measures in
322 their analysis. This previous research also employed logistic regression models to create
323 likelihoods of injury instead of comparing against actual injury incidents. There is very
324 little research comparing EWMA to SMA and both have theoretical concerns. However,
325 if applying the principle of parsimony (Occam's razor)³⁵ to help decide between moving
326 average methods, SMA may be a superior alternative as it is a simpler for practitioners to
327 apply. In this study, it appeared more sensitive to performance than the EWMA variations.
328 However, further research is warranted in order to fully understand moving average
329 methods impact on TL variables, their appropriateness in different sports and use with
330 internal/external TL constructs. This would also include if other moving average methods
331 (e.g. double exponential smoothing) may be more appropriate than those presented in this
332 investigation.

333

334 Limitations of this investigation include the sole use of sRPE TL measures without any
335 comparison with an external TL measure. As mentioned in the methods section, we were
336 unable to use external TL measures (i.e. volume load, reps, sets, or intensity) due to the
337 respective National Olympic Committee not consenting to record or release this data for
338 any form of publication. Another potential limitation of this investigation was the
339 requirement that subjects post a competition total (i.e. a successful lift in both snatch and
340 clean & jerk) to be included in analysis. This excluded four subjects from the analysis that
341 may have strengthened/weakened any results. These subjects were excluded from analysis
342 due to methodological (i.e. calculating correlations with percentage of 12-month personal
343 best competition total is skewed if only one lift is completed) and conceptual issues with
344 determining in which group these athletes should be assigned due to potential confounding
345 factors. **Finally, due to the number of subjects, the specific context of this investigation
346 and not having repeated measures of performance over time, practitioners should interpret
347 this investigation's findings and level of evidence as a case study that may only be
348 applicable for weightlifting athletes.** More research is needed in other elite populations on
349 the relationship between internal TL and performance.

350

351 PRACTICAL APPLICATIONS

352 Based on the outcomes of this study we suggest that a large amount of change or volatility
353 in internal TL TSB or ACWR during the competition taper was detrimental to performance,
354 at least when calculated using SMA. This suggests that large changes in internal TL TSB
355 or ACWR should be avoided in the 21 days before competition. This would seem
356 important for both technical coaches and other staff (e.g. strength & conditioning coaches)
357 involved in training and taper planning before competition to consider. Practitioners may
358 use different moving average methods to calculate internal TL however the SMA is a
359 simpler method and appeared to better explain performance in this study. Lastly, the
360 application of this data to other sports besides weightlifting requires further consideration.

361

362 CONCLUSIONS

363 The change and volatility of the TSB and ACWR in the taper were moderately correlated
364 to performance and also differentiated between higher and lower performers in this
365 cohort of elite weightlifters. The correlation results were present when analysing the data
366 with all three different moving average methods. However, the simple moving average
367 was the only training load calculation method that demonstrated a significant difference
368 between higher and lower weightlifting performance. There were no consistent
369 relationships between performance and the TSB or ACWR on the day of competition in
370 this group of elite weightlifters; regardless of moving average method used. Although
371 training load monitoring with sRPE can be applied to a number of sports, it remains to be
372 seen whether there are similar relationships with performance in other sports. Further, in
373 this investigation, calculating training load with a simple moving average seemed to
374 better explain performance compared to the exponentially weighted moving averages.

375

376 ACKNOWLEDGEMENTS

377 JC drafted the initial concept and all authors contributed to drafting, critical revision and
378 approval of the final manuscript. Thank you to Aaron Coutts and Sophia Nimphius for
379 advice and feedback on the theory and methods applied in this investigation. There was
380 no additional financial or material support.

381

382 SUPPLEMENTAL FILE

383 A supplemental file is provided with the code in R for all of the statistical methods provided
384 in this response.

For Peer Review

For Peer Review

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Table 1. Descriptive statistics of elite weightlifters’ competition results and modified training due to injury and illness prior to a qualifying competition for the 2016 Olympic Games.

	<i>n</i>	<i>%12PB</i>	<i>p</i>	<i>g</i>	<i>%WR</i>	<i>p</i>	<i>g</i>	<i>%INJ</i>	<i>p</i>	<i>g</i>
OVERALL	21	99.1 ± 3.0			95.4 ± 3.5			34.8 ± 41.5		
S	10	101 ± 1.7			97.7 ± 2.8			28.1 ± 41.0		
NS	8	96.1 ± 1.7	0.00**	3.03	93.3 ± 3.2	0.01**	1.40	46.1 ± 48.9	0.47	0.24
TOP5	5	103 ± 1.5			99.5 ± 1.6			16.2 ± 20.6		
BOT5	5	95.1 ± 1.3	0.00**	4.93	93.2 ± 2.6	0.00**	2.61	38.1 ± 51.3	0.48	0.20

*Note: OVERALL – complete cohort, S – successful performance group, NS – non-successful performance group, TOP5 – top five performance group, BOT5 – bottom five performance group, n – number of subjects, %12PB – percentage of 12 month personal best total, %WR – percentage of world record total, %INJ – percentage of training affected by injury in last 6 weeks, g – Hedge’s effect size, * - $p > 0.05$, ** $p > 0.01$, $p > 0.001$ ****

Table 2. Correlations between different internal training load variables and performance for elite weightlifters at a qualifying competition for the 2016 Olympic Games.

