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Original Research

Resting Metabolic Rate Prediction Equation Accuracy in Structural Firefighters

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Abstract

International Journal of Exercise Science 19(2): 1-14, 2026. It remains unclear whether predictive resting metabolic rate (RMR) equations accurately predict RMR in firefighters. The purpose of this study was to examine the accuracy of six RMR prediction equations (Cunningham, De Lorenzo, Harris-Benedict, Mifflin-St Jeor, Nelson, and Jagim) in firefighters. Male firefighters (n=26; [mean ± SD] age: 38.2 ± 7.6 y; height: 180.9 ± 6.8 cm; body mass: 92.0 ± 15.6 kg; BMI: 28.1 ± 4.4 kg · m^{-2}) participated in annual fitness and health evaluations including RMR determination and body composition assessment. A repeated measures ANOVA with Bonferroni post hoc analyses was selected to determine mean differences between measured and predicted RMR. Linear regression analysis was used to assess the accuracy of each RMR prediction method ($p<0.05$) and to determine standard error of the estimate (SEE). All prediction equations significantly underestimated RMR (all, $p<0.001$), except the Jagim equation, which significantly overestimated RMR ($p<0.001$). Equations with the closest agreement to measured RMR were the Harris-Benedict ($R^2 = 0.696$, $p = 0.004$, root mean square prediction error (RMSE) = 314 kcals, %RMSE = 14.2%) and the DeLorenzo ($R^2 = 0.675$, $p<0.001$, RMSE = 242 kcals, %RMSE = 10.9%). The Nelson equation yielded the highest RMSE (412 kcals, %RMSE = 18.6%). The variance in equations ranged from an SEE = 173 kcal · d^{-1} (Harris-Benedict) to an SEE = 215 kcal · d^{-1} (Cunningham), accounting for 70% and 53% of the variance in RMR, respectively. RMR prediction equations underestimate the energy requirements of firefighters; thus, caution should be exercised when interpreting values.

Keywords: Tactical personnel, metabolic demands, energy expenditure; firefighters, metabolism

Introduction

Firefighting is a physically demanding occupation requiring varying degrees of aerobic fitness, muscular strength, and muscular endurance, depending on the specific role and position within a department.[1,2] While unpredictable at times, occupational tasks may require levels of exertion at or near maximal heart rate for extended periods, which substantially elevates

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oxygen consumption and, consequently, energy expenditure.[3-5] Because heart rate typically rises in proportion to metabolic demand during physical activity, sustained elevations in heart rate during firefighting operations likely reflect periods of markedly increased caloric expenditure.[6-8] Therefore, accurately estimating resting metabolic rate (RMR) is critical, as RMR serves as the primary component used to calculate total daily energy expenditure (TDEE). Errors in RMR estimation may lead to substantial inaccuracies in TDEE calculations, which have practical implications for nutrition planning, weight management, and recovery. Consequently, evaluating the validity of commonly used RMR prediction equations in firefighters is necessary to ensure appropriate application within this population.

Indirect calorimetry is a validated laboratory technique commonly used to assess RMR in humans through the measurement of oxygen consumption.[9,10] However, this approach requires specialized, costly equipment and trained personnel, which limits its feasibility for practitioners working in field settings. Given these constraints, predictive RMR equations are frequently used to estimate TDEE and inform dietary recommendations across diverse populations.[11,12] Notably, RMR typically accounts for approximately 60–70% of TDEE and is strongly influenced by body size and composition. [13,14]. In particular, fat-free mass (FFM) is a primary determinant of metabolic rate, contributing an estimated ~50–75% of whole-body energy expenditure relative to other tissues and organs.[10,15-17] Although widely used prediction equations incorporate basic anthropometric variables (e.g., body mass, height, age, and sex), most were developed using general population samples and may not accurately reflect the metabolic demands of physically active groups. Indeed, previous research indicates that commonly used RMR equations systematically underestimate measured RMR in athletic individuals, likely due to their greater FFM and elevated metabolic activity, suggesting similar limitations may exist when these equations are applied to firefighters.[11]

Accurate estimation of RMR is essential for determining TDEE and developing appropriate nutrition strategies for firefighters. This is particularly important given the physically demanding and unpredictable nature of firefighting duties, which require sufficient energy availability to support performance, recovery, and long-term health.[4,18,19] Firefighters often possess relatively high levels of FFM, a primary determinant of metabolic rate, which may contribute to elevated RMR and TDEE values similar to those observed in athletic populations.[11] Consequently, reliance on prediction equations derived from general population samples may introduce meaningful error when applied to this group. Validating commonly used RMR prediction equations against measured RMR in firefighters is therefore an important step toward improving the accuracy of TDEE estimation and informing evidence-based dietary recommendations for this population.

