Comparison between predicted and measured resting energy expenditures in Korean male collegiate soccer players

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INTRODUCTION

In athletes, excessive energy expenditure during exercise and training without adequate energy intake can result in energy deficiency1. Previous studies have focused on this imbalance between exercise and recovery in athletes, and this has prompted the introduction of the term ‘Relative Energy Deficiency in Sport (RED-S)’ in the International Olympic Committee consensus statement2,3. Most initial studies mainly focused on athletes competing in endurance and weight-sensitive sports; however, later studies involving athletes competing in racquet, ball, and team sports (such as soccer) also showed a risk of energy deficiency4-6. Energy deficiency can trigger disturbances in physiological homeostasis thereby inducing alterations in reproductive and immune functions, anabolic actions (bone and protein synthesis), and metabolism1. Furthermore, chronic energy deficiency can result in metabolic adaptations to reduce energy expenditure in order to prevent a decrease in essential tissues and physiological functions7. Studies involving athletes during intensified exercise periods revealed less than expected or no changes in body composition with alterations in resting energy expenditure (REE) and metabolic hormones8,9. To monitor energy deficiency regardless of metabolic adaptation, the estimation of the ratio between measured REE (REEm) and predicted REE (REEp), the REEm/REEp ratio, has been suggested, and the latter has been shown to present significant correlations with energy deficiency, menstrual disorder, and low triiodothyronine level10-13.

For precise REEm estimation, it is important to use validated REE measurement and prediction methods. Indirect calorimetry is a widely used validated method that estimates energy metabolism using gas exchange measurements, and it has low error ranges under optimal conditions and preparation14-15. However, for the prediction of REE, various equations have been developed from different populations16-22. Previous reviews on the effect of race/ethnicity on REE presented differences in REE between African Americans and Caucasians after adjusting for fat-free mass (FFM), and suggested a validation study on REE-prediction.
equations in different ethnic groups\textsuperscript{23,24}. Studies have been conducted to examine the validity of REE-prediction equations in non-athletic Asian populations, and the importance of developing new race/ethnicity-specific equations has been pointed out\textsuperscript{25-27}. Furthermore, compared to the general population, athletes have a higher FFM, which consists of metabolically active tissues, and the use of equations that do not account for FFM can result in underestimation of REE in athletes\textsuperscript{22}. Previous studies that examined REE-prediction equations in athletes demonstrated that FFM-based equations presented better estimations than body weight (BW)-based equations\textsuperscript{28,29}. In addition, a study on the accuracy of REE-prediction equations in Korean athletic and non-athletic adolescents showed that the appropriate equations were different for each group\textsuperscript{30}.

To the best of our knowledge, a limited number of studies have examined the differences between REEm and REE\textsubscript{p} among Asian athletes. The validity of previously developed REE-prediction equations have been studied in athletes in Western countries\textsuperscript{28,29,31,32}. A Japanese study involving 205 Japanese female athletes suggested a new prediction equation [REE = 27.5 × FFM + 5], and a study involving 100 Korean adolescent athletes and non-athletes also suggested a new FFM-based prediction equation [REE = 15 × FFM + 730.4]\textsuperscript{30,32,34}. However, the differences between REEp using these equations and REEm have not been examined in Asian athletes. Therefore, this study aimed to compare differences between REEp using different FFM-based REE-prediction equations, and REEm in Korean male collegiate soccer players.

METHODS

Participants

Fifteen male Korean collegiate soccer players, aged 18-21 years, were recruited from a local university team competing in the Korean National University League (U-League). All participants were non-smokers without any health issues and had exercised for 7-12 years. Data were collected during the training season in October 2018. Participants followed scheduled team training (06:00-08:00 & 15:00-17:00) on weekdays and had rest on the weekends. Some participants voluntarily scheduled additional training sessions. Each participant provided a written informed consent after having been informed of the study design and risks of the experimental procedures. This study was approved by the Human Research Ethics Committee of Waseda University for the use of human subjects in accordance with the Declaration of Helsinki (2018-082).

Body composition

Before the REE measurement, height was measured using a digital stadiometer (BSM 330, Biospace, Seoul, Korea) and BW was measured using a digital scale (UC-321, A&D Medical, Tokyo, Japan). The FFM of participants were measured using a dual-energy X-ray absorptiometry (DXA) scanner (Lunar Prodigy Advance with enCORE software version 16, GE Healthcare, Wisconsin, USA) by a certified technician.