	<i>SMA</i>		<i>EWMA-W</i>			<i>EWMA-L</i>		
	<i>r [95% CI]</i>	<i>p</i>	<i>r [95% CI]</i>	<i>p</i>	<i>SMA R-z p</i>	<i>r [95% CI]</i>	<i>p</i>	<i>SMA R-z p</i>
<i>ABSOLUTE</i>								
Acute TL	0.18 [-0.27, 0.57]	0.43	0.11 [-0.33, 0.52]	0.63	0.83	0.11 [-0.34, 0.52]	0.64	0.83
Chronic TL	0.01 [-0.42, 0.44]	0.97	0.08 [-0.36, 0.49]	0.73	0.83	0.06 [-0.38, 0.48]	0.80	0.88
TSB	-0.27 [-0.63, 0.19]	0.24	-0.07 [-0.49, 0.37]	0.77	0.54	-0.12 [-0.53, 0.33]	0.59	0.64
ACWR	0.19 [-0.27, 0.57]	0.42	0.01 [-0.42, 0.44]	0.96	0.59	0.02 [-0.42, 0.44]	0.95	0.61
<i>CHANGE21</i>								
Acute TL	0.39 [-0.05, 0.70]	0.08	0.35 [-0.09, 0.68]	0.12	0.89	0.31 [-0.14, 0.65]	0.17	0.78
Chronic TL	-0.03 [-0.45, 0.41]	0.90	0.24 [-0.21, 0.61]	0.29	0.41	0.14 [-0.31, 0.54]	0.55	0.61
TSB	-0.49 [-0.76, 0.07]	0.02*	-0.36 [-0.68, 0.09]	0.11	0.63	-0.34 [-0.67, 0.11]	0.13	0.59
ACWR	0.43 [-0.01, 0.72]	0.05*	0.33 [-0.12, 0.67]	0.14	0.73	0.42 [-0.01, 0.72]	0.06	0.97
<i>VOL21</i>								
Acute TL	-0.28 [-0.63, 0.17]	0.22	-0.22 [-0.59, 0.24]	0.34	0.85	-0.17 [-0.56, 0.29]	0.47	0.73
Chronic TL	0.04 [-0.40, 0.47]	0.86	-0.05 [-0.48, 0.39]	0.81	0.79	0.28 [-0.17, 0.64]	0.21	0.46
TSB	-0.34 [-0.67, 0.10]	0.13	-0.30 [-0.65, 0.16]	0.19	0.89	-0.31 [-0.65, 0.14]	0.17	0.92
ACWR	-0.41 [-0.71, 0.03]	0.07	-0.48 [-0.75, -0.06]	0.03*	0.79	-0.43 [-0.73, 0.00]	0.05*	0.94

Note: *ABSOLUTE* - the value on the day of the competition, *CHANGE21* - the value 21 days prior to competition subtracted from the value on the day of the competition, *VOL21* - the volatility (standard deviation) of values in the last 21 days prior to competition, *TL* – training load, *TSB* – training stress balance; *ACWR* – acute to chronic workload ratio, *SMA* – simple moving average, *EWMA-W* – exponentially weighted moving averages as per Williams et al ²⁶, *EWMA-L* - exponentially weighted moving averages as per Lazarus et al ¹⁹, * - $p > 0.05$

Table 3. The differences in internal training load variables between successful and non-successful performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.

	<i>SMA</i>					<i>EWMA-W</i>					<i>EWMA-L</i>				
	<i>NS</i>	<i>S</i>	$\beta\%$	<i>p</i>	<i>g</i>	<i>NS</i>	<i>S</i>	$\beta\%$	<i>p</i>	<i>g</i>	<i>NS</i>	<i>S</i>	$\beta\%$	<i>p</i>	<i>g</i>
<i>ABSOLUTE</i>															
Acute TL	159 ± 101	156 ± 101	-1.5	0.84	0.12	153 ± 85.3	138 ± 85.7	-10.2	0.58	0.16	201 ± 86.8	186 ± 93.9	-7.3	0.74	0.16
Chronic TL	272 ± 108	255 ± 107	-6.4	0.74	0.15	235 ± 89.1	221 ± 91.3	-6.0	0.74	0.15	246 ± 88.3	237 ± 77.3	-3.6	0.82	0.10
TSB	113 ± 90.7	98.6 ± 45.5	-14.4	0.63	0.24	81.8 ± 44.5	83.4 ± 30.7	-2.0	0.64	0.04	45.3 ± 48.5	51.1 ± 37.1	12.5	0.78	0.13
ACWR	0.60 ± 0.25	0.57 ± 0.16	-4.1	0.80	0.12	0.64 ± 0.15	0.59 ± 0.12	-7.8	0.46	0.34	0.82 ± 0.15	0.75 ± 0.15	-7.8	0.40	0.39
<i>CHANGE21</i>															
Acute TL	-223 ± 181	-170 ± 107	-26.1	0.45	0.35	-254 ± 183	-187 ± 125	-30.5	0.36	0.42	-178 ± 126	-144 ± 103	-20.8	0.54	0.28
Chronic TL	-74.2 ± 59.0	-99.7 ± 83.1	28.4	0.48	0.33	-106 ± 83.3	-94.3 ± 85.6	-11.8	0.77	0.13	-14.4 ± 42.0	-17.5 ± 60.5	21.5	0.91	0.05
TSB	149 ± 155	70.3 ± 77.1	-69.3	0.18	0.63	148 ± 114	92.2 ± 67.1	-46.1	0.21	0.59	163 ± 101	126 ± 58.7	-24.8	0.34	0.44
ACWR	-0.46 ± 0.44	-0.36 ± 0.25	-24.0	0.56	0.27	-0.50 ± 0.12	-0.44 ± 0.09	-13.2	0.60	0.24	-0.62 ± 0.22	-0.55 ± 0.18	-12.5	0.47	0.34
<i>VOL21</i>															
Acute TL	93.5 ± 65.1	74.5 ± 33.0	-22.4	0.93	0.04	94.9 ± 59.7	82.1 ± 31.3	-14.4	0.94	0.01	65.1 ± 44.4	60.8 ± 23.8	-0.07	0.71	0.26
Chronic TL	35.1 ± 18.2	39.2 ± 23.4	11.0	0.69	0.18	42.6 ± 28.2	43.8 ± 17.9	-3.0	0.91	0.05	20.0 ± 11.0	23.9 ± 10.2	18.1	0.44	0.36
TSB	80.0 ± 53.5	44.4 ± 27.4	-56.6	0.03*	1.15	57.1 ± 33.6	42.3 ± 21.0	-29.3	0.27	0.52	53.3 ± 36.3	44.2 ± 18.0	-18.8	0.94	0.16
ACWR	0.25 ± 0.10	0.16 ± 0.06	-46.2	0.03*	1.07	0.19 ± 0.05	0.16 ± 0.03	-0.15	0.16	0.72	0.19 ± 0.07	0.17 ± 0.05	-8.9	0.59	0.25

Note: *ABSOLUTE* - the value on the day of the competition, *CHANGE21* - the value 21 days prior to competition subtracted from the value on the day of the competition, *VOL21* - the volatility (standard deviation) of values in the last 21 days prior to competition, *TL* – training load, *TSB* – training stress balance; *ACWR* – acute to chronic workload ratio, *SMA* – simple moving average, *EWMA-W* – exponentially weighted moving averages as per Williams et al ²⁶, *EWMA-L* - exponentially weighted moving averages as per Lazarus

*et al*¹⁹, *S* – successful performance group, *NS* – non-successful performance group, $\beta\%$ - beta percentage difference, *p* – *p*-value, *g* – Hedge's effect size, * - $p > 0.05$

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Table 4. The differences in internal training load variables between the top 5 and bottom 5 performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.