Determining RMR is a critical step in identifying energy requirements for active tactical populations. Although RMR prediction equations have been evaluated in athletic and select tactical populations, their validity in structural firefighters remains poorly understood. Firefighters represent a unique occupational group characterized by high levels of FFM, intermittent bouts of extreme physical exertion, and irregular work schedules, all of which may influence basal metabolic demands. Because most widely used RMR equations were derived from general population samples and rely primarily on anthropometric predictors, their accuracy may be compromised in populations with atypical physiological profiles. From a theoretical perspective, greater lean mass and occupational physical demands may elevate true RMR beyond values predicted by generalized models, leading to systematic bias and increased prediction error. Therefore, the purpose of this study was to evaluate the validity of commonly used RMR prediction equations in structural firefighters by comparing predicted values to measured RMR obtained via indirect calorimetry.

We hypothesized that (1) commonly used RMR equations would demonstrate bias relative to measured RMR and (2) no single equation would meet all predefined accuracy criteria when applied to this population.

Methods

Participants

Twenty-six career male structural firefighters completed annual fitness testing. All participants were actively cleared for duty at the time of fitness testing. The testing was part of annual fitness and health evaluations conducted with the local fire department, and thus the data for the current study were retrospectively evaluated as a cross-sectional analysis. The data were not identifiable to the research team and therefore was not considered human subjects research and did not require IRB review and approval, under 45 CFR 46 policy. As such, the Institutional Review Board determined the study protocol was exempt from IRB review, and informed consent was not required (IRB# 23-008278; Exempt Date: 08/28/2023), as all information was deidentified and retrospectively analyzed. This research was carried out fully in accordance with the ethical standards of the *International Journal of Exercise Science*.[20]

Based on previous research examining differences in resting and predicted metabolic rate in active individuals,[11,21] in order to detect a meaningful difference using a repeated-measures ANOVA (within-subjects design), indicative of an effect size of 0.6 (moderate) for RMR, using a two-tailed test (alpha = 0.05) with 80% power, a sample size of 19 participants would be required. A priori power analysis was completed using the G*Power software G*Power software (latest ver. 3.1.9.7; Heinrich-Heine-Universität Düsseldorf, Düsseldorf, Germany; http://www.gpower.hhu.de/).

Protocol

During their regularly scheduled annual fitness testing, firefighters completed body composition and RMR assessments between 0700-1000 after an 8-hour fast and refraining from intense physical activity for >24 hours before testing. During a single morning of testing, participants were assessed for RMR and body composition. Results from RMR determination were then compared against six previously developed RMR prediction equations.

Procedures

Anthropometrics

Body mass and height were initially assessed using a self-calibrating physician's scale and stadiometer to the nearest 0.1 kg and 0.5 cm, respectively. These values were then used to compute body mass index (BMI).

Body Composition

Body composition was assessed using Dual-x-ray absorptiometry (iDXA) (Lunar Prodigy, GE Healthcare, USA) and the enCORE version 15.00 software. The DXA was calibrated daily prior to use, using the manufacturer-provided calibration block. Participants were asked to remove any metal and metal-containing clothing prior to measurement. Participants were instructed to lie in a supine position, with their arms resting at their sides with palms in a pronated position. The participant's legs were held in place using a Velcro strap around the lower leg. All scans were completed by the same member of the research staff.

Measured and Predicted Resting Metabolic Rate

Indirect calorimetry (ParvoMedics True One Metabolic System, Utah, USA) was used for RMR measurement. Participants were instructed to remain motionless in a supine position on an exam table. A clear, hard plastic hood and soft, clear plastic drape (TrueOne Canopy System, ParvoMedics, Utah, USA) were then placed over the participant's neck, head, and shoulders to determine resting oxygen uptake and energy expenditure. Participants were instructed to remain awake throughout the duration of testing. Ten minutes of data were initially collected and discarded. Next, data were recorded after the first ten minutes of testing during a five-minute period in which criterion variables (i.e., VO_2 L/min) did not vary by more than 5% using previously published methods.[22,23] Energy expenditure values were obtained from the ParvoMedic software program and reported as $kcal \cdot d^{-1}$, reflecting RMR values across a 24-hour period. Daily gas and flowmeter calibration procedures were performed the morning of each scheduled testing session according to manufacturer recommendations. In the event more than five participants completed testing in a single morning, the calibration procedures were completed again prior to subsequent assessments.