Measurements of resting energy expenditure

The REEm was assessed by open-circuit indirect calorimetry using the Douglas bag method. The participants were instructed to avoid strenuous exercise, caffeine, and alcohol for at least 24 h before the measurement, and they arrived at the laboratory next to their dormitory at 07:00 a.m. after an overnight fast. After 20 min of rest in the supine position to get acclimatized with room temperature, participants rested wearing a mask (Hans Rudolph, Kansas, Missouri, USA) and were familiarized with the equipment. The resting heart rate and body temperature were measured to confirm the resting status. After the confirmation, 10 min of expired gas samples were collected in Douglas bags. Oxygen uptake (VO\textsubscript{2}) and carbon dioxide production (VCO\textsubscript{2}) were analyzed with a gas analyzer using AE-100t (Minato Medical Science, Osaka, Japan), and the expired volume and temperature were assessed with a dry gas volume meter using DC-5A (Shinagawa, Tokyo, Japan). REEm was calculated using the Weir equation: 3.94 × (VO\textsubscript{2}) + 1.1 × (VCO\textsubscript{2})\textsuperscript{35}. The gas analysis was continued until less than 5 % of REEm differences existed between two samples among the collected samples, and the mean value of the two samples was used for the analysis (coefficient of variation = 3.2 %).

Prediction of resting energy expenditure

For the prediction of REE, the Cunningham, Owen, Taguchi, ten Haaf and Wejs, and Kim equations were used in this study\textsuperscript{16,20,28,30,34}. The selection of the equations was based on their components and on the database of the population included in their development. FFM-based equations developed from participants, involving athletes, were selected, and the Cunningham equation (1980) was also included, considering its high validity in athletes\textsuperscript{39}.

Statistical analysis

The IBM software, Statistical Packages for the Social Sciences (SPSS statistics version 26, IBM, Somers, NY, USA), was used for statistical analysis, with a significance level of \( p \) set at \(< 0.05\). The distribution of the collected data was checked using the Shapiro-Wilk test, and non-normally distributed data were analyzed using non-parametric tests. All data were expressed as means ± standard deviation (SD). To analyze the differences between REEm and REEp, paired t-tests were used, and the constant error (CE) and Cohen’s d effect size (ES) were calculated. The relationships between REEm and REEp were analyzed using Pearson’s correlation coefficient (\( r \)) and the coefficient of determination (\( R^2 \)). The errors in the REE-prediction equations were analyzed by calculating the standard error of the estimate (SEE) and root mean square error (RMSE). Additionally, the Bland-Altman method was used to determine the 95 % limits of agreement (LOA) between the REEm and REEp to analyze the accuracies of the prediction equations\textsuperscript{36}. Linear regression analysis was used to analyze the proportional bias between REEm and REEp\textsuperscript{37}. 

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RESULTS

The descriptive characteristics of the participants are presented in Table 2. The differences between the \( REE_m \) and \( REE_p \) are presented in Table 3. \( REE \) using the Cunningham and ten Haaf and Weijs equations were significantly different from \( REE_m \) (\( REE_m \) 1,634 ± 122 kcal/d vs. Cunningham 1,808 ± 99 kcal/d, \( p < 0.001 \); vs. ten Haaf and Weijs 1,838 ± 103 kcal/d, \( p < 0.001 \)). However, the \( REE \) using the Owen, Taguchi, and Kim equations were not significantly different from \( REE_m \) (Owen 1,589 ± 106 kcal/d, \( p = 0.159 \); Taguchi 1,640 ± 124 kcal/d, \( p < 0.852 \); Kim 1,622 ± 68 kcal/d, \( p = 0.670 \)). The Taguchi and Kim equations had a low \( CE \) ± SD and very small (<0.2) Cohen’s d ES (Taguchi -6 ± 125, -0.05; Kim 12 ± 107, 0.11) than the Owen equation (45 ± 117, 0.38). The relationships between the \( REE_m \) and the accuracy of the \( REE \)-prediction equations are presented in Table 4, and Figures 1 to 5 show the Bland-Altman plots for the \( REE_m \) and \( REE_p \). All the equations showed a similar \( r \), \( R^2 \), \( p \) values, and 95% LOA. The Kim equation showed the lowest SEE and RMSE (62 kcal/d and 104 kcal/d, respectively), but it also showed a significantly positive proportional bias (0.75, \( p = 0.02 \)). The Taguchi equation also showed a low RMSE (121 kcal/d) but no significant proportional bias (-0.02, \( p = 0.95 \)).

### Table 1. \( \text{REE prediction equations.} \)

| Author                  | Equation                  | Participants                             | Accuracy     |
|-------------------------|---------------------------|------------------------------------------|--------------|
| Cunningham (1980)       | \( REE = 22 \times FFM + 500 \)  | 120 males and 103 females (no athletes)  | \( r = 0.84 \), \( R^2 = 0.70 \) |
| Owen et al (1988)       | \( REE = 23.6 \times FFM + 186 \)  | 60 males and 44 females (6 athletes)     | N/A          |
| Taguchi et al (2011)    | \( REE = 27.5 \times FFM + 5 \)   | 205 Japanese female athletes             | \( r = 0.81 \), \( R^2 = 0.653 \) |
| ten Haaf & Weijs (2014) | \( REE = 22.771 \times FFM + 484.264 \) | 53 male and 37 female athletes          | 95% LOA, 17.2% to -15.9% |
| Kim et al (2015)        | \( REE = 15 \times FFM + 730.4 \)  | 60 male (30 athletes) and 40 female      | \( R^2 = 0.755 \) |
|                         |                           | (20 athletes) adolescents                |              |

\( \text{REE} = \) resting energy expenditure, \( \text{FFM} = \) fat-free mass, \( \text{DRI} = \) dietary reference intakes, \( \text{LOA} = \) limits of agreement.