	<i>SMA</i>					<i>EWMA-W</i>					<i>EWMA-L</i>				
	<i>BOT5</i>	<i>TOP5</i>	$\beta\%$	<i>p</i>	<i>g</i>	<i>BOT5</i>	<i>TOP5</i>	$\beta\%$	<i>p</i>	<i>g</i>	<i>BOT5</i>	<i>TOP5</i>	$\beta\%$	<i>p</i>	<i>g</i>
<i>ABSOLUTE</i>															
Acute TL	184 ± 117	191 ± 131	4.1	0.93	0.05	178 ± 98.0	164 ± 116	-9.0	0.84	0.11	224 ± 97.9	212 ± 123	-5.6	0.88	0.09
Chronic TL	294 ± 109	265 ± 125	-10.5	0.71	0.22	256 ± 95.7	242 ± 116	-5.8	0.84	0.12	261 ± 89.0	249 ± 92.1	-4.4	0.85	0.11
TSB	109 ± 91.3	74.1 ± 19.0	-34.5	0.44	0.42	78.1 ± 41.3	78.0 ± 28.7	-0.0	1.00	0.00	36.9 ± 48.0	37.3 ± 47.1	0.7	0.99	0.01
ACWR	0.62 ± 0.25	0.66 ± 0.17	-6.9	0.77	0.17	0.67 ± 0.15	0.62 ± 0.17	-7.9	0.64	0.27	0.85 ± 0.16	0.81 ± 0.21	-5.3	0.73	0.20
<i>CHANGE21</i>															
Acute TL	-277 ± 185	-123 ± 135	-76.0	0.17	0.85	-304 ± 192	-161 ± 154	-64.6	0.23	0.74	-203 ± 136	-118 ± 135	-52.4	0.35	0.56
Chronic TL	-67.8 ± 57.3	-93.0 ± 113	28.1	0.67	0.26	-113 ± 89.1	-71.7 ± 117.5	-40.5	0.55	0.35	-6.5 ± 41.9	-1.9 ± 85.5	-32.4	0.92	0.06
TSB	210 ± 147	30.1 ± 61.2	-158.8	0.04*	1.43	192 ± 113	88.8 ± 71.5	-84.5	0.12	0.97	196 ± 104	116 ± 64.8	-54.3	0.18	0.83
ACWR	-0.65 ± 0.26	-0.24 ± 0.28	-99.9	0.05*	1.33	-0.60 ± 0.16	-0.41 ± 0.25	41.1	0.28	0.35	-0.74 ± 0.18	-0.52 ± 0.22	-37.4	0.20	0.95
<i>VOL21</i>															
Acute TL	110 ± 74.0	65.1 ± 20.6	-53.6	0.25	0.66	109 ± 65.1	76.4 ± 19.7	-37.2	0.33	0.55	75.7 ± 48.0	56.4 ± 19.4	-31.0	0.43	0.47
Chronic TL	34.5 ± 16.0	38.1 ± 30.1	9.6	0.82	0.13	48.4 ± 29.5	42.2 ± 19.1	-14.7	0.70	0.22	22.4 ± 10.2	28.1 ± 12.1	26.4	0.44	0.46
TSB	91.6 ± 66.9	40.7 ± 23.6	-81.0	0.15	0.91	66.2 ± 38.6	39.7 ± 16.6	-52.6	0.20	0.80	64.3 ± 39.5	39.0 ± 9.4	-51.7	0.23	0.69
ACWR	0.24 ± 0.09	0.14 ± 0.06	-50.1	0.08	1.16	0.19 ± 0.06	0.15 ± 0.02	-25.8	0.19	0.95	0.22 ± 0.06	0.16 ± 0.04	-38.0	0.12	1.35

Note: *ABSOLUTE* - the value on the day of the competition, *CHANGE21* - the value 21 days prior to competition subtracted from the value on the day of the competition, *VOL21* - the volatility (standard deviation) of values in the last 21 days prior to competition, *TL* – training load, *TSB* – training stress balance; *ACWR* – acute to chronic workload ratio, *SMA* – simple moving average, *EWMA-W* – exponentially weighted moving averages as per Williams et al ²⁶, *EWMA-L* - exponentially weighted moving averages as per Lazarus

*et al*¹⁹, *S* – successful performance group, *NS* – non-successful performance group, $\beta\%$ - beta percentage difference, *p* – *p*-value, *g* – Hedge's effect size, * - $p > 0.05$

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FIGURE CAPTIONS

Figure 1A-C. A comparison of internal training load variables between successful and non-successful performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.

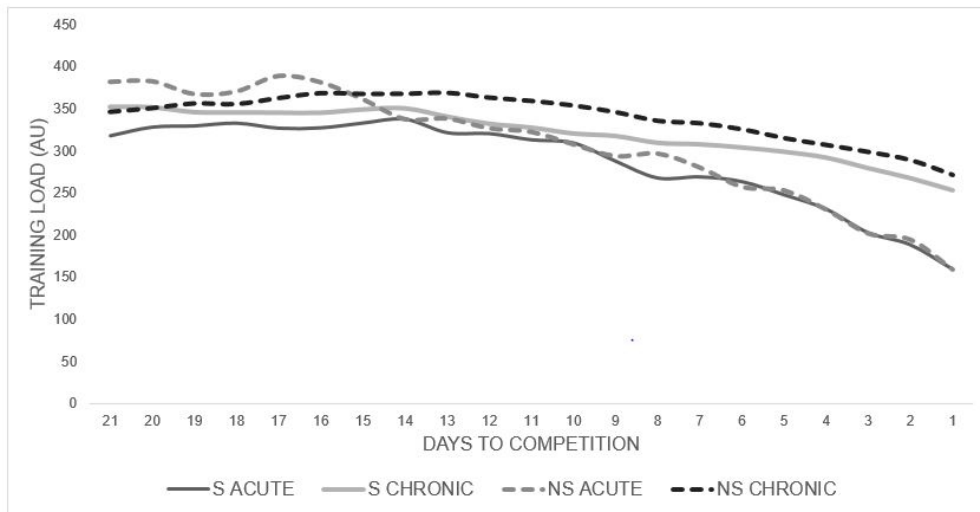
NOTES: NS – non-successful group, S – successful group, AU – arbitrary units, TSB – training stress balance, ACWR – acute to chronic workload ratio

Figure 2A-C. A comparison of internal training load variables between the top five and bottom five performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.