Resting metabolic rate values for each participant were then estimated from six previously developed prediction equations: Cunningham, De Lorenzo, Harris-Benedict, Mifflin-St Jeor, Jagim, and Nelson (Table 1).

Table 1. Summary of resting metabolic rate prediction equations used for cross-validation.

Reference	Equation
Cunningham[16]	RMR ($kcal \cdot d^{-1}$) = 22*FFM + 500
DeLorenzo[24]	RMR ($kcal \cdot d^{-1}$) = 9*BW + 11.7*H - 857
Harris-Benedict[25]	RMR ($kcal \cdot d^{-1}$), Males = 13.75 *BW + 5 *H – 6.76 $* age$ + 66.47 RMR ($kcal \cdot d^{-1}$), Females = 9.56*BW + 1.85*H - 4.68 $* age$ + 655.1
Mifflin-St Jeor[26]	RMR ($kcal \cdot d^{-1}$) = 9.99*BW + 6.25*H – 4.92*age + 166*sex - 161
Jagim[27]	RMR ($kcal \cdot d^{-1}$), Males = 19.46*BW + 775.33 RMR ($kcal \cdot d^{-1}$), Females = 21.1*BW + 288.6
Nelson[28]	RMR ($kJ \cdot d^{-1}$) = (108 x FFM) + (16.9*FM)

Units for these equations are: FFM (kg), BW (kg), FM (kg), H (cm), age (y). RMR = resting metabolic rate; FFM = fat-free mass; FM = fat mass; BW = body weight; kg = kilograms; yrs. = years; cm = centimeters; H = height; kcal = kilocalories; d = day

Statistical Analysis

Normality was assessed via visual inspection of normal Q-Q plots and skewness/kurtosis values (acceptable range: ±1 and ±1, respectively).[29] A repeated measures analysis of variance (RM-ANOVA) with Bonferroni post hoc analyses were selected to determine mean differences between measured and predicted RMR. Linear regression analysis assessed the agreement between measured and predicted RMR by calculating the slope, intercept, and coefficient of determination ($p<0.05$). Root-mean squared error (RMSE), also known as total error, was calculated as follows:

$$\sqrt{\sum \frac{\left(RMR_{predicted} - RMR_{measured}\right)^2}{n}}$$

The RMSE is interpreted as the average deviation of individual values from the line of identity between the reference method and each prediction equation.[30] The %RMSE was calculated by dividing the RMSE by the mean of the measured RMR for each predictive equation.[31] A %RMSE value of ≤10% was used to consider an equation an acceptable prediction method.[31]

Agreement between measured and predicted RMR was further evaluated using Bland–Altman analyses.[32] For each equation, the mean of measured and predicted RMR values was plotted on the x-axis, and the difference between predicted and measured RMR was plotted on the y-axis. Mean bias was calculated as the average difference between predicted and measured RMR, and 95% limits of agreement were defined as the mean bias ± 1.96 standard deviations of the differences. Systematic bias and variability across the range of RMR values were also assessed.

The relationship between RMR (measured) and body composition parameters was assessed using linear regression All data were analyzed using SPSS (Version 25.0, IBM, Armonk, NY, USA).

Results

A summary of anthropometric and body composition variables is presented in Table 1.

Table 2. Anthropometric and body composition characteristics of participants (n = 26).

	Mean ± SD
Age (yrs.)	38.2 ± 7.7
Height (cm)	180.9 ± 6.8
Weight (kg)	92.0 ± 15.6
BMI ($kg \cdot m^{-2}$)	28.1 ± 4.4
BF%	25.3 ± 7.5
FFM (kg)	68.5 ± 7.8
FFMI ($kg \cdot m^{-2}$)	20.9 ± 7.8

cm = centimeter. kg = kilograms; BMI = Body mass index; BF% = Body fat percentage; FFM = Fat-free mass; FFMI = Fat-free mass index; $kg \cdot m^{-2}$ = kilograms per meter squared

Examination of data normality indicated acceptable distribution characteristics for measured RMR values, with skewness (−0.204) and kurtosis (−0.707) values falling within commonly accepted thresholds for normality. All prediction equations significantly underestimated RMR, except for the Jagim equation, which significantly overestimated RMR. Mean differences, linear regression variances and coefficient values can be found in Table 3. Linear regression indicated the Harris-Benedict equation had the closest agreement to measured RMR (R^2 = 0.696, RMSE = 314 kcals, %RMSE = 14.2%), along with the DeLorenzo equation (R^2 = 0.675, RMSE = 242 kcals, %RMSE = 10.9%). The variance in predicted RMR values from the equations ranged from an SEE = 173 $kcal \cdot d^{-1}$ (Harris-Benedict) to an SEE = 215 $kcal \cdot d^{-1}$ (Cunningham), accounting for 70% and 53% of the variance in RMR, respectively.