### Table 2. Descriptive characteristics of the participants.

|                                                                 | Total (n=15) |
|-----------------------------------------------------------------|--------------|
| Age (years)                                                     | 19.1 ± 0.8   |
| Height (cm)                                                     | 175.1 ± 4.8  |
| Weight (kg)                                                     | 68.88 ± 5.48 |
| BMI (kg/m\(^2\))                                                | 22.4 ± 1.1   |
| Body fat (%)                                                    | 13.6 ± 2.5   |
| Body fat (kg)                                                   | 9.4 ± 2.1    |
| FFM (kg)                                                        | 59.5 ± 4.5   |

All data were presented as mean ± SD. BMI = body mass index, FFM = fat-free mass.

### Table 3. Differences between measured and predicted \( \text{REE}. \)

| \( \text{REE} \) | \( \text{REE}_m \) (kcal/d) | \( \text{REE}_m/\text{FFM} \) (kcal/kg) | \( p \) value | \( \text{CE} \) ± SD (kcal/d) | Cohen’s d |
|------------------|-------------------------------|---------------------------------------|--------------|-------------------------------|-----------|
| \( \text{REE} \) | 1,634 ± 122                   | 27.6 ± 2.1                            |              |                               |           |
| Cunningham (1980)| 1,808 ± 99                    | <0.001                                | -174 ± 114   | -1.52                         |           |
| Owen et al (1988)| 1,589 ± 106                   | 0.159                                 | 45 ± 117     | 0.38                          |           |
| Taguchi et al (2011)| 1,640 ± 124                   | 0.852                                 | -6 ± 125     | -0.05                         |           |
| ten Haaf & Weijs (2014)| 1,838 ± 103                   | <0.001                                | -204 ± 116   | -1.77                         |           |
| Kim et al (2015)| 1,622 ± 68                    | 0.670                                 | 12 ± 107     | 0.11                          |           |

All data were presented as mean ± SD. \( \text{REE} = \) resting energy expenditure, \( \text{CE} = \) constant error, \( \text{REE}_m = \) measured resting energy expenditure, \( \text{FFM} = \) fat-free mass, \( \text{REE}_p = \) predicted resting energy expenditure.

### Table 4. Statistical analysis between measured and predicted \( \text{REE}. \)

| \( r \)  | \( R^2 \) | \( p \) value | \( \text{SEE} \) (kcal/d) | \( \text{RMSE} \) (kcal/d) | 95% LOA (kcal/d) | \( B_{pb} \) | \( p \) value\(_{pb} \) |
|---------|----------|-------------|----------------|----------------|-----------------|------------|----------------|
| Cunningham (1980) | 0.48 | 0.23 | 0.07 | 90 206 | ±224 | 0.28 | 0.41 |
| Owen et al (1988) | 0.48 | 0.23 | 0.07 | 97 122 | ±230 | 0.18 | 0.59 |
| Taguchi et al (2011) | 0.48 | 0.23 | 0.07 | 113 121 | ±246 | -0.02 | 0.95 |
| ten Haaf & Weijs (2014) | 0.48 | 0.23 | 0.07 | 93 233 | ±226 | 0.23 | 0.49 |
| Kim et al (2015) | 0.48 | 0.23 | 0.07 | 62 104 | ±210 | 0.75 | 0.02 |

\( \text{SEE} = \) standard error of the estimate, \( \text{RMSE} = \) root means square error, \( \text{LOA} = \) limits of agreement, \( B_{pb} = \) regression coefficient of the proportional bias, \( p \) value\(_{pb} = \) statistical significance of the proportional bias.
DISCUSSION

This study aimed to compare the differences between the $\text{REE}_p$, using different FFM-based REE-prediction equations, and the $\text{REE}_m$ in Korean male collegiate soccer players. The main finding of this study was that the Taguchi equation provided a better estimation of REE than other FFM-based REE-prediction equations in Korean male collegiate soccer players. The Cunningham and ten Haaf and Weijs equations provided a significant overestimation of the REE. The Owen equation showed a higher CE and ES than the Taguchi equation, and the Kim equation showed a positive proportional bias.