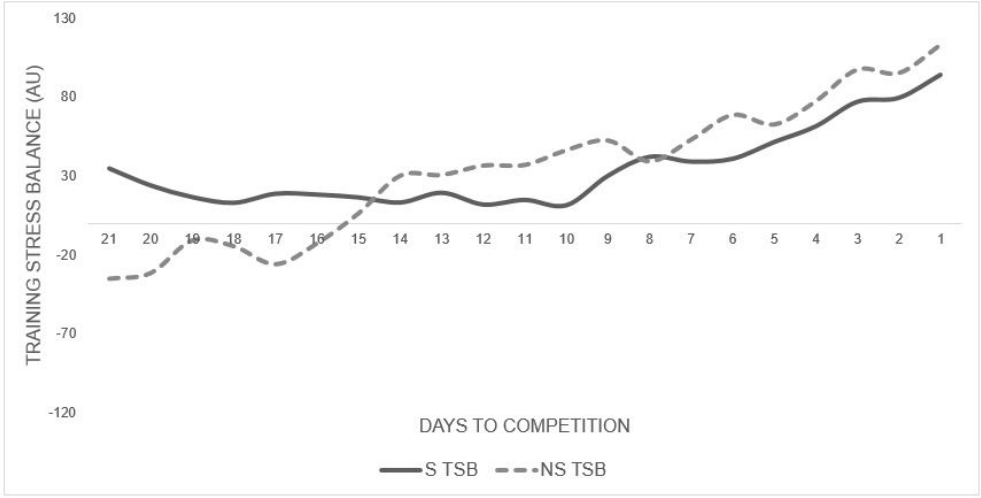
NOTES: NS – non-successful group, S – successful group, AU – arbitrary units, TSB – training stress balance, ACWR – acute to chronic workload ratio

Figure 3A-B. Cumming estimation plots of (A) Training stress balance and (B) Acute to chronic workload ratio differences as simple moving averages between successful and non-successful performances at a qualifying competition for the 2016 Olympic Games in elite weightlifters.

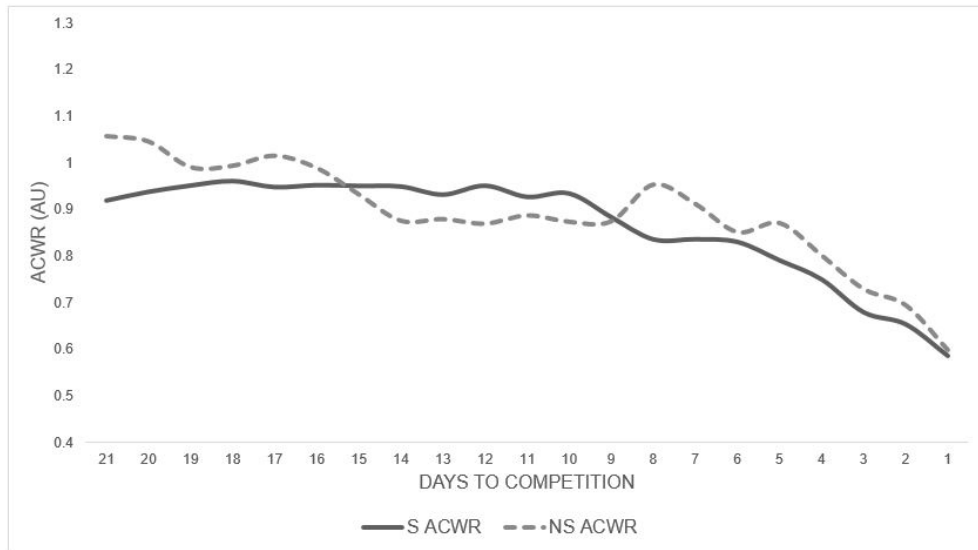
NOTES: NS – non-successful group, S – successful group, ABSOLUTE - the value on the day of the competition, CHANGE21 - the value 21 days prior to competition subtracted from the value on the day of the competition, VOL21 - the volatility (standard deviation) of values in the last 21 days prior to competition, TSB – training stress balance, ACWR – acute to chronic workload ratio, AU – arbitrary units



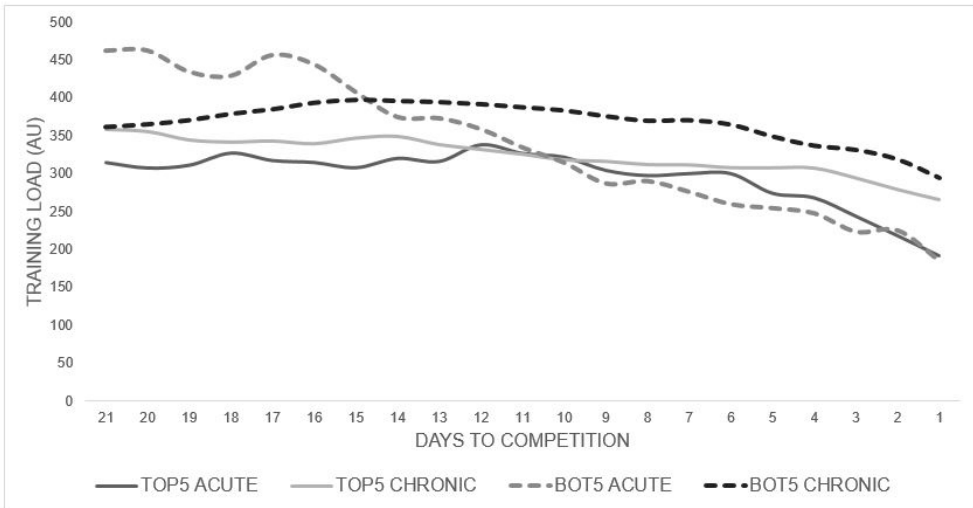
224x118mm (96 x 96 DPI)



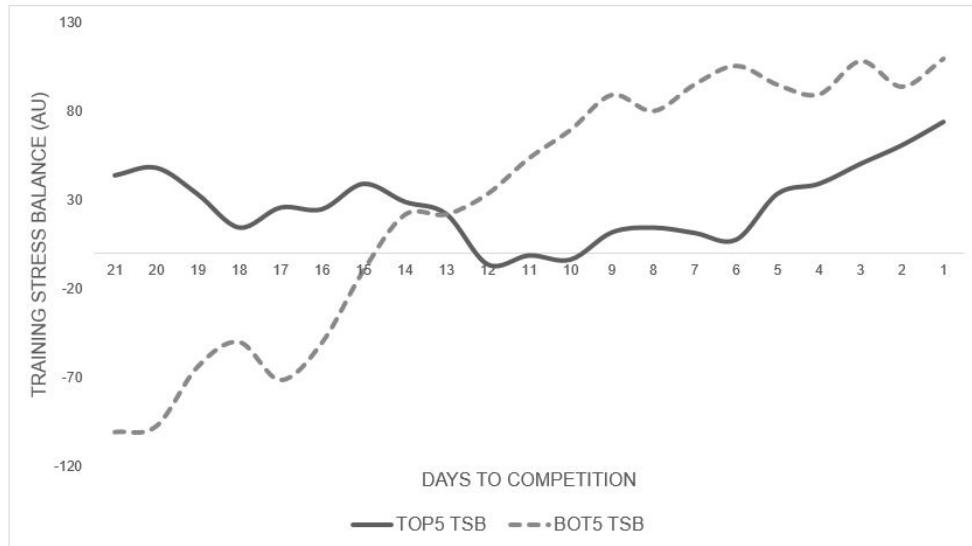
230x118mm (96 x 96 DPI)