Table 3. Differences between predicted and measured resting metabolic rate and cross-validation.

	Mean ± SD	CE ± SE	95% CI	95% CI	p#	R^2	SEE	β	P^	RMSE	%RMSE
Measured ($kcal \cdot d^{-1}$)	2244±307										
Cunningham ($kcal \cdot d^{-1}$)	2007±172	-237±42.5	-325	-150	<.001	0.529	215	0.727	<.001	307	13.8
DeLorenzo ($kcal \cdot d^{-1}$)	2084±185	-160±38.7	-240	-80	<.001	0.675	192	0.788	<.001	242	10.9

HB (kcal ·d^{-1})	1973±223	-272±33.8	-341	-202	<.001	0.696	173	0.834	<.001	314	14.2
Mifflin-St Jeor (kcal ·d^{-1})	1863±174	-381±37.2	-458	-305	<.001	0.686	175	0.828	<.001	409	18.4
Jagim (kcal ·d^{-1})	2558±291	313±39.1	233	394	<.001	0.607	196	0.779	<.001	356	16.1
Nelson (kcal ·d^{-1})	1862±220	-383±38.2	-461	-304	<.001	0.601	197	0.775	<.001	412	18.6

CE = constant error (predicted – measured). SE = standard error; HB = Harris-Benedict; SEE = standard error of the estimate; Reg. = regression; β = regression coefficient; RMSE = root mean square error; HB = Harris-Benedict. ^ = p value corresponding to regression analysis; # = p value corresponding to repeated measures ANOVA.

Bland–Altman analyses revealed systematic bias for all prediction equations, with mean differences that were not equal to zero. Five of the six equations (Cunningham, DeLorenzo, Harris–Benedict, Mifflin-St Jeor, and Nelson) demonstrated consistent underestimation of measured RMR, with mean biases ranging from approximately −160 to −380 kcal · day^{-1}. In contrast, the Jagim equation overestimated RMR, with a mean positive bias of approximately +310 kcal · day^{-1}. Across equations, limits of agreement were wide, indicating substantial individual-level variability and limited precision in predicting RMR within this firefighter sample (Figure 1).

