

Award Number: W81XWH-12-2-0013

TITLE: Locomotion with loads: Practical Techniques for Predicting Performance Outcomes

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REPORT DATE: May 2018

TYPE OF REPORT: Annual

PREPARED FOR: U.S. Army Medical Research and Materiel Command
Fort Detrick, Maryland 21702-5012

DISTRIBUTION STATEMENT: Approved for Public Release; Distribution Unlimited

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REPORT DOCUMENTATION PAGE			Form Approved OMB No. 0704-0188	
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1. REPORT DATE May 2018		2. REPORT TYPE Annual		3. DATES COVERED 15 Apr 2017- 14 Apr 2018
4. TITLE AND SUBTITLE Locomotion with loads: practical techniques for predicting performance outcomes			5a. CONTRACT NUMBER	
			5b. GRANT NUMBER W81XWH-12-2-0013	
			5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) Peter Weyand E-Mail: pweyand@smu.edu			5d. PROJECT NUMBER	
			5e. TASK NUMBER	
			5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Southern Methodist University, Office of Research Administration, 6425 Boaz Lane, Suite 103, Dallas, TX 75205			8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Army Medical Research and Materiel Command Fort Detrick, Maryland 21702-5012			10. SPONSOR/MONITOR'S ACRONYM(S)	
			11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION / AVAILABILITY STATEMENT Approved for Public Release; Distribution Unlimited				
13. SUPPLEMENTARY NOTES				
14. ABSTRACT Here, load carriage interventions for walking <i>energy expenditure</i> and <i>running speed</i> have been designed to: 1) advance existing models and 2) contribute needed data to the broader effort to develop load-carriage decision-aid tools for modern soldiers. We hypothesize first that our height, weight (including load), speed, and grade algorithms proposed will allow walking metabolic rates to be predicted to within 6.0 and 12.0% in laboratory and field settings, respectively. We hypothesize second that the speed-load carriage algorithms will allow load-induced decrements in all-out sprint running speeds to be predicted to within 6.0% in both laboratory and field settings. Respective load-carriage algorithms for <i>walking energy expenditure</i> and <i>running speed</i> will be developed and tested (Technical Objectives 1.0 and 2.0) in the laboratory and the field.				
15. SUBJECT TERMS gait, metabolism, performance, load carriage				
16. SECURITY CLASSIFICATION OF: Unclassified			17. LIMITATION OF ABSTRACT UU	18. NUMBER OF PAGES 38
a. REPORT U	b. ABSTRACT U	c. THIS PAGE U		19a. NAME OF RESPONSIBLE PERSON USAMRMC
				19b. TELEPHONE NUMBER (include area code)

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INTRODUCTION

The Need for Load Carriage Decision-Aid Tools

Load carriage is a foot-soldier requirement with direct consequences for a broad array of physiological, performance and health outcomes. Metabolic energy expenditure, heat production, macronutrient requirements, water requirements, and injury risks are all directly elevated by the weight of the equipment soldiers carry while both short- and long-term mobility are substantially reduced (Knapik et al., 1996; Knapik et al., 2004). Clearly, the physiological stresses and mobility losses induced by load carriage do not constitute desirable field outcomes. Indeed, anecdotal (Knapik & Reynolds, 2010) and formal (Dean, 2004) accounts of the negative consequences of pack overloads are readily available from a multitude of field combat situations.

In both modern and historical warfare environments alike, the physiological status and mobility of foot soldiers influence combat performance, wound and survival rates. Accordingly, exacting considerations of the value of carried equipment evaluated against the negative performance, wound and mortality consequences of added weight are a matter of vital military importance.

A priori, one might expect that the major advances in both material science and electronics in the modern era would provide soldiers with more effective equipment while simultaneously reducing the loads soldiers carry. However, the historical record indicates a marked trend in the opposite direction. During the 150-year period from the Civil War through the present day, the pack weights of American foot soldiers have *increased* by a factor of approximately 3-fold, from 15 kg during the Civil War to 35 kg in World War II to approximately 45 kg in Desert Shield (Knapik & Reynolds, 2010), and 45 kg or above in Afghanistan (Dean, 2004). For an average-sized male US soldier, a load of 45 kg constitutes well over 50% of the body's weight. Thus, the theoretical potential for technological advances in equipment and materials to lighten the pack and total body loads carried by modern foot soldiers has not been realized.