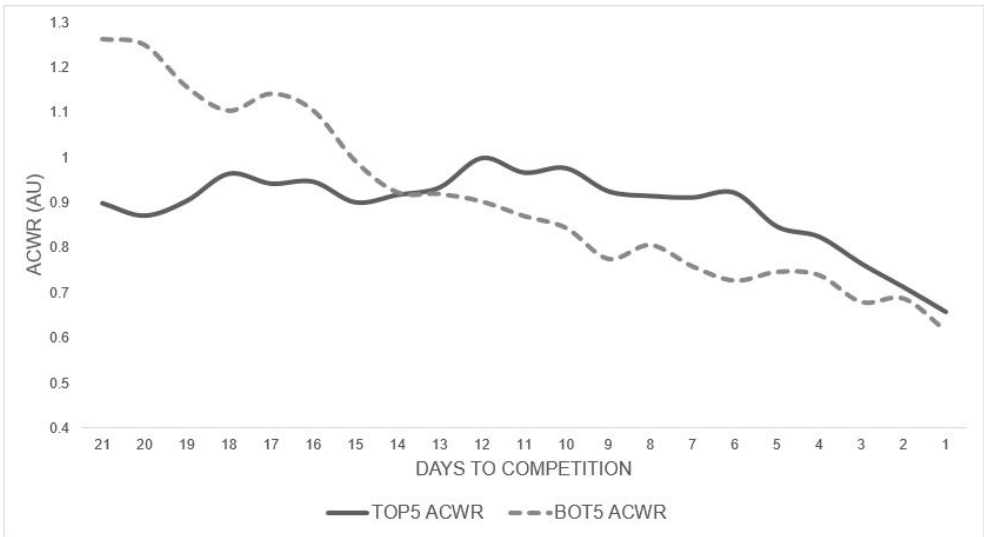
225x128mm (96 x 96 DPI)



226x120mm (96 x 96 DPI)



226x127mm (96 x 96 DPI)



224x123mm (96 x 96 DPI)

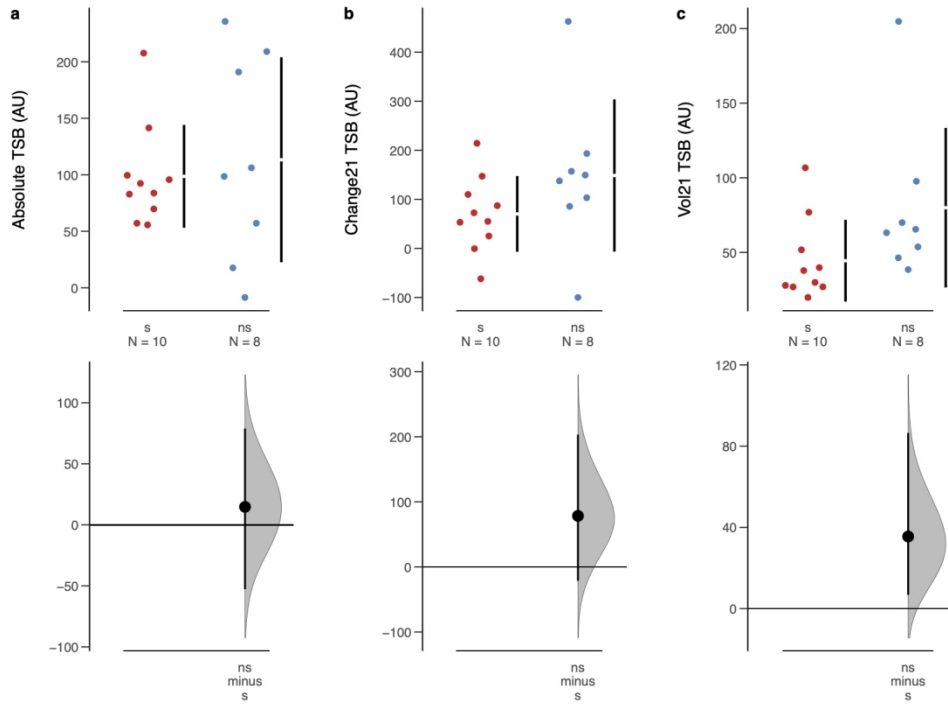


Figure 3A.

296x209mm (150 x 150 DPI)

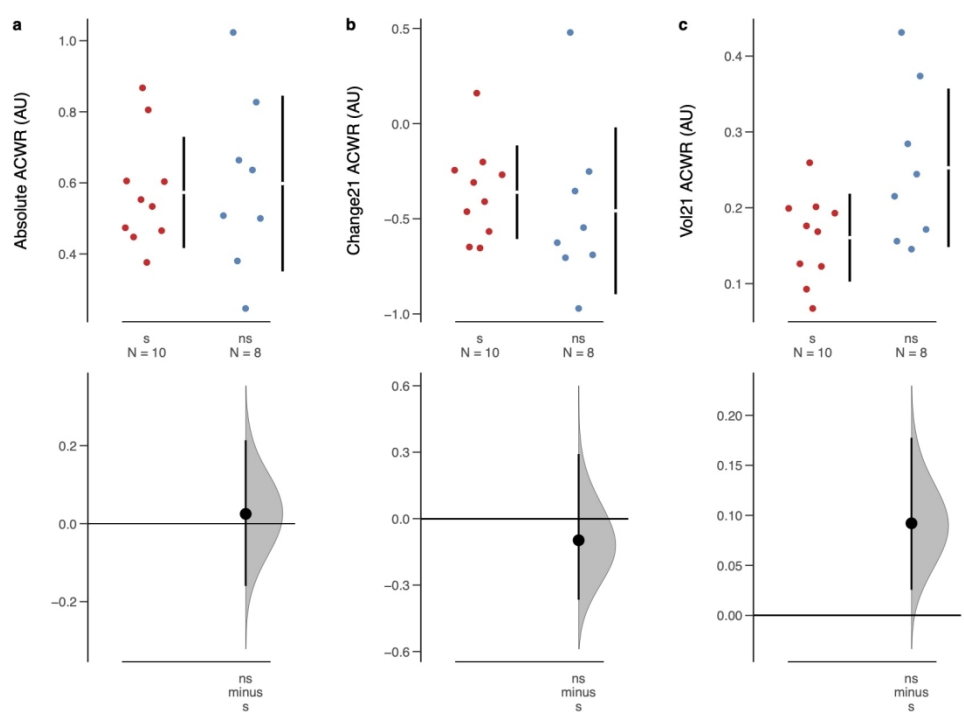


Figure 3B.