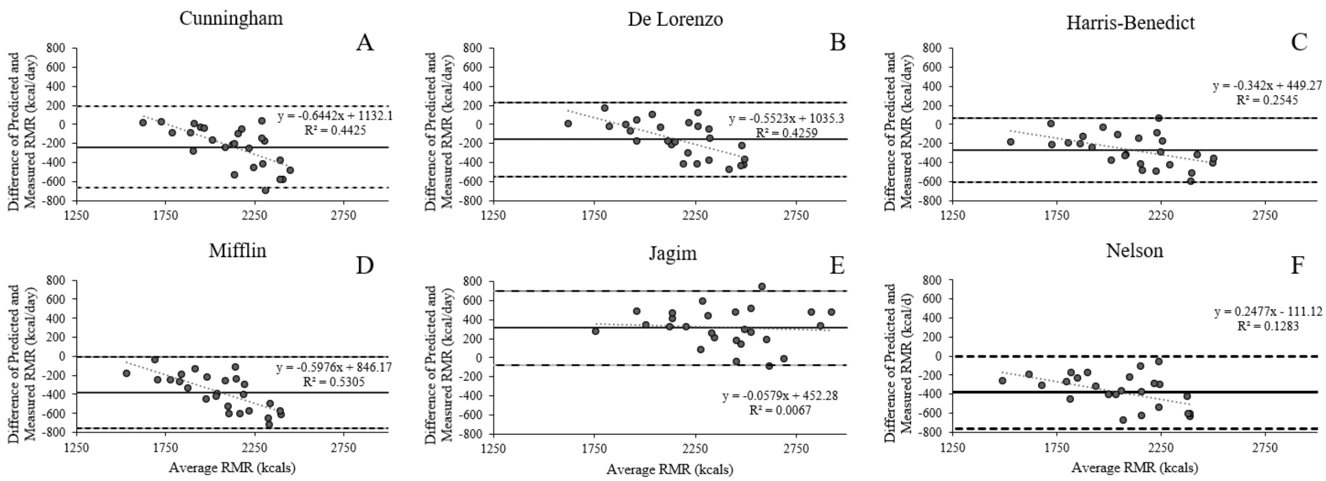

Figure 1. Bland-Altman plots for measured and resting metabolic rate (RMR) prediction values. The dotted lines represent upper and lower 95% limits of agreement. The solid line represents the mean of the difference between measured RMR and the prediction equations.

The results of the linear regression analysis indicated that body weight ($R^2 = 0.619$, $\beta = 0.79$; $p < 0.001$) and FFM ($R^2 = 0.529$, $\beta = 0.73$; $p < 0.001$) were the strongest predictors of RMR. Height ($R^2 = 0.256$, $\beta = 0.51$; $p < 0.001$), BMI ($R^2 = 0.421$, $\beta = 0.65$; $p < 0.001$), BF% ($R^2 = 0.199$, $\beta = 0.45$; $p < 0.001$), and BMD ($R^2 = 0.302$, $\beta = 0.55$; $p < 0.001$) were also significant predictors of RMR.

Discussion

The primary purpose of this study was to evaluate the validity of commonly used RMR prediction equations in a cohort of firefighters by comparing estimated RMR values to measured RMR obtained via indirect calorimetry. The primary findings indicate that most prediction equations demonstrated significant bias and limited accuracy at the individual level, with the majority underestimating measured RMR, while one equation (Jagim equation)[27] overestimated RMR. In the current study, several of the RMR prediction equations evaluated significantly underestimated RMR compared to measured RMR values, with estimates ranging from -160 to -380 kcals. The Harris-Benedict and DeLorenzo equations demonstrated the closest agreement with measured

RMR values, although both still produced RMSE values above the 10% error threshold suggested by Freire et al.[31] for acceptable predictive accuracy. Specifically, RMR values derived from the Harris-Benedict[25] equation yielded the closest agreement to measured RMR (R^2 = 0.729, %RMSE = 14.3%), along with the DeLorenzo[24] equation (R^2 = 0.662, %RMSE = 11.0%), whereas the Nelson[28] equation yielded the least agreement as noted by the highest RMSE (431 kcals, %RMSE = 19.5%) (Table 3). The variance in predicted RMR values from the equations ranged from an SEE = 172 kcal $\cdot$ d^{-1} (Harris-Benedict) to an SEE = 208 kcal $\cdot d^{-1}$ (Cunningham), accounting for 73% and 59% of the variance in RMR, respectively. Although some equations showed relatively smaller mean bias, substantial interindividual variability was observed across all models, suggesting limited precision when applied to this population.

These findings align with previous research demonstrating that RMR prediction equations derived from general population samples often perform poorly in physically active or occupationally demanding populations.[11,21,33] Studies in athletic cohorts have similarly reported systematic underestimation of measured RMR, likely due to greater fat-free mass and elevated metabolic activity not fully captured by traditional anthropometric predictors.[11,21,31] For example, Fields et al.[11] reported significant underestimations of RMR in collegiate athletes using traditional models, which parallels the discrepancies observed in the current sample of career firefighters. Firefighters share several physiological characteristics with athletic populations, including higher lean mass and greater energy demands, which may partially explain the observed discrepancies between measured and predicted RMR.

Previous work in active adult athlete populations has shown commonly used RMR prediction equations to underestimate measured RMR values, particularly in larger individuals (e.g., higher BMI).[11,34,35] However, findings are inconclusive in healthy adult populations with select RMR prediction equations over- or under-estimating RMR.[36-39] Similar to the finding in the current study, Flack et al.[39] found the Harris-Benedict equation performed best compared to three other RMR prediction equations with a mean bias of (mean ± SD) -14 ± 378 kcal $\cdot$ d^{-1} within a population of healthy adults. The remaining RMR prediction equations in the study by Flack et al[39] resulted in large limits of agreement ranging from 314 to 445 kcal $\cdot d^{-1}$, despite accounting for differences in FFM. Additionally, RMR prediction equations tend to be less accurate and more likely to underestimate RMR in active individuals and those with greater amounts of FFM, which has been shown in both active and sedentary populations.[37,39] Linear regression analyses indicated that body weight and FFM were the strongest predictors of RMR, explaining 61.9% and 52.9% of the variance, respectively. These findings are consistent with established physiological principles demonstrating that metabolically active tissue mass is a primary determinant of RMR.[15-17,28,40] Although height, BMI, BF%, and BMD were also significant predictors, their comparatively lower R^2 values suggest they provide less explanatory power beyond overall body size and FFM. Collectively, these results reinforce the importance of incorporating body composition, particularly FFM, when estimating RMR in physically active populations.