The body composition of the participants (height 175.1 ± 4.8 cm; weight 68.88 ± 5.48 kg; body fat 13.6 ± 2.5 %; and FFM 59.5 ± 4.5 kg) was similar to that in previous study on Korean male collegiate soccer players (height 177.1 ±
5.9 cm; weight 71.60 ± 6.26 kg; body fat 13.9 ± 3.4 %; and FFM 77.1 ± 2.9 kg; body fat 13.1 ± 3.5 %; and FFM 66.7 ± 1.9 kg) groups of the mentioned study. The metabolically active compartments of the FFM can be categorized as bone mass, adipose tissue, skeletal muscle, and residual mass, and a larger body size can change the contribution of these metabolically active tissues to the REE, resulting in the decrease in the REE/FFM ratio in untrained adults. However, studies involving Japanese collegiate athletes have demonstrated that the contribution of organ tissues to REE remains constant regardless of the body size of the participants. A longitudinal study involving American football players during a 1-year period of overfeeding and physical training demonstrated an increase in organ-tissue mass with a consistent proportion of organ-tissue mass in FFM, which can be explained by the adaptation of organ tissue to increased functional load. The contribution of fat mass (FM) to REE prediction cannot be ignored in obese individuals and older healthy individuals; however, FM in non-obese individuals and athletes is relatively constant, and the contribution of FM to REE prediction is small. Thus, the prediction of REE using the FFM-based equations in athletes can be recommended regardless of body size; however, it should take into account the effect of sport types and training practices that can affect the proportion of organ-tissues in body composition and REE prediction.

The REE, using the Cunningham and ten Haaf and Weijs equations were significantly overestimated (Table 1), and they showed a high RMSE (Table 2). However, previous studies have shown that the Cunningham equation predicted REE with high accuracy in both male and female athletes. A recent study involving trained male athletes reported significantly underestimated REE using the Cunningham equation. The measured REE and REE/FFM of male athletes in the previous studies were 1,868 ± 239 kcal/d and 29.5 ± 2.5 kcal/kg FFM/d, 2,007 ± 206 kcal/d and 30.0 kcal/kg FFM/d, and 2,405 ± 290 kcal/d and 30.4 kcal/kg FFM/d approximately, which were higher than the values obtained in this study (1,634 ± 122 kcal/d and 27.6 ± 2.1 kcal/kg FFM/d). The different REE measurement procedures and devices might have an influence on these under/overestimations of REE, and the effect of race/ethnicity on the REE could also explain these differences. Furthermore, the Cunningham and ten Haaf and Weijs equations were both developed from Caucasian participants, and the contribution of FFM and the constants of the two equations were similar (Cunningham 22 × FFM + 500 and ten Haaf and Weijs 22.771 × FFM + 484.264). However, the Cunningham equation excluded athletes from the Harris and Benedict study, and ten Haaf and Weijs included only athletes. The similar contribution of the FFM to the REE-prediction equations of these two studies might be a coincidence, considering the differences between the participants and measurement methods; however, it still demonstrates the importance of the FFM in the prediction of REE.

The REE, using the Owen equation was not significantly different from the REEm, but it showed a high CE ± SD and RMSE. The Owen equation was developed from a study involving 60 males and 44 females including lean, obese, and trained athletes with a variation of age, BW, and race/ethnicity. To develop the Owen equation, data from relatively diverse populations were used, unlike the Taguchi and Kim equations; this could result in a higher rate of error during REE prediction. The Taguchi and Kim equations showed a higher accuracy of REE prediction with non-significant differences and lower errors than the other FFM-based equations. However, the Kim equation showed a significantly positive proportional bias (0.75, p = 0.02); this implies the Kim equation may underestimate REE in participants with high REE and overestimate REE in participants with low REE. The Kim equation was developed from the data of 100 Korean adolescents, including athletes and non-athletes, and there were significant differences in body composition and the degree of correlation between FFM and REE in the participant groups; these might have affected the accuracy of REE prediction. The Taguchi equation was developed using data obtained from 205 Japanese female athletes with various body sizes, but the ratio between REE and FFM was constant regardless of body size, an aspect which might have increased the accuracy of REE prediction in this study. The generalized equations could be convenient for REE prediction in large population groups with various characteristics; however, the accuracy of the prediction can be significantly decreased in specific population groups such as athletes. Thus, it is important to consider the characteristics of the participants when choosing the equation for REE prediction. Moreover, further studies are required to develop athlete-specific REE-prediction equations.

In conclusion, the Taguchi equation provides the best REE prediction for Korean male collegiate soccer players. The Owen and Kim equations also provided fair estimations of REE in this study, but the narrow characteristics of the participants in this study might have increased the differences with the REEm. Therefore, it is recommended to consider
the characteristics of the target population, especially athletic nature and race/ethnicity, for a precise REE prediction. Future studies should consider using a larger number of participants to analyze the validity of these equations.

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