Novel daily energy expenditure estimation by using objective activity type classification: where do we go from here?

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ACCURATE ESTIMATION of daily energy expenditure (DEE) in population studies is challenged by factors such as feasibility, cost, and validity of the method under consideration. The use of wearable sensors, in particular accelerometers, is possibly the most promising currently available method to estimate DEE. Numerous accelerometer-based prediction models for estimating DEE and physical activity energy expenditure (PAEE) have been developed (5). Most of the prediction models published so far are based on linear regression analysis in experimental populations. To increase precision of these regression models, group-specific or even individual-specific regression models may be necessary. An alternative and potentially more effective and feasible approach may be to assess other individually specific characteristics that explain those yet unexplained differences between populations and between individuals. Assessing the major types of physical activity usually performed in daily life may improve the explained variation in DEE.

In their article in the Journal of Applied Physiology, Bonomi and colleagues (3) present results from a study aimed to develop a model for estimating energy expenditure from accelerometer-based classification of types of physical activity in combination with published data on the energy cost [metabolic equivalent (MET) compendium values] of these activities (1, 3). The method proposed is novel because it does not rely on the use of regression analysis for predicting energy expenditure, nor does it rely on manufacturer-dependent information such as activity counts, the usual output from activity monitors based on accelerometry. Bonomi and colleagues compare their newly developed method with the more traditional method of using activity counts for DEE prediction. The high level of transparency of the proposed method is likely to inspire future research in this area. However, there are some additional issues that remain to be elucidated.

The importance of classifying activity types when estimating energy expenditure is not yet fully understood. Previous studies have shown that the slope of the linear relation between energy expenditure and body acceleration varies across types of physical activity (6, 9). Theoretically, knowledge about the slope for each type of activity explains the variation in energy expenditure between types of activity within individuals that cannot be explained by acceleration (i.e., counts) alone. Between-individual differences in time spent in each type of physical activity may therefore be related to the average individuals’ slope across activities over a day and thus explain between-individual differences in DEE. In the model proposed by Bonomi and colleagues the types of physical activity identified by accelerometer and an accelerometer-based estimation of the speed of movement are used to estimate the MET intensity level defined by the compendium (1). In contrast to the assessment of counts by accelerometer, the compendium, at least in theory, takes into account differences in slope between types of activity because the activities included are based on measured or estimated energy expenditure rather than body acceleration. Therefore, the activity classification from accelerometer may have accounted for differences in slope between types of activity via the compendium. Future research will have to evaluate whether the main contribution of activity classification truly lies in the ability to account for differences in slope, which would indicate that activity classification needs to focus on explaining differences in slope rather than the activity type itself. Additionally, the y-intercept of the linear relation may also be an important parameter.

A better understanding of the sources of explained variation and sources of error may provide guidance for further methodological improvement. The contribution of activity type classification to the total explained variation in DEE by the classification-based model cannot be separated from the explained variation by intensity as assessed by the MET compendium. The MET compendium (1) passes through knowledge about the intensity within types of activity to the classification-based model developed by Bonomi and colleagues, which may not be comparable to intensity assessment by accelerometer counts. For certain types of activity the intensity assessment by the MET compendium (1) may be more precise compared with the activity count-based model. For example, energy expenditure during cycling or running may be better predicted by the MET compendium and estimated speed of movement than by the accelerometer counts. Unfortunately, it seems impossible to assess the partial contribution of each variable (intensity from activity type classification vs. intensity from activity counts) to the validity of the overall DEE prediction model.

The way in which Bonomi and colleagues combine the activity type classified by the activity monitor in combination with MET compendium information to estimate DEE is similar to DEE estimations from self-reported questionnaire data. Despite this similarity, the validity of the proposed accelerometer-based method appears to be much higher than previously reported for questionnaire-based energy expenditure estimations (7). An obvious difference is that the accelerometer-based energy expenditure prediction is not affected by recall bias, which may contribute to the higher validity. Another explanation for the higher validity could be the ability of the accelerometer-based activity classification to accurately quantify the amount of time spent sedentary. However, the true benefit of accelerometer-based activity classification over questionnaire-based activity classification for estimating daily energy expen-
diture was not addressed in the paper by Bonomi et al. (3) and needs further examination.

Several previous studies have shown that data collected by accelerometry can be used to detect types of activity (2, 10). However, the use of accelerometer-based activity classification to estimate energy expenditure is a relatively new area. So far two different approaches have been proposed: the use of activity type-specific prediction equations (9) and the use of MET compendium estimates (3). Future research needs to address the difference between these approaches and examine whether a combination of the two approaches results in even more accurate prediction of DEE. Here, the key question is, “What characteristics of physical activity could explain the variation in energy expenditure not explained by intensity assessment alone?” Potentially interesting characteristics of physical activity that may increase the explained variance in DEE include, for example, walking speed, identification of weight-bearing activities, and muscle fatigue.

Another topic of interest for future research relates to detecting measurement error. Accurate identification of monitor nonwearing time, failure to attach the monitor correctly, and the identification of acceleration not related to body movement (e.g., sitting in a bus) would allow for appropriate measurement error corrections. Nonwearing time can be regarded as missing data. Catellier et al. (4) showed that the replacement of missing data by imputations increases precision. Incorrect monitor attachment and the measurement of movement not related to muscle contractions may require more sophisticated imputations to be made, as has been suggested recently for heart rate data (8).

The method as proposed by Bonomi and colleagues may be relevant for developing and evaluating health guidelines related to the types of physical activity performed in daily life. Timely questions such as “How many minutes of walking are needed to maintain energy balance over a long period of time?” and “What amount of running or cycling time instead of sitting in a bus) would allow for appropriate measurement error corrections. Nonwearing time can be regarded as missing data. Catellier et al. (4) showed that the replacement of missing data by imputations increases precision. Incorrect monitor attachment and the measurement of movement not related to muscle contractions may require more sophisticated imputations to be made, as has been suggested recently for heart rate data (8).

In conclusion, objective classification of activity types by accelerometry performed in daily life may have the potential to improve the estimation of DEE, but the contribution of individual variables to the explained variation in DEE and the role of measurement error need to be addressed in the future.

REFERENCES