This study adds to a growing body of literature emphasizing the limitations of one-size-fits-all predictive models and highlights the importance of validating equations within the specific populations they intend to serve. Importantly, while repeated measures ANOVA identified group-level bias, regression and agreement analyses further demonstrated that equations differed in their ability to explain variance in measured RMR, emphasizing the importance of considering both systematic bias and individual-level prediction error when evaluating equation utility. Future research should focus on the development and external validation of firefighter-specific

RMR equations using gold-standard techniques such as doubly labeled water to further improve nutritional and occupational health strategies in this unique population.

When interpreting these findings, it is important to recognize that although select equations demonstrated acceptable performance for individual metrics such as %RMSE, no single equation satisfied all predefined criteria across bias, agreement, and variance based on the a priori accuracy thresholds established for this study. From a practical standpoint, this indicates that reliance on any single predictive model should be undertaken with caution when estimating RMR in firefighters. For example, the Jagim equation exhibited relatively favorable average error metrics; however, Bland–Altman analyses revealed systematic overestimation and wide limits of agreement, suggesting that its utility may be limited for individual-level prescription despite reasonable group-level performance. Similarly, other equations demonstrated either substantial underestimation or poor agreement despite modest group-level bias. The Harris-Benedict and De Lorenzo RMR prediction equations provided the most accurate estimates of RMR for the structural firefighters participating in the current study and should be considered for use until a firefighter-specific RMR prediction equation is developed. Accordingly, these models may be acceptable for group-level estimation and represent a "best available" (i.e., Harris-Benedict and De Lorenzo equations), but should be applied cautiously for individualized energy prescription in firefighters. Collectively, the results underscore the need for population-specific refinement of RMR prediction equations in this cohort.

Several limitations of the present study should be acknowledged. First, although indirect calorimetry was used as the criterion measure for RMR, measurements were obtained under laboratory-controlled conditions that may not fully reflect free-living metabolic variability in firefighters. Second, the sample consisted of active-duty firefighters from a single department, which may limit generalizability to other fire service populations with differing demographics, training practices, or occupational demands. Third, while body composition was assessed and incorporated into select prediction equations, additional physiological factors known to influence RMR (e.g., hormonal status, sleep quality, and recent training load) were not directly measured or controlled and may have contributed to interindividual variability.

Additionally, although Bland–Altman analyses and regression-based accuracy metrics were used to evaluate agreement and prediction error, no universally accepted a priori thresholds exist for acceptable bias or limits of agreement in RMR equation validation. As such, interpretation relied on complementary statistical approaches (e.g., RMSE, R^2) to provide context regarding practical utility.

The findings of this study build upon previous research that has identified limitations in the accuracy of generalized RMR prediction equations when applied to highly active populations. While differences in physical characteristics between the populations originally included in the initial validation studies for the included RMR prediction equations and the firefighters included in the current study may partially explain the poor validity of the prediction equations, it is also possible that chronic exposure stress and sleep deprivation may influence measured RMR values[41] in firefighters and subsequently, the accuracy of the equations. Collectively, these results support concerns regarding the external validity of commonly used RMR equations when applied to specialized populations. These inaccuracies have meaningful implications, as miscalculations in energy needs may hinder recovery, compromise performance, and contribute to poor body composition management, especially in professions with high physical and metabolic demands.

The present findings have practical implications for the estimation of TDEE in firefighters. Because RMR serves as the foundation for most TDEE estimation approaches[42,43] including those that apply standardized physical activity level (PAL) multipliers, systematic error in RMR estimation may be magnified when extrapolated to daily energy needs. This may have downstream consequences for occupational recovery, body weight management, and long-term health. As such, individualized approaches to energy requirement estimation are warranted, given the variability in body size and composition among firefighter.[44-47] Moreover, adjustments may be needed to account for any weight management strategies, which is an important consideration due to the high rates of obesity among the fire service and their unique occupational demands.[45,47-49]

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