296x209mm (150 x 150 DPI)

```
#load required packages
library(tidyverse)
library(dplyr)
library(ggplot2)
library(cocor)
library(corrplot)
library(corr)
library(car)
library(dabestr)
library(GGally)
library(Hmisc)
library(readxl)
library(cowplot)
library(pwr)
library(ggpubr)
library(psych)
library(lattice)
library(mbir)

#import data
wl_desc <- read_excel("~/Desktop/PhD ECU [ACU]/Weightlifting Success/Weightlifting IL
R.xlsx", sheet = "desc")
wl_t121 <- read_excel("~/Desktop/PhD ECU [ACU]/Weightlifting Success/Weightlifting IL
R.xlsx", sheet = "t121")
wl_compl <- read_excel("~/Desktop/PhD ECU [ACU]/Weightlifting Success/Weightlifting IL
R.xlsx", sheet = "tl")
View(wl_desc)
View(wl_t121)
View(wl_compl)

##### PREPARE DATA #####

#get data for overall stats
#apply multi.sapply function for descriptive stats
multi.sapply <- function(...) {
  arglist <- match.call(expand.dots = FALSE)$...
  var.names <- sapply(arglist, deparse)
  has.name <- (names(arglist) != "")
  var.names[has.name] <- names(arglist)[has.name]
  arglist <- lapply(arglist, eval.parent, n = 2)
  x <- arglist[[1]]
  arglist[[1]] <- NULL
  result <- sapply(arglist, function (FUN, x) sapply(x, FUN, na.rm=T), x)
  colnames(result) <- var.names[-1]
  return(result)
}
```



```
#get mean/sd for overall cohort
overall_wl <- multi.sapply(wl_compl[,2:13], mean, sd)
overall_wl

#get correlations between moving average methods
movAv_corData <- wl_compl[c(4:5, 8:9, 12:13)]
movAv_cor <- corr.test(movAv_corData, alpha=0.05, ci=T)
print(movAv_cor, short=F)

#get data for group stats
#include change function
change <- function(x){
  last(x)-first(x)}

wl_data1 <- wl_tl21 %>%
  group_by(id) %>%
  summarise(abs_raA = last(raA),
            abs_raC = last(raC),
            abs_raCA = last(raCA),
            abs_raACWR = last(raACWR),
            change_raA = change(raA),
            change_raC = change(raC),
            change_raCA = change(raCA),
            change_raACWR = change(raACWR),
            vol_raA = sd(raA),
            vol_raC = sd(raC),
            vol_raCA = sd(raCA),
            vol_raACWR = sd(raACWR))

wl_data2 <- wl_tl21 %>%
  group_by(id) %>%
  summarise(abs_ewma1A = last(ewma1A),
            abs_ewma1C = last(ewma1C),
            abs_ewma1CA = last(ewma1CA),
            abs_ewma1ACWR = last(ewma1ACWR),
            change_ewma1A = change(ewma1A),
            change_ewma1C = change(ewma1C),
            change_ewma1CA = change(ewma1CA),
            change_ewma1ACWR = change(ewma1ACWR),
            vol_ewma1A = sd(ewma1A),
            vol_ewma1C = sd(ewma1C),
            vol_ewma1CA = sd(ewma1CA),
            vol_ewma1ACWR = sd(ewma1ACWR),
            abs_ewma2A = last(ewma2A),
            abs_ewma2C = last(ewma2C),
```

```

abs_ewma2CA = last(ewma2CA),
abs_ewma2ACWR = last(ewma2ACWR),
change_ewma2A = change(ewma2A),
change_ewma2C = change(ewma2C),
change_ewma2CA = change(ewma2CA),
change_ewma2ACWR = change(ewma2ACWR),
vol_ewma2A = sd(ewma2A),
vol_ewma2C = sd(ewma2C),
vol_ewma2CA = sd(ewma2CA),
vol_ewma2ACWR = sd(ewma2ACWR),
abs_strain = last(strain),
abs_mono = last(mono),
change_strain = change(strain),
change_mono = change(mono),
mean_strain = mean(strain),
mean_mono = mean(mono))

wl_data <- left_join(wl_data1, wl_data2, by="id")
wl_data <- left_join(wl_data, wl_desc, by="id")
wl_data <- wl_data[,1:49]

wl_data <- wl_data %>%
mutate(beta_abs_raA = abs_raA/mean(abs_raA),
beta_abs_raC = abs_raC/mean(abs_raC),
beta_abs_raCA = abs_raCA/mean(abs_raCA),
beta_abs_raACWR = abs_raACWR/mean(abs_raACWR),
beta_change_raA = change_raA/mean(change_raA),
beta_change_raC = change_raC/mean(change_raC),
beta_change_raCA = change_raCA/mean(change_raCA),
beta_change_raACWR = change_raACWR/mean(change_raACWR),
beta_vol_raA = vol_raA/mean(vol_raA),
beta_vol_raC = vol_raC/mean(vol_raC),
beta_vol_raCA = vol_raCA/mean(vol_raCA),
beta_vol_raACWR = vol_raACWR/mean(vol_raACWR),
beta_abs_ewma1A = abs_ewma1A/mean(abs_ewma1A),
beta_abs_ewma1C = abs_ewma1C/mean(abs_ewma1C),
beta_abs_ewma1CA = abs_ewma1CA/mean(abs_ewma1CA),
beta_abs_ewma1ACWR = abs_ewma1ACWR/mean(abs_ewma1ACWR),
beta_change_ewma1A = change_ewma1A/mean(change_ewma1A),
beta_change_ewma1C = change_ewma1C/mean(change_ewma1C),
beta_change_ewma1CA = change_ewma1CA/mean(change_ewma1CA),
beta_change_ewma1ACWR = change_ewma1ACWR/mean(change_ewma1ACWR),
beta_vol_ewma1A = vol_ewma1A/mean(vol_ewma1A),
beta_vol_ewma1C = vol_ewma1C/mean(vol_ewma1C),
beta_vol_ewma1CA = vol_ewma1CA/mean(vol_ewma1CA),
beta_vol_ewma1ACWR = vol_ewma1ACWR/mean(vol_ewma1ACWR),

```

```

beta_abs_ewma2A = abs_ewma2A/mean(abs_ewma2A),
beta_abs_ewma2C = abs_ewma2C/mean(abs_ewma2C),
beta_abs_ewma2CA = abs_ewma2CA/mean(abs_ewma2CA),
beta_abs_ewma2ACWR = abs_ewma2ACWR/mean(abs_ewma2ACWR),
beta_change_ewma2A = change_ewma2A/mean(change_ewma2A),
beta_change_ewma2C = change_ewma2C/mean(change_ewma2C),
beta_change_ewma2CA = change_ewma2CA/mean(change_ewma2CA),
beta_change_ewma2ACWR = change_ewma2ACWR/mean(change_ewma2ACWR),
beta_vol_ewma2A = vol_ewma2A/mean(vol_ewma2A),
beta_vol_ewma2C = vol_ewma2C/mean(vol_ewma2C),
beta_vol_ewma2CA = vol_ewma2CA/mean(vol_ewma2CA),
beta_vol_ewma2ACWR = vol_ewma2ACWR/mean(vol_ewma2ACWR))

```

```
##### CORRELATIONS WITH PERFORMANCE #####
```

```
#scatterplot of pb v CA and ACWR abs, change21 and vol21 rolling averages with linear regression lines
```

```

pb_CA_plot <- ggplot(wl_data, aes(x = abs_raCA, y = pb)) + geom_point(position="jitter",
alpha=0.8) + geom_smooth(method = "lm", se =F) + theme(legend.position = "bottom") +
labs(x="SMA Chronic - Acute", y="%12PB")
pb_ACWR_plot <- ggplot(wl_data, aes(x = abs_raACWR, y = pb)) +
geom_point(position="jitter", alpha=0.8) + geom_smooth(method = "lm", se =F) +
theme(legend.position = "bottom") + labs(x="SMA ACWR", y="%12PB")
pb_changeCA_plot <- ggplot(wl_data, aes(x = change_raCA, y = pb)) +
geom_point(position="jitter", alpha=0.8) + geom_smooth(method = "lm", se =F) +
theme(legend.position = "bottom") + labs(x="SMA Chronic - Acute Change", y="%12PB")
pb_changeACWR_plot <- ggplot(wl_data, aes(x = change_raACWR, y = pb)) +
geom_point(position="jitter", alpha=0.8) + geom_smooth(method = "lm", se =F) +
theme(legend.position = "bottom") + labs(x="SMA ACWR Change", y="%12PB")
pb_volCA_plot <- ggplot(wl_data, aes(x = vol_raCA, y = pb)) + geom_point(position="jitter",
alpha=0.8) + geom_smooth(method = "lm", se =F) + theme(legend.position = "bottom") +
labs(x="SMA Chronic - Acute Volatility", y="%12PB")
pb_volACWR_plot <- ggplot(wl_data, aes(x = vol_raACWR, y = pb)) +
geom_point(position="jitter", alpha=0.8) + geom_smooth(method = "lm", se =F) +
theme(legend.position = "bottom") + labs(x="SMA ACWR Volatility", y="%12PB")
plot_grid(pb_CA_plot, pb_ACWR_plot, pb_changeCA_plot, pb_changeACWR_plot,
pb_volCA_plot, pb_volACWR_plot, align = "v", labels = "auto", ncol = 2)

```

```
#get rolling average correl data
```

```

wlRa_corData <- wl_data[c(2:13, 46)]
wlRa_cor <- corr.test(wlRa_corData, alpha=0.05, ci=T)
print(wlRa_cor, short=F)

```

```
#get ewma1 correl data
```

```

wlEwma1_corData <- wl_data[c(14:25, 46)]
wlEwma1_cor <- corr.test(wlEwma1_corData, alpha=0.05, ci=T)
print(wlEwma1_cor, short=F)

```

```
#get ewma2 correl data
wlEwma2_corData <- wl_data[c(26:37, 46)]
wlEwma2_cor <- corr.test(wlEwma2_corData, alpha=0.05, ci=T)
print(wlEwma2_cor, short=F)

#compare correlations in rolling average v ewma 1 (refer back to correlation data)
absA_compare <- cocor.indep.groups(0.18, 0.11, 21, 21, alternative = "two sided")
absC_compare <- cocor.indep.groups(0.01, 0.08, 21, 21, alternative = "two sided")
absCA_compare <- cocor.indep.groups(-0.27, -0.07, 21, 21, alternative = "two sided")
absACWR_compare <- cocor.indep.groups(0.19, 0.01, 21, 21, alternative = "two sided")
changeA_compare <- cocor.indep.groups(0.39, 0.35, 21, 21, alternative = "two sided")
changeC_compare <- cocor.indep.groups(-0.03, 0.24, 21, 21, alternative = "two sided")
changeCA_compare <- cocor.indep.groups(-0.49, -0.36, 21, 21, alternative = "two sided")
changeACWR_compare <- cocor.indep.groups(0.43, 0.33, 21, 21, alternative = "two sided")
volA_compare <- cocor.indep.groups(-0.28, -0.22, 21, 21, alternative = "two sided")
volC_compare <- cocor.indep.groups(0.04, -0.05, 21, 21, alternative = "two sided")
volCA_compare <- cocor.indep.groups(-0.34, -0.30, 21, 21, alternative = "two sided")
volACWR_compare <- cocor.indep.groups(-0.41, -0.48, 21, 21, alternative = "two sided")

#call results
absA_compare
absC_compare
absCA_compare
absACWR_compare
changeA_compare
changeC_compare
changeCA_compare
changeACWR_compare
volA_compare
volC_compare
volCA_compare
volACWR_compare

#compare correlations in rolling average v ewma 2 (refer back to correlation data)
absA_compare1 <- cocor.indep.groups(0.18, 0.11, 21, 21, alternative = "two sided")
absC_compare1 <- cocor.indep.groups(0.01, 0.06, 21, 21, alternative = "two sided")
absCA_compare1 <- cocor.indep.groups(-0.27, -0.12, 21, 21, alternative = "two sided")
absACWR_compare1 <- cocor.indep.groups(0.19, 0.02, 21, 21, alternative = "two sided")
changeA_compare1 <- cocor.indep.groups(0.39, 0.31, 21, 21, alternative = "two sided")
changeC_compare1 <- cocor.indep.groups(-0.03, 0.14, 21, 21, alternative = "two sided")
changeCA_compare1 <- cocor.indep.groups(-0.49, -0.34, 21, 21, alternative = "two sided")
changeACWR_compare1 <- cocor.indep.groups(0.43, 0.42, 21, 21, alternative = "two sided")
volA_compare1 <- cocor.indep.groups(-0.28, -0.17, 21, 21, alternative = "two sided")
volC_compare1 <- cocor.indep.groups(0.04, 0.28, 21, 21, alternative = "two sided")
volCA_compare1 <- cocor.indep.groups(-0.34, -0.31, 21, 21, alternative = "two sided")
```

```
volACWR_compare1 <- cocor.indep.groups(-0.41, -0.43, 21, 21, alternative = "two sided")
```

```
#call results
```

```
absA_compare1
```

```
absC_compare1
```

```
absCA_compare1
```

```
absACWR_compare1
```

```
changeA_compare1
```

```
changeC_compare1
```

```
changeCA_compare1
```

```
changeACWR_compare1
```

```
volA_compare1
```

```
volC_compare1
```

```
volCA_compare1
```

```
volACWR_compare1
```

```
##### DIFFERENCES BETWEEN HIGH AND LOWER PERFORMERS #####
```

```
#seperate groups
```

```
wlS <- wl_data %>%
```

```
  subset(group1 == "s")
```

```
wlNs <- wl_data %>%
```

```
  subset(group1 == "ns")
```

```
wlSNs <- bind_rows(wlNs, wlS)
```

```
wltop5 <- wl_data %>%
```

```
  subset(group2 == "top5")
```

```
wlbot5 <- wl_data %>%
```

```
  subset(group2 == "bot5")
```

```
wl5 <- bind_rows(wlbot5, wltop5)
```

```
#get mean/sd for overall cohort in last 21 days
```

```
wl_desc <- multi.sapply(wl_data[,46:49], mean, sd)
```

```
wl_desc
```

```
#get mean/sd for descriptive stats for S and Ns groups
```

```
wlS_desc <- multi.sapply(wlS[,2:49], mean, sd)
```

```
wlNs_desc <- multi.sapply(wlNs[,2:49], mean, sd)
```

```
wlS_desc
```

```
wlNs_desc
```

```
#get mean/sd for descriptive stats for top5 and bot5 groups
```

```
wltop5_desc <- multi.sapply(wltop5[,2:49], mean, sd)
```

```
wlbot5_desc <- multi.sapply(wlbot5[,2:49], mean, sd)
wltop5_desc
wlbot5_desc

#get beta differences between groups
wlSbeta_desc <- sapply(wlS[50:85], mean)
wlNsbeta_desc <- sapply(wlNs[50:85], mean)
wlSbeta_desc - wlNsbeta_desc

wltop5beta_desc <- sapply(wltop5[50:85], mean)
wlbot5beta_desc <- sapply(wlbot5[50:85], mean)
wltop5beta_desc - wlbot5beta_desc

#get standardised mean diffs for SNs rolling average data (including normality, variance and mbi)
mbi_raSNs <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wlS[,c(2:13)], wlNs[,c(2:13)])

#standardised mean diff for SNs ewma1 data (including normality, variance and mbi)
mbi_ewma1SNs <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wlS[,c(14:25)], wlNs[,c(14:25)])

#standardised mean diff for SNs ewma2 data (including normality, variance and mbi)
mbi_ewma2SNs <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wlS[,c(26:37)], wlNs[,c(26:37)])

#magnitude based inferences for other data (including normality, variance and mbi)
mbi_otherSNs <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wlS[,c(46:48)], wlNs[,c(46:48)])

#convert SNs r to g (refer to results)
abs_raA_esSNs <- es_convert(-0.06, from="r", to="d")
abs_raCA_esSNs <- es_convert(0.12, from="r", to="d")
vol_raA_esSNs <- es_convert(0.02, from="r", to="d")
vol_raCA_esSNs <- es_convert(-0.5, from="r", to="d")
abs_ewma1A_esSNs <- es_convert(-0.08, from="r", to="d")
abs_ewma1CA_esSNs <- es_convert(0.02, from="r", to="d")
vol_ewma1A_esSNs <- es_convert(0, from="r", to="d")
vol_ewma1ACWR_esSNs <- es_convert(-0.34, from="r", to="d")
vol_ewma2A_esSNs <- es_convert(0.13, from="r", to="d")
vol_ewma2CA_esSNs <- es_convert(-0.08, from="r", to="d")
inj_esSNs <- es_convert(-0.12, from="r", to="d")

#standardised mean diff for top/bot5 rolling average data (including normality, variance and mbi)
```

```
mbi_ra5 <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wltop5[,c(2:13)], wlb5[,c(2:13)])

#standardised mean diff for top/bot5 ewma1 data (including normality, variance and mbi)
mbi_ewma15 <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wltop5[,c(14:25)], wlb5[,c(14:25)])

#standardised mean diff for top/bot5 ewma2 data (including normality, variance and mbi)
mbi_ewma25 <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wltop5[,c(26:37)], wlb5[,c(26:37)])

#standardised mean diff for top/bot5 other data (including normality, variance and mbi)
mbi_other5 <- mapply(function(x, y) smd_test(x, y, paired = F, conf.int = 0.95, swc = 0.2),
wltop5[,c(46:48)], wlb5[,c(46:48)])

#convert top/bot5 r to g
change_ewma1ACWR_es5 <- es_convert(-0.17, from="r", to="d")
vol_ewma1ACWR_es <- es_convert(-0.43, from="r", to="d")
change_ewma2ACWR_es5 <- es_convert(-0.43, from="r", to="d")
vol_ewma2ACWR_es5 <- es_convert(-0.56, from="r", to="d")

#convert other factors r to g
inj42SNs_es <- es_convert(-0.12, from="r", to="d")
inj425_es <- es_convert(-0.1, from="r", to="d")

#Cumming estimation plots for differences in rolling average ACWR
absACWR_est <- dabest(wlSNs, group1, abs_raACWR, idx=c("s", "ns"))
changeACWR_est <- dabest(wlSNs, group1, change_raACWR, idx=c("s", "ns"))
volACWR_est <- dabest(wlSNs, group1, vol_raACWR, idx=c("s", "ns"))

absACWR_est_plot <- plot(absACWR_est, rawplot.ylabel = "Absolute ACWR (AU)",
effsize.ylabel = "", float.contrast = F)
changeACWR_est_plot <- plot(changeACWR_est, rawplot.ylabel = "Change21 ACWR (AU)",
effsize.ylabel = "", float.contrast = F)
volACWR_est_plot <- plot(volACWR_est, rawplot.ylabel = "Vol21 ACWR (AU)",
effsize.ylabel = "", float.contrast = F)
plot_grid(absACWR_est_plot, changeACWR_est_plot, volACWR_est_plot, nrow=1, labels =
"auto")
```