This brief consideration of the historical trends for the loads carried by US soldiers across different eras begs two immediate questions: are the loads carried by modern soldiers excessive? And if so, how harmful is the additional weight carried to warfighter performance?

This answer depends on a fundamental and long-standing load carriage trade-off assessment that balances the *benefits of the equipment carried* vs. the *detrimental performance consequences* imposed by carrying additional weight. On a qualitative level, the benefits of modern body armor, firepower, and communication equipment are relatively obvious, as are the negative physiological and mobility consequences of carrying heavy loads. However, at present, the data needed for quantitative, evidence-based considerations are unavailable. Consequently, well-informed decisions about the pack and total body loads that will be most effective for soldiers in operational environments are not possible.

Given that warfighter field effectiveness is crucial to the efforts of the US military, moving beyond qualitative considerations of the load carriage cost-benefit trade-offs constitutes minimum due diligence to the soldiers in the field as well as to the enormous national investment in our military initiatives. The work proposed here will contribute to a broader experimental work effort to develop **load-carriage, decision aid tools** that take an evidence-based approach to determining loads for foot-soldiers. The specific experimental work we propose focuses on the cost, or detriment side of the load carriage trade-off equation. This work is expected to provide

data that are currently lacking, but necessary for informing strategic decisions regarding pack and total load carriage weights.

We present a series of experiments designed to quantify the negative physiological and performance consequences of the loads modern soldiers carry. The work has been formulated using two promising physiological-mechanical models: 1) a stature-based model to explain walking energy expenditure, and 2) a ground force model to explain brief, all-out running speeds. Fulfilling our experimental objectives should allow predictions of the specific physiological, performance and mobility decrements that would be expected across a broad continuum of potential loads.

Objective One: Walking Energy Expenditure

Previous Scientific Efforts of Direct Military Relevance: Because metabolic rates are so fundamentally related to physiological status and sustained performance capabilities, the Army has a long-standing interest in developing techniques to predict and monitor the metabolic rates of soldiers walking in the field. As with most efforts to acquire or predict physiological data in field environments, this has proven to be a challenging undertaking. However, modern monitoring capabilities and improved predictive modeling should allow for meaningful progress.

The pioneering efforts of Pandolf and others in the 1970's (Givoni & Goldman, 1971; Pandolf et al., 1977) established generalized equations that predict the metabolic rates of walking soldiers from total weight (i.e. body weight + load), speed and grade. However, the utility of these equations depends heavily on the ability to acquire walking speed and grade data in the field. This ability was formerly quite limited, but in recent decades has become fully feasible and highly accurate.

In part, because the ability to monitor speed and distance in field environments limited the original applicability of the Pandolf et al. equations, other approaches were pursued. In the 1990's, Hoyt and colleagues (Hoyt et al., 1994; Hoyt & Weyand, 1996; Hoyt et al., 2004; Weyand et al., 2001) adopted an innovative technological approach that, in contrast to the Pandolf approach, did not require speed and distance data. Hoyt devised a bio-monitoring strategy to predict locomotor metabolic rates from the body's weight and the periods of foot-ground contact. This approach was inspired by algorithms (Kram & Taylor, 1990) that explained the metabolic rates of different-sized terrestrial running and hopping animals. Hoyt and colleagues successfully developed biosensors that accurately monitored ambulatory foot-ground contact times and predicted metabolic rates under some conditions (Hoyt et al., 1994; Hoyt et al., 2004; Weyand et al., 2001). However, this approach was not without limitations. Foot-ground contact monitoring requires a functioning sensor and a wireless network, and current monitors cannot detect the surface inclinations that have a substantial effect on walking energy expenditure (Margarita et al., 1968; Minetti et al., 1994; Minetti et al., 2002).

Modeling Walking Metabolism: Recently, we have developed a promising model for predicting walking metabolic rates that combines the strengths of the Pandolf and Hoyt approaches that can be readily implemented in the field using the accurate geo-location systems now available.

Our model may advance predictive accuracy beyond that provided by the two generalized models most commonly used to estimate the metabolic rates of human walkers at present: the Pandolf

and American College of Sports Medicine (ACSM) equations. Both use *body weight* and *walking speed*, but not stature to predict metabolic rates. Although comparative physiologists have long recognized (Alexander, 1976; Taylor et al., 1982; Kram & Taylor, 1990) that the mass-specific metabolic cost of locomotion varies in a systematic manner with the linear dimensions of the body, the leading models for predicting locomotor costs of humans have not incorporated body or leg lengths. The inverse relationship between the body's length (i.e., height) and the mass-specific metabolic rates of individual human walkers has been recently demonstrated (Weyand et al., 2010)

The Stature-Based Model of Walking Metabolism: Our new stature-based model of walking energy expenditure (Weyand et al., 2010) includes three fully independent variables: body mass, stature and walking speed. The quantitative form of the model is as follows:

$$E_{\text{metab}} = \text{RMR} + C_1 \cdot \text{RMR} + C_2 \cdot V^e/\text{Ht} \quad (\text{eq. 1})$$

where E_{metab} is the body's total metabolic rate, RMR is resting metabolic rate, V is the velocity of walking, and Ht is height. C_1 and C_2 are empirically derived coefficients, and e is an exponent that quantifies equivalent walking velocities for individuals who differ in height. All metabolic rates in the equation are expressed in mass-specific terms.

In our model, RMR is the body's minimum or baseline rate of energy expenditure, the quantity ($C_1 \cdot \text{RMR}$) represents the factorial increase above resting metabolic rate needed to maintain a walking posture (i.e. a postural metabolic rate, or PMR), and the term ($C_2 \cdot V^e/\text{Ht}$) describes the curvilinear, or exponential, increase in mass-specific metabolic rates that occurs with increases in walking velocities standardized to height in accordance with the original suggestion of Alexander (Alexander, 1976; Alexander, 2003) to use the Froude Number ($= V^2/\text{gravity} \cdot \text{leg length}$). The product of our slightly modified (for utility and convenience) model term V^e/Ht , and the coefficient C_2 , represents the metabolic energy expended to lift, support and accelerate the body's center of mass with each step as walking speed is increased.

Two critical assumptions were involved in our development of the stature-based model to predict walking metabolic rates. First, we assumed that the mass-specific **metabolic energy expended per stride is the same at equivalent walking speeds** regardless of the height and weight of the individual. Second, we assumed that individuals who differ in stature **walk in a mechanically similar way at equivalent walking speeds** (i.e. the same Froude Number or value of V^2/Ht). Here, mechanical similarity is defined as stride lengths and times being related by a constant proportion across individuals of different heights.

Extending the Stature-Based Model to Load Carriage and Graded Walking:

Load Carriage: Two aspects of the model seem promising with respect to extending the stature-based model to the load carriage conditions: the predictive accuracy of the model on the independent and heterogeneous subjects evaluated so far, and a clear conceptual and quantitative basis from which to predict the effect that loading will have. Per below, our stature-based model breaks total walking metabolism into resting and walking components.

$$\dot{E}_{\text{metab}} = \underbrace{\text{RMR}}_{\text{Resting}} + \underbrace{C_1 \cdot \text{RMR} + C_2 \cdot V^e / Ht}_{\text{Walking}}$$

Because the relationship between the weight supported and both of the walking, or non-resting component of our model is 1:1, the predictions of the model for the effect of loading are straightforward: loading will increase the *walking* portion of the total metabolic rate in direct proportion to the load added. Thus, a load equal to 10% body's weight will increase walking metabolic rates by 10%; a load equal to 20% of body's weight will increase walking metabolic rates 20%, etc.

While there is a relatively large body of literature on the consequences of loading for walking metabolism (Bastien et al., 2003; Das & Saha, 1966; Duggan & Haisman, 1992; Falola et al., 2000; Griffin et al., 2003; Holewijn, 1990; Martin & Nelson, 1986; Pimental & Pandolf, 1979), none of the studies available provide the data needed to evaluate the predictive accuracy of the stature-based model under these conditions. Two quantitative issues prevent this: existing data sets and models have not included the influence of stature on walking metabolism, and previous studies have not quantified or reported resting metabolic rates that can be quantitatively related to the resting and postural terms in our model. However, the best data available for evaluating our model (Griffin et al., 2003) indicate that loading results in gross walking metabolic rates being elevated slightly less than in direct proportion to load, while net walking rates (subtracting a standing value) are elevated in slightly greater than 1:1 proportion are consistent with our model predictions.

Graded Walking: Similarly, our expectation is that our model will also apply to graded walking, although per above, quantitative evaluations of our model using the existing literature (Margaria, 1968; Minetti et al., 1994; Minetti et al., 2002; Wanta et al., 1993) are not possible. For graded walking, our approach will be to extend our findings of a constant metabolic cost per stride at equivalent speeds for different individuals to inclined and declined conditions. Under level walking conditions, we found that the lower mass-specific metabolic rates of taller vs. shorter individuals are fully explained by differences in body lengths (i.e. height) and proportional differences in the horizontal distance traveled with each stride (i.e. stride length). Extending our stature-based model to explain metabolic rates during inclined and declined walking involves similar quantification of the distance traveled by the body during each stride. During horizontal walking, including only the horizontal displacements is sufficient. During graded walking, our stature-based model predicts metabolic rates will be a function of both the *horizontal* and *vertical* displacements of the body over the course of each stride. Stride lengths during graded walking are expected to be proportional to stature at equivalent walking speeds as during horizontal walking. However, the vertical displacements of the body over the course of each stride will be a function of both the surface grade and stature. Per intuition, the vertical distance per stride traveled will be greater on any inclined or declined walking surface for taller vs. shorter individuals. Accordingly, metabolic rate deviations from the level condition for taller vs. shorter individuals are also expected to be greater on any given incline or decline. Mechanically, this is most easily conceptualized as the metabolic cost per stride increasing and decreasing in accordance with the positive and negative displacements of the body during each stride. This metabolic pattern is well described in the comparative literature for large and small animals (Taylor et al., 1972), but the data needed to assess humans of different statures is unavailable.

Our expectation is that we can use stature and percent grade to quantify this effect. In the specific terms of our model, our expectation is that our coefficient, C_2 that describes the increases in metabolic rate in relation to increases in equivalent walking speeds, will have the same value for any given positive or negative vertical displacements of the body per stride. Although this relationship will need to be determined empirically, we can make the simple prediction that the value of C_2 during inclined and declined walking will be proportional to the product of the stature of the individual and the percent grade of the surface (i.e. $C_2 \propto Ht \cdot \% \text{ grade}$).

The experiments proposed here represent the most fundamental empirical steps needed to extend and validate our stature-based model. Once the basic work needed to develop algorithms including load, incline and decline conditions has been completed, additional work to incorporate the effects of fatigue (Epstein et al., 1988; Patton et al., 1991), terrain (Pandolf et al., 1977) and very steep downhill grades (Margaria, 1968; Santee et al., 2001) may then be explored in the context of the model.

Objective Two: Sprint Running Speed

Previous Scientific Efforts: The scientific literature on the basis of brief, all-out running performance is far less extensive than that devoted to the energy cost of walking. Early efforts focused primarily on explaining performance in terms of the metabolic power available for these events (Hill, 1925; Hill, 1950; Ward-Smith, 1985; Ward-Smith, 1999; Ward-Smith, 2000). While some investigators have continued to use metabolic models to explain these performances (Rittweger et al., 2009), the predominant scientific focus has shifted to mechanical models (Bundle et al., 2006; Usherwood & Wilson, 2005; Usherwood & Wilson, 2006; Chang & Kram, 2007; Weyand et al. 2000; Weyand et al., 2000b; Weyand et al., 2010) to explain sprint exercise performances. In our view, this shift is scientifically warranted as mechanical approaches can directly explain the motion of the body and promising force models using this approach are being developed (Weyand et al., 2006; Weyand et al., 2010). In contrast, metabolic models continue to be difficult to validate at present due to the ongoing inability to quantify the whole-body anaerobic and total metabolic energy released during sprinting (Bangsbo, 1998; Van Praagh, 2007).

For the purposes of predicting sprint exercise performance here, we have opted to quantify load-induced decrements in speed as fractional decrements from the unloaded condition. Our interpretation of the existing literature indicates that this approach is likely to provide the greatest predictive accuracy from a simple, practical model. There are at least two sound, literature-based reasons for adopting this approach. First, maximal sprint performances vary considerably between individuals for physiological and mechanical reasons that are incompletely understood and likely cannot be modeled simply. Second, the relationship between all-out sprint running speeds and the average ground forces applied during each step, both within and across individuals, is reasonably linear during sprint running (Weyand et al., 2000; Weyand et al., 2010) which simplifies model predictions.

We expect to be able to predict load-induced decrements in speed with a high degree of accuracy because loads are not likely to alter the maximum forces runners can apply to the ground, but will predictably increase the ground force required to run at any speed. Accordingly, we should be able to use a runner's force maximum at his or her unloaded sprinting speed maximum, load-

induced increases in the ground forces required, and the general force-speed relationship to predict load-induced decrements in all-out speed.

Our speed model takes the simple following form:

$$V_L = C_1 \cdot (L/W_b) \cdot V_{UL} \quad (\text{eq. 2})$$

where V_L is the maximum velocity of loaded running for all-out runs of brief duration, W_b is body weight, L is the weight of the load carried, C_1 is the coefficient describing the load-induced decrements in speed resulting from fractional additions to the body's weight (L/W_b) via loading, and V_{UL} is the maximum velocity of running in the unloaded condition.

Our force-speed model has its basis in both basic Newtonian mechanics and the ground force capabilities of individual runners. An extensive body of scientific evidence supports the view that a primary mechanical requirement of running is supporting the body's weight against gravity. Successful characterizations of running energetics and even speed and distance monitoring have been realized from this conceptual starting point (Kram & Taylor, 1990; Weyand et al., 2001). Our force-speed model also begins with this basic recognition.

The mechanical basis of our empirically-formulated force model of sprint running is most easily understood by considering how the ground contact and aerial phases of a running stride change across speed for individual runners. The relative durations of the aerial and foot-ground contact phases of a running stride vary with speed. As runners increase their speeds, they spend relatively more time in the air and relatively less time on the ground. Consequently, the ground support forces that runners apply increase in an approximately linear fashion with speed and are set by body mass. For runners regardless of ability, stance-averaged ground support forces are 1.5 times the body's weight while jogging, and increase to 2.0 times the body's weight or more when running at sprinting speeds.

Here, we expect that loading will result in proportional increases in the stance-average ground reaction forces required with little effect on the time course of ground force application. This result has also been reported from studies examining loaded running at slower speeds (Chang & Kram, 2000). The consistency observed in the foot-ground contact times at any given speed across different loads suggests that our general approach is sound

Beyond this, we have found that the limit to running speed occurs when runners reach that speed at which they are repositioning their limbs as quickly as possible while simultaneously applying maximum ground forces. Contrary to intuition, the minimum times runners require to reposition their limbs at their top running speeds does not vary in relation to how fast they can run. Consequently, individual differences in speed are explained all but entirely by the mechanics of the stance phase. These mechanical observations support a modeling approach that focuses on the ground force required and available for speed.

At present, firm predictions of the decrements in brief, all-out running speeds that will occur with loading and that will be quantified by the coefficient C_1 in our force-running speed model are difficult. This is the case because only small number of studies to date have examined the effects of loading on sprint running performance (Alcaraz et al., 2008; Cronin et al., 2008; Holewijn & Lotens, 1992). The few studies that do present loaded and unloaded all-out sprinting speed data

do so under conditions that make more generalized predictions difficult, and none of these studies include the ground reaction force data. The most informative study with respect to our experimental objectives here is that of Holewijn & Lotens (1992) who reported that a load equal to 21% of body weight reduced all-out running velocities by 13 and 18% for all-out 80- and 400-meter runs. More recently, Alcaraz et al. (2008) reported only 3% reductions in brief, all-out running speeds with loads equal to 9% of the body's mass, while Cronin et al. reported fractional reductions in all-out loaded sprinting speeds that were approximately half as large as the fractional increases in load/body weight ratios. The disparity in the different results reported to date could result from a large number of factors, and is therefore difficult to interpret. These empirical results project a C_1 value in our model somewhere between 0.4 and 1.0.

Fractional reductions in brief, all-out running speeds that are, in some cases only half as large as the fractional loading of the body's weight reported are surprising. The relatively shallow slope of the force-speed relationship portends a much greater sensitivity. The mechanistic factors that explain a much more limited effect than would be theoretically expected from unloaded force-speed data only are almost certainly rooted in the mechanics of the stance phase ground force application that occurs under loaded conditions. These likely involve mechanical adaptations to loading that improve the leverage of the limb (Biewener et al., 2004) and thereby reduce the muscle forces required in relation to the load being carried.

However, in the complete absence of ground reaction force data or the accompanying video data to determine limb leverage, speculating about the adjustments that may constrain load-induced decrements in speed is difficult. The limited existing data available point to a critical need to acquire ground reaction force and video data under a variety of load and duration conditions to develop a robust predictive model. These data should provide the key to understanding how musculoskeletal mechanics, loading strategies, training and conditioning strategies, and conceivably external aids like exoskeletons, may be utilized to minimize detrimental losses in the short-term mobility of soldiers that result from carrying heavy loads.

BODY

The majority of the calendar year has been devoted to analysis, synthesis and report and manuscript writing. Individuals receiving support from the award during the last calendar year were: Jennifer Nollkamper, Lindsay Ludlow and Peter Weyand.

The load carriage experiments have two specific objectives: 1) to develop and validate algorithms that predict walking metabolic rates from height, weight (including load), speed and grade, and 2) to develop and validate algorithms that predict brief, all-out running speeds from the body and pack weights of the individual. These objectives will be pursued in parallel per the following experimental timeline.

Objective 1 – Walking Energy Expenditure:

We intend to acquire energy expenditure data in the laboratory on those subjects on whom our predictive metabolic equations will be developed using our stature-based model. Subjects will

complete walking trials at a number of different walking speeds treadmill grades while their rates of oxygen uptake and energy expenditure are measured.

We will also complete the aforementioned laboratory walking trials across speed and grade needed for our original subjects as needed for algorithm development. In addition, we will undertake field data acquisition by having subjects will undergo a field march on a surveyed field course of known elevations and grades while instrumented to acquire the metabolic and position data.

Objective 2 – Sprint Running Speed:

We will first conduct high-speed running tests in the laboratory on subjects under three different loading conditions: unloaded, +15% body weight, and +30% body weight. Subjects will complete protocols to determine their maximum speeds for efforts ranging from 2 to 90 s while force and video data are acquired.

Next, we will acquire all-out overground running data in both indoor and outdoor settings on subjects. These subjects will complete 25 meter runs indoors and 60 meter runs outdoors under four different loading conditions: unloaded, +15% body weight, +30% body weight, and +45% body weight. Simultaneous force and video data will be acquired during the indoor 25-meter running trials.

KEY RESEARCH ACCOMPLISHMENTS

Key accomplishments over the 12 month reporting-period of the grant year were as follows:

April 2017 - July 2017

- 1) Laboratory testing for extreme declines on an expanded subset of subjects has been identified as a need. Recruiting has commenced.
- 2) Analysis of field testing of loaded and unloaded walking metabolism has continued.
- 3) Modeling of the laboratory data base for walking metabolism for objective 1 continued.
- 4) Modeling efforts on our loaded running mechanics data for objective 2 continued.
- 5) Preparation of a manuscript that presents our expanded, generalized model of walking metabolism has continued and continued.
- 6) An analysis of standing metabolism is underway for a more in-depth understanding of the metabolic requirements for postural support continues.

July 2017 – October 2017

- 1) Analysis of field testing of loaded and unloaded walking metabolism has continued.
- 2) Modeling efforts on our loaded running mechanics data for objective 2 continued.
- 3) Preparation of a manuscript that presents our expanded, generalized model of walking metabolism has continued and continued.

- 4) Revision of our manuscript on predicting walking metabolism commenced after receiving reviews of the first submission.
- 5) Preparation of a provisional patent on our method of predicting walking energy expenditure is also in progress.

Oct 2017 – Jan 2018

- 1) Analysis of field testing of loaded and unloaded walking metabolism has continued.
- 2) Modeling efforts on our loaded running mechanics data for objective 2 continued.
- 3) A manuscript reporting our field testing of our walking metabolic model is in progress.
- 4) Analysis of stride mechanics data to assess the mechanical basis of our walking model has been engaged as a first part of a comprehensive evaluation.
- 5) A footwear test of our running mechanics model is being analyzed.
- 6) A video abstract of our November J Applied Physiology manuscript was completed and published online.

January 2018 - April 2018

- 1) Analysis of field testing of loaded and unloaded walking metabolism has continued.
- 2) Modeling efforts on our loaded running mechanics data for objective 2 continued.
- 3) A short manuscript using our running mechanics model to predict impact forces has been prepared, submitted and accepted at *Current Issues in Sport Sciences*.
- 4) A manuscript reporting our field testing of our walking metabolic model is in progress.
- 5) Reduction of stride mechanics data to assess the mechanical basis of our walking model has been completed. This required time-extensive quantification of foot-ground contact and stride times from 21 subjects on six grades under three load conditions. This will allow the mechanical basis of our model predicting walking metabolic rates to be assessed via ongoing analysis.
- 6) A footwear test of our running mechanics model is being analyzed.
- 7) A manuscript modeling the mechanics of maximal acceleration during running is now in progress.

REPORTABLE OUTCOMES

Reportable outcomes follow directly from the key accomplishments listed for each quarter above. These were:

April 2017 - July 2017

1. A manuscript introducing our multi-conditional model of walking metabolism was revised and re-submitted to the Journal of Applied Physiology.
2. Objective 2 testing on loaded running continues in the analysis phase.
3. Two invention disclosures were submitted to SMU's Office of Research Administration.
4. A provisional patent for a method for predicting walking metabolism continues to be prepared.

5. An invited keynote lecture on locomotor performance was delivered at the meeting of the International Society for Biomechanics in Sports.
6. Our walking metabolism manuscript was accepted and is in press at the *Journal of Applied Physiology*. A copy of the manuscript has been submitted with this report.

July 2017 - October 2017

1. A manuscript introducing our multi-conditional model of walking metabolism was accepted and has been published at the *Journal of Applied Physiology*.
2. Objective 2 testing on loaded running continues in the analysis phase.
3. Two invention disclosures were submitted to SMU's Office of Research Administration.
4. A provisional patent for a method for predicting walking metabolism has been submitted.
5. Work on our running mechanics model has continued.
6. Data acquisition for downhill walking metabolism has continued to support our field validation effort.

October 2017 – January 2018

1. Objective 2 testing on loaded running continues in the analysis phase.
2. Kinematic data analysis of our loaded walking data set has been completed.
3. Work on our running mechanics model has continued.
4. Model comparisons for our field walking trials are being implemented and analyzed as part of our manuscript preparation process.
5. Some acquisition of downhill walking data continues to finalize recommendations for field uses of our walking model.

January 2018 – April 2018

1. Objective 2 testing on loaded running continues in the analysis phase.
2. Kinematic data analysis of our loaded walking data set has been completed allowing integration of the stride mechanics data with our walking metabolic rate model (see Figure 1 below for data from one subject).
3. Work on our running mechanics model has continued.
4. Model comparisons for our field walking trials are being implemented and analyzed as part of our manuscript preparation process.
5. Some acquisition of downhill walking data continues to finalize recommendations for field uses of our walking model.

PUBLICATIONS, ABSTRACTS, PRESENTATIONS

- Ludlow LW, Weyand PG. Walking economy is predictably determined by speed, grade and gravitational load, *Journal of Applied Physiology*, 123(5): 1288-1302.
- Clark K, Udofa A, Ryan L, Weyand P. Running impact forces: from half a leg to holistic understanding. *Current Issues in Sport Sciences*, in press.

- Weyand P. Force, motion, speed: a grounded perspective on human running performance. Proceedings of the International Conference on Biomechanics in Sports, July, 2017.
- Udofa A, Ryan L, Clark K, Weyand P. Ground reaction forces during competitive track events: a motion-based assessment method. *Proceedings of the International Conference on Biomechanics in Sports*. July, 2017.
- From Muybridge to Motion: The Physics of running ground force application. Invited lecture, Dickinson College, October, 2017.
- Weyand P. New insights into Sprint Running Performance, invited lecture, American College of Sports Medicine, National