Investigating the association between workload data and fitness in elite soccer

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“ONDERGETEKENDE

Justin Dirk Quint,

bevestigt hierbij dat de onderhavige verhandeling mag worden geraadpleegd en vrij mag worden gefotokopieerd. Bij het citeren moet steeds de titel en de auteur van de verhandeling worden vermeld.”

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ABSTRACT

Background

The development of soccer has led to congested schedules, resulting in higher risks of overload. Therefore, monitoring the workload and fitness of players has become more important. Using fitness tests to monitor players' fitness imposes extra burden and interferes with regular training program. If it is possible to measure players' fitness using workload data, this will decrease the need for fitness tests. And with that it could create some space to rest or recover in the congested schedule and thereby this will decrease the chance of overload.

Aim

The aim of this study is to investigate if with the use of workload data it is possible to measure player's fitness in elite soccer.

Methods

Workload data (distance and sRPE-TL) of every training and match and fitness data (Interval Shuttle Run Test (ISRT)) collected from one elite soccer team playing on the second highest level in Dutch soccer during the season 2018 – 2019 was used. Data was collected for three moments (T1, T2 and T3). Training efficiency index scores were calculated for workload data for every day and for ISRT data. For workload these scores were transformed to one value using the exponentially weighted movement averages for the timeframes of 1, 2, 3 and 4 weeks before ISRT. Structural equitation modelling was used to calculate overall and separate correlations over T1, T2 and T3.

Results

All participants were male (n=27), with mean age of 24.0 years (± 3.8 years). Completed ISRT-test were available for 100% at T1 and T3 and 88.9% at T2. Found overall correlation is almost equal between the timeframes ranging from r = 0.108 – 0.152, which can be interpreted as weak. Correlations on T1, T2 and T3 were also weak (respectively r = 0.088 – 0.341).

Conclusion and key findings

We conclude that it is not possible to measure players fitness with the use of distance and sRPE data. For now, it is not possible to stop using fitness tests to determine players' fitness. It might be rewarding to use different workload metrics (e.g. acceleration/deceleration and heart-rate), or small sided games to measure players' fitness in future studies.

Keywords: fitness, workload, elite soccer, training efficiency index

INTRODUCTION

Is it possible to derive players' fitness trough workload data? Elite soccer has developed considerably in recent years. The game has become faster, which leads to a higher intensity for the players. And with that players' fitness becomes more important. In addition, there are more competitions, with national and international cups whereof the matches alternate. This has led to a congested schedule with more travel time and less time to rest(1,2). Both, the congested schedule and the high intensity of the game is accompanied by higher physical load and psychological pressure for players(1–5). This higher load could lead to positive adaptations such as an increase in physical fitness, but could also lead to an increase in fatigue and chronic overload during a season(5–7). Chronic overload appears to be related to reduced fitness, increased fatigue, non-functional overreaching and injuries(8–11). Therefore it is essential to prevent chronic overload on players and with that, monitoring players' workload and fitness has become very important in soccer(12–15).

Player workloads are monitored using the data from training sessions and matches. Workload data can be divided in External Load (EL) and Internal Load (IL). EL is the physical work a player performs during a training session or match expressed through, for example velocity, distance, acceleration and deceleration(14–16). IL is the player's physical and physiological response, accounting for the player-specific characteristics, to the external training load measured. IL is usually measured using heart-rate (HR) and session rate of perceived exertion total load (sRPE-TL)(16–19).

Fitness is the physical capacity consisting of different components. The maximum oxygen uptake (VO2Max), intermittent endurance and strength are key factors for fitness(20–22). Various tests are available to monitor these parameters, like submaximal- and maximal Interval Shuttle Run Test (ISRT), Running-based Anaerobic Sprint Test (RAST) and Repeated Sprint Ability Test (RSA)(23–26). However, a disadvantage of these tests is that they interfere with the regular training program and impose an extra burden on the players and staff in an already congested schedule. This could lead to an overload which is related to fatigue, non-functional overreaching injuries and reduced fitness(8–11). Therefore, the medical and performance staff seek opportunities to monitor players' fitness in different ways, like player workload monitoring(27).

The EL and IL can be transformed into one value; the Training Efficiency Index (TE¡). The TE¡ is described as a system to track the internal response to a prescribed external load during team-sport training(19). To calculate the TE¡ and detect subtle changes in TE¡, it is crucial to choose the right load metrics depending on the correlation between external and internal workload and the activity(19). In literature there is a lack of consensus on which load metrics should be used within the TE¡(19,28–30). For EL, for example the total distance and acceleration-deceleration, and for the IL the heart rate derived training impulse (TRIMP) and sRPE-TL, can be used as load metric. The external load metrics have a stronger correlation with sRPE-TL than with TRIMP(29). Within the external load metrics, Total Distance (TD) seems to correlate best with the internal load metrics. With that, the strongest correlations was found between the sRPE-TL and the Total Distance (TD) respectively r = 0.79 (95% CI: 0.74 – 0.83)(29). Therefore, it is suggested to use these variables.

In current literature it is unknown if workload data can be used to measure players' fitness. While deriving the physical fitness of soccer players from workload data through the TE_i would significantly decrease the need for physical testing as it is part of the usual routine. With that the disadvantages of these tests (interfere with training program and extra burden) will be eliminated. This will create some space to rest or recover in the congested schedule and thereby this will decrease the chance of overload. We hypothesize that the workload data is positively correlated with physical fitness and therefore can be used as a substitute for physical fitness tests. Therefore, the aim of this study is to investigate if with the use of workload data it is possible to measure player's fitness in elite soccer.

METHODS

In this cohort study, data collected from one elite male soccer team (n=27) in the Netherlands playing in the second highest level in Dutch soccer (Keuken Kampioen Divisie) during the season 2018 – 2019 was used. Data was collected by the medical and performance staff as part of usual training, match and fitness tests monitoring. Keepers were excluded from this study, because they have a different training program than field players and encounter different workloads during matches and training session. All players provided informed consent prior to the start of the season, withdrawal from the study was possible at any time. This study was conducted according to the Declaration of Helsinki, the Medical Research Involving Human Subjects Act (WMO) and Good Clinical Practice (GCP). This study was approved by the Medical Ethics Committee of the University Medical Center Utrecht, Netherlands (reference number WAG/mb/19/000338).

Procedures

Player characteristics (e.g. age, weight, BMI and position) were collected at the start of the season. During each match and training-session players' data were monitored, using Heart-rate technology (10 Hz) and GPS-technology (Polar Team Pro, Kempele, Finland). This data was digitally reported using Microsoft Excel for every player for every day. In addition, players filled in their Rate of Perceived Exertion (sRPE) using SurveyMonkey on their smartphone immediately after every match and training session. Data was extracted from SurveyMonkey and added to the Microsoft Excel file. Additionally, the Interval Shuttle Run $Test_{max}$ (ISRT) was performed at the start of the season and the $ISRT_{submax}$ was performed every six weeks, if the congested schedule allowed, to determine players' fitness(25,26,31).

Training Efficiency Index

For both workload and fitness data a Training Efficiency Index (TE_i) was calculated using the formula of Delaney (TE_i = EL / (IL ^x), where x represents the average slope of the relationship between the log-transformed EL and IL for each training day and match session(19)). The average slope (x) was determined by the R-squared of the correlation between EL and IL variable for every player for every day. This average slope was used for workload and fitness data. Delaney indicates that with less than 10 observations the average slope has to be set at 0.85. With more than 10 observations the test becomes more accurate because of the calculated individual slope(19). We have data of one month before every measurement moment (T1, T2 and T3), so we used these data to calculate a personal average slope for every player for T1, T2 and T3. This personal average slope was also used in workload data and fitness data when this data consisted less than 10 observations. This was done to correct for personal characteristics and thereby increasing the precision of the TE_i(19,28).

Outcome measures

Workload data

Workload data consists of external load and internal load. The external load comprises multiple load metrics, like total distance (TD), acceleration, deceleration and number of sprints, which were measured using GPS-technology(9,19,30). For the external load we choose the TD as load metric, the TD has the best correlation with the internal load metrics(29). TD was measured as all meters covered by a player during training session or match. The internal load comprises the Session Rate of Perceived Exertion Total Load (sRPE-TL) and heart-rate data(9,19,30). The best correlation with the external load metrics was found with the sRPE-TL(29). Therefore, we choose the sRPE-TL as load metric for the internal load, the sRPE-TL was calculated using the sRPE-score multiplied by the time in minutes of the session in. The sRPE is a score ranging from 1 – 10 (1 = not hard at all and 10 = extremely hard), representing the question: "How hard did you think this training/match was?"(32,33). This was filled out by every player immediately after every training and match. Workload data was collected over different timeframes, respectively 1, 2, 3 and 4 weeks prior to the ISRT-date. This was done to investigate which timeframe is the best to measure fitness. This resulted in multiple TE_i-scores per timeframe (7, 14, 21 and 28 scores). To transform these scores into one TE_i-score we used the Exponentially Weighted Movement Average (EWMA). The EWMA is considered to give a more appropriate representation of the chronic workload correcting for time(34). The EWMA uses a weighted model, which assigns a decreasing weighting to older load values and thereby giving more weight to the recent load(34,35). EWMA was calculated using the formula: $\text{EWMA-TE}_{i\,today} = (TE_{i\,today} * (2/(\beta+1))) + ((1-(2/(\beta+1)))*\text{EWMA-TE}_{i\,yesterday})$(34,36). Herein β represents the number of days in the set timeframes of 1, 2, 3 and 4 weeks (7, 14, 21 and 28 days respectively). Resulting for workload data in $EWMA_{1week}$, $EWMA_{2weeks}$, $EWMA_{3weeks}$ and $EWMA_{4weeks}$.

Fitness

The submaximal Interval Shuttle Run Test (ISRT), was used to measure fitness. During the test participant alternately run and walk, running distance is 20 meters and walking distance is 8 meters. The running speed starts at 10km/h and is increased with 1.0km/h every 90 seconds until 13.0km/h. From 13.0km/h speed is increased with 0.5km/h every 90 seconds. The ISRT was executed up to level 73 (14.5 km/h)(31). For fitness data the same load metrics were used as for workload data, respectively the TD and sRPE-TL.

Statistical Analyses

For continuous variables of the player characteristics (age, weight and BMI) and workload and fitness data (TE_{iISRT} and $TE_{iworkload}$) standard deviations (SD) and ranges were reported. For categorical data (Sex and Field position) frequencies and percentage were used.

For analyses the structural equation method (SEM) was used. This method analyzed all players regardless of missing TE_i using the maximum likelihood estimation. However, before analyses missing data were manually replaced. Missing data for IL, in workload and fitness data, were manually replaced within each player using the following formula: $sRPE\text{-}TL_{missing} = TD_{day} / (\text{Total } sRPE\text{-}TL_{4weeks} / \text{Total } TD_{4weeks})$. For missing data in regarding EL workload data, the following formula was used: $TD_{missing} = sRPE\text{-}TL_{day} * (\text{Total } sRPE\text{-}TL_{4weeks} / \text{Total } TD_{4weeks})$. However, for fitness data the missing TD-data were replaced using the average of available ISRT-TD-data within the player.

After replacing missing data, data was checked to determine if assumptions for SEM were met (respectively multivariate normality, equal variance, no systematic missing data, sufficiently large sample size and correct model specification)(37). Multiple correlations were calculated between workload data and fitness (table 1). Correlation coefficients were interpreted according to Schober (<0.10 = negligible, 0.11 – 0.39 = weak, 0.40 – 0.69 = moderate, 0.70 – 0.89 = strong and >0.90 = very strong correlation)(38). Analyses were performed using SPSS version 25 and R 4.0.0.

Table 1: Performed analyses

	Correlation variable 1	Correlation variable 2
Overall correlation	$EWMA_{T1+T2+T3}$	$Fitness_{T1+T2+T3}$
Correlation on T1	$EWMA_{T1}$	$Fitness_{T1}$
Correlation on T2	$EWMA_{T2}$	$Fitness_{T2}$
Correlation on T3	$EWMA_{T3}$	$Fitness_{T3}$

EWMA = exponentially weighted movement average

RESULTS

Descriptive statistics

A total of 27 participants were included in this study. All were males, with a mean age of 24.0 years (± 3.8 years). Field positions were quite equally divided between defenders, midfielders and attackers (37.0%, 37.0% and 25.9% respectively). TE_i EWMA and fitness were available for three test-moments; 2018-08-02 (T1), 2018-09-04 (T2) and 2018-10-24 (T3). Completed ISRT-test were available for 100% at T1 and T3 and 88.9% at T2 (table 2).

Assumptions

Variation within the TE_i EWMA differs significantly between T1 and T2 + T3. So the assumption of equal variance was not met in this variable(39,40). Therefore we choose for relaxation of this assumption to use four more parameters within the EWMA, so that analyses were not influenced by this difference(39,40). All other assumptions were met.

Missing data

No missing data were reported in the player characteristics. A total of 21.3% missing not at random (MNAR) (due to absence of training or match) and a total of 3.9% missing at random (MAR) (due to missing sRPE or GPS-data) was reported. Within the missing MAR a total of 170 missing values were reported for IL (93.9%) and for EL 11 missing values were reported (6.1%). These data were manually replaced as described in the method section.

Table 2: Descriptive statistics

	N	%	Mean (±SD)
Sex (male)	27	100.0	
Age	27	100.0	24.0 (±3.8)
Weight	27	100.0	77.3 (±7.2)
BMI	27	100.0	23.0 (±1.5)
Field position	27	100.0	
Defender	10	**37.0**	
Midfield	10	**37.0**	
Attacker	7	**25.9**	
Reported number of days	87	100.0	
Training days	**41**	**47.1**	
T1	13	31.7	
T2	14	34.1	
T3	14	34.1	
Match days	**20**	**23.0**	
T1	6	30.0	
T2	7	35.0	
T3	7	35.0	
Days off	**26**	**29.9**	
T1	10	38.5	
T2	8	30.8	
T3	8	30.8	
TE_i EWMA (T1)	24	88.9	3.37 (±1.00)

TEi EWMA (T2)	27	100.0	4.87 (±2.37)
TEi EWMA (T3)	25	92.6	4.52 (±2.12)
TEi ISRT (T1)	27	100.0	1.83 (±0.39)
TEi ISRT (T2)	24	88.9	1.64 (±0.36)
TEi ISRT (T3)	27	100.0	1.81 (±0.41)

BMI = body mass index, **EWMA** = exponentially weighted movement average, **ISRT** = interval shuttle run test, **N** = number of participants providing information, **SD** = standard deviation, **TEi** = training efficiency index

Workload vs. Fitness

The average overall correlation between the workload data and fitness is almost equal between the timeframes ranging from r = 0.108 – 0.152 (table 3), which can be interpreted as a weak correlation(38). None of these correlations were significant. The correlations found on T1 for 2, 3 and 4 weeks are significant. Correlations seems to slightly improve with the increasing of data (1 week vs. 4 weeks). Which might indicate that the use of workload data over a longer period had a better correlation with fitness. Besides the correlation on T1 is slightly higher than the correlation on T2 and T3. However, these differences were not significant. This could potentially indicate that the correlation of workload and fitness differs during the season.

Table 3: Calculated correlation coefficients

	r	*95% CI*
Overall correlation		
EWMA 1 week	0.108	(-0.156 – 0.372)
EWMA 2 weeks	0.136	(-0.128 – 0.400)
EWMA 3 weeks	0.141	(-0.120 – 0.403)
EWMA 4 weeks	0.152	(-0.107 – 0.411)
Correlation on T1		
EWMA 1 week	0.213	(-0.208 – 0.568)
EWMA 2 weeks	0.315	(0.102 – 0.637)
EWMA 3 weeks	0.340	(0.074 – 0.653)
EWMA 4 weeks	0.341	(0.072 – 0.655)
Correlation on T2		

EWMA 1 week	0.168	(-0.253 – 0.535)
EWMA 2 weeks	0.165	(-0.255 – 0.533)
EWMA 3 weeks	0.140	(-0.279 – 0.514)
EWMA 4 weeks	0.122	(-0.296 – 0.501)
Correlation on T3		
EWMA 1 week	0.088	(-0.319 – 0.467)
EWMA 2 weeks	0.093	(-0.314 – 0.471)
EWMA 3 weeks	0.095	(-0.312 – 0.472)
EWMA 4 weeks	0.100	(-0.308 – 0.476)

CI = confidence interval, **EWMA** = exponentially weighted movement average, **r** = correlation-coefficient

DISCUSSION

With this study we aimed to investigate if with the use of workload data it is possible to measure player's fitness in elite soccer. Statistical analyses showed a weak overall correlation for all four timeframes between the workload data and the fitness of players using the Training Efficiency Index (TE¡) with total distance and sRPE-TL as load metrics. This indicates that regardless of EWMA timeframe there is almost no correlation between the workload data and the fitness of players over a three months period.

Comparing the data of T1 with T2 and T3 we see that also the mean of workload on T1 is significantly lower. This could possibly be explained by two reasons. First, workload data of T1 contains both preseason and competitive season data, while T2 and T3 only consists of competitive season data. It is known that during the preseason players' fitness is lower than during the season, which could lead to higher IL-scores and with that in lower TE¡-scores(2,6,18,19,32). Another reason may be the fact that the adaptation of load, and thereby prevention of overload, is easier within the preseason. For example, more substitutes are allowed during preseason matches, and the preseason is scheduled by the medical and performance staff itself, whereby a congested schedule can be avoided. This could lead to lower external load metrics and with that lower TE¡-scores.

For calculating TE¡, there is no consensus in literature on which load metrics should be used(19,28–30). Multiple studies showed that acceleration and total distance are main parameters of external load in elite soccer(19,20,29,47). Within the internal load sRPE-TL and TRIMP are considered as main parameters, with sRPE-TL as best parameter(29). We have considered to calculate different TE¡-scores using acceleration and total distance for external load. However, due to the lack of availability of acceleration data in this study, we choose the total distance as external load metrics. At the same time it is known that the total distance and sRPE-TL have a high correlation (r = 0.79) and therefore it is valid to use these load metrics for calculating TE¡-scores(29).

It is known that the intensity and resistance differs enormously during training and matches(10,41,42), while during a (sub)maximal standardized fitness test these factors are equal(26,31). In addition, it is known that environmental factors influence performance and perceived exertion(32,33,43). For this study, it was not possible to correct for or eliminate these factors, which might be the cause of the lack of correlation that has been found(44). To create equal circumstances, for both workload and fitness data, it could be helpful to standardize the workload data using a standardized training session(small sided games)(44–46). The use of these small sided games could lead to several benefits. For instance these small sided games can become a part of the regular training program, and thereby deduct the extra burden that comes with fitness tests(44–46). Therefore it might be rewarding to investigate the correlation between small sided games and players' fitness in the future.

The precision of the submaximal ISRT test is highly dependent on the submaximal running speed. In this study the submaximal running speed was set on 14.5 km/h, while the study of Lemmink et al. (2004) showed that submaximal running speed should be higher for elite soccer players (>15 km/h)(25,26). Therefore the $ISRT_{submax}$ as performed with submaximal running speed of 14,5 km/h, might not be valid as submaximal test because it is too easy for the players in this study. However, three correlations (correlation on T1 for 2, 3 and 4 weeks) are significant. This might be caused by the reduced fitness during the preseason, which is included on T1, and the $ISRT_{submax}$ performed up to 14,5 km/h. It is known that with reduced fitness the submaximal running test should be set on a lower level than with better fitness(25,26). Therefore it might be that the $ISRT_{submax}$ on T1 is a better reflection on the actual state at T1 than on T2 and T3, resulting in a significant correlation. However, the difference between these correlations is very small and therefore must be interpreted with care.

In this study, with 27 players included and just three measurement moments, we did not met the criteria of our power analyses. It is known that within elite soccer it is difficult to obtain large populations, therefore it was important that more measurement moments (>6) were included to obtain the power in this study(48). The ISRT was scheduled every six weeks during the season, but due to the congested schedule only three ISRT's were performed during the season.

Data collection of the external workload and ISRT data GPS-technology was used, which is very reliable to measure distance in intermittent team sports(49). Despite the fact that the ISRT is standardized, the total distance on the test can differ(25). Therefore, it is very important to measure the total distance during the test, rather than estimate the distance by the protocol. Additionally, it is known that sRPE-score is strongly influenced by different factors in the time between delivered effort and filling out of the sRPE, like individual characteristics, music, image and video watching, consuming of food or pharmacological products, environmental temperature and efferent or afferent sensory signals(32,33). To eliminate these factors as much as possible, data collection of sRPE-TL always took place immediately after every training or match. The use of GPS for workload and ISRT and the procedure of the sRPE have ensured that bias of data is reduced as much as possible in our study.

For the training efficiency index the formula of Delaney was used, which is considered to be a reliable formula for training intensity(19). In the formula we used a calculated individual slope for every player for T1, T2 and T3. With this individual slope, the TE_i is corrected for personal characteristics, and with that the TE_i becomes more accurate(19,28). Since we had this individual slope we were also able to correct for personal characteristics within the periods with less than 10 observations (TE_{i1week} and TE_{iISRT}). This method has reduced the chance of bias within the TE_i-scores. In addition the exponentially weighted movement average (EWMA) was used to correct the workload data for time. The EWMA is considered to give a more appropriate representation of the chronic workload correcting for time(34,35). Thereby, EWMA-scores were calculated for multiple timeframes to investigate if there is a difference between the different timeframes.

We recommend that future studies that focus on the relationship between workload data and fitness to choose different parameters for external and internal load metrics. It is known that fitness in soccer is influenced by acceleration and deceleration(29,47), and for internal load the heart-rate data must be considered(29,50). Additionally, it might be rewarding to investigate the possibility to calculate the TE_i using multiple metrics for external and internal load. Besides, it might be helpful to evaluate which submaximal- or maximal test is appropriate to measure fitness in elite soccer players. On the other hand, it might be rewarding to investigate the correlation between small sided games and players' fitness in elite soccer.

CONCLUSION

In short, this study provides insight in the relationship between workload data (total distance and sRPE-TL) and fitness (submaximal ISRT), in elite soccer players. Looking at the main outcome we found a weak correlation between the workload data and fitness in our study. For now, we conclude that with workload monitoring, and in specific the Training Efficiency Index, it is not possible to measure players' fitness using the Training Efficiency Index. Therefore, it may currently not be possible to stop using fitness tests to determine players' fitness even though these tests interfere with the regular training program and impose an extra burden on the players and staff in an already congested schedule. However, with the use of other workload variables (e.g. acceleration and deceleration) or standardized training and matches this might be possible in the future.

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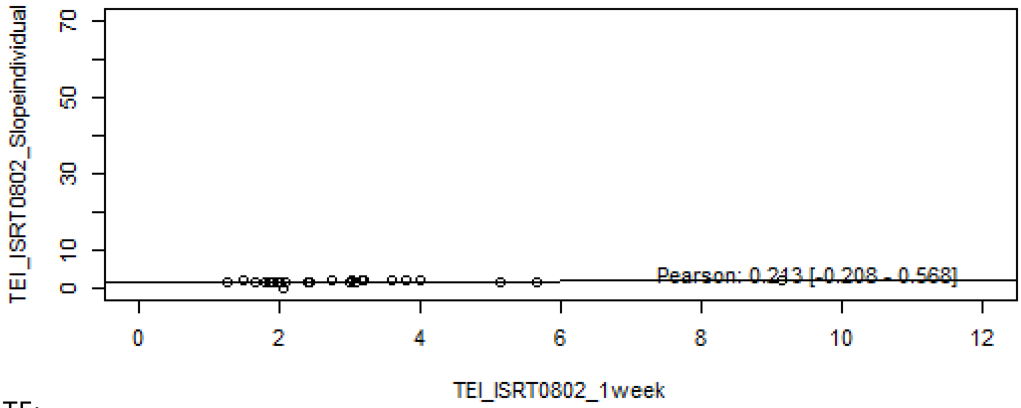
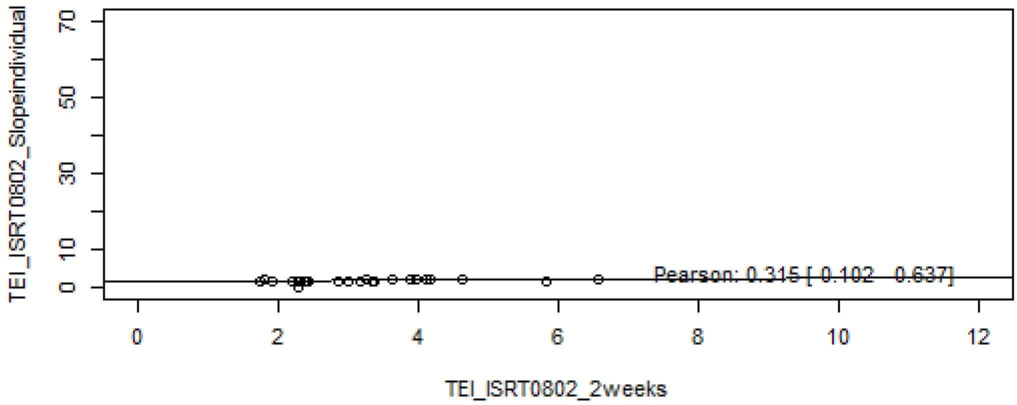
APPENDIX

Correlations on T1

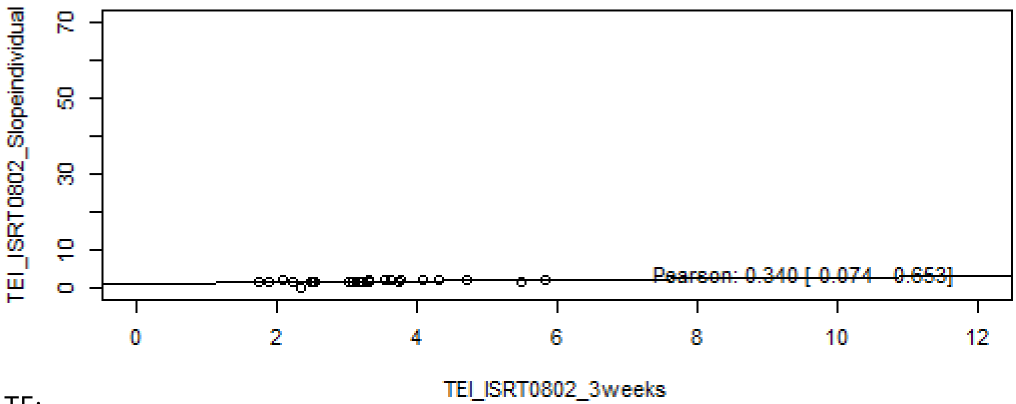
$TE_{i\,1week}$



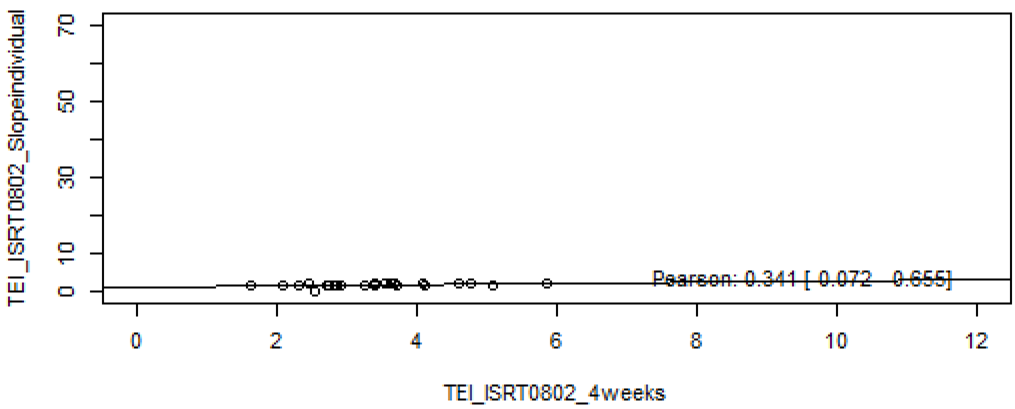
$TE_{i\,2weeks}$



$TE_{i\,3weeks}$

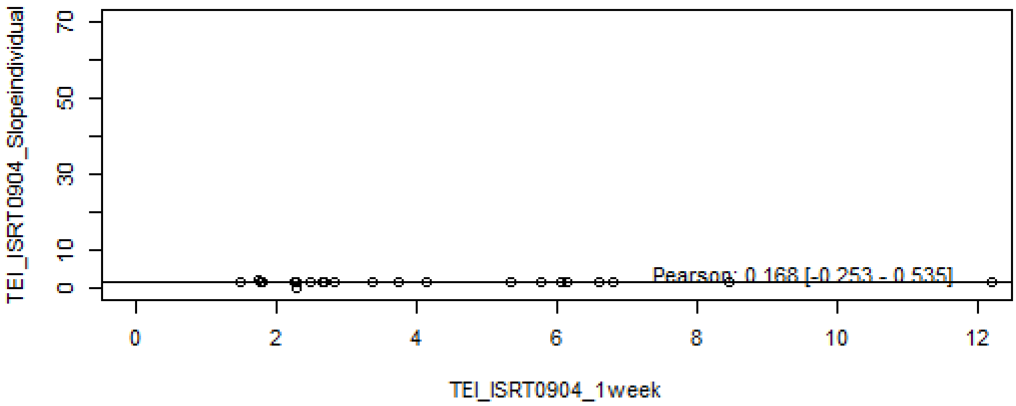


$TE_{i\,4weeks}$

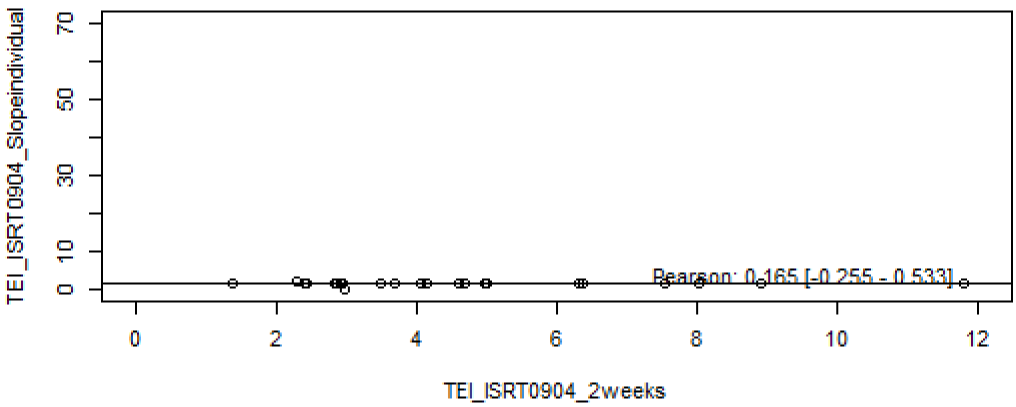


Correlations on T2

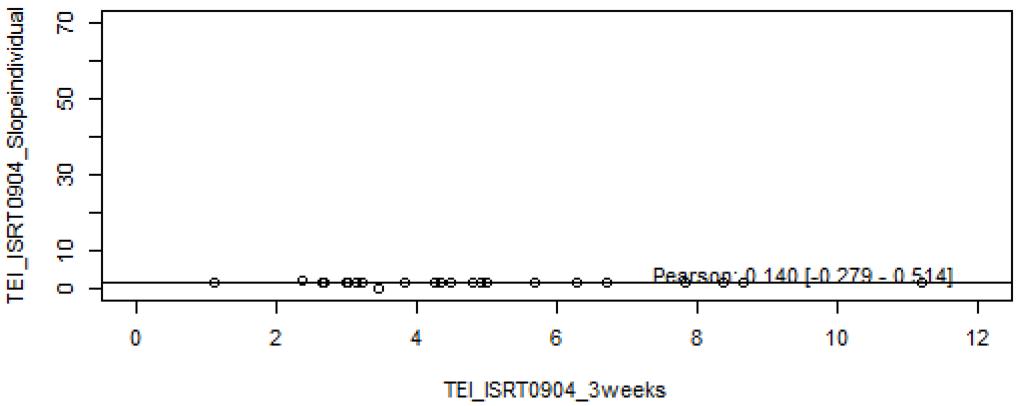
TE_{j1week}



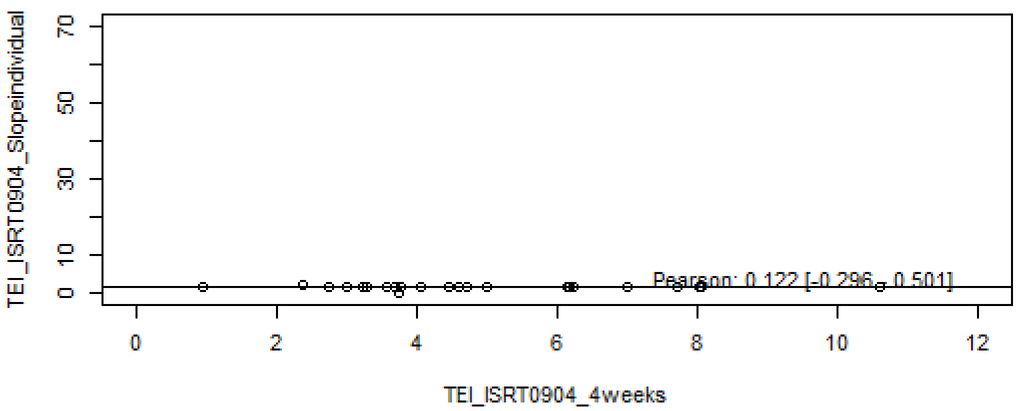
$TE_{j2weeks}$



$TE_{j3weeks}$

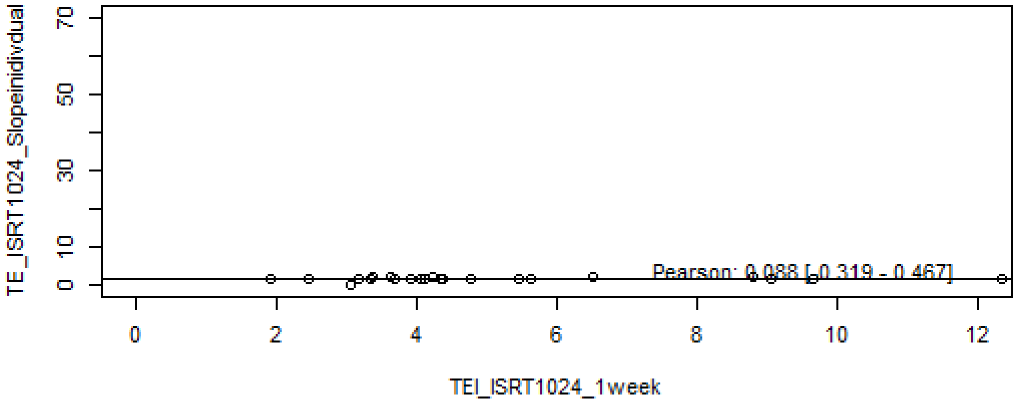


$TE_{j4weeks}$

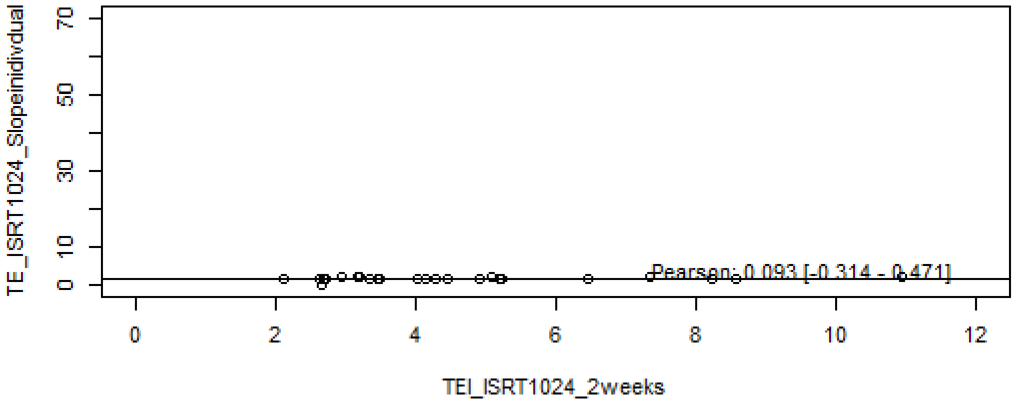


Correlations on T3

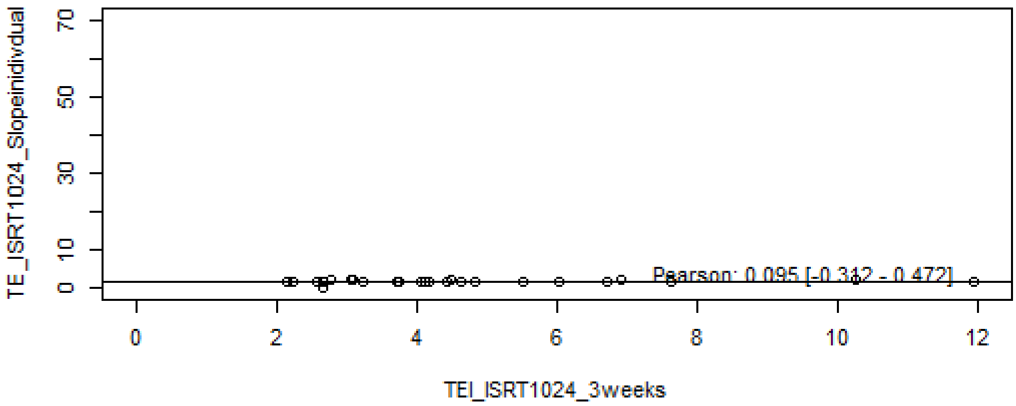
TE$_{i1week}$



TE$_{i2weeks}$



TE$_{i3weeks}$



TE$_{i4weeks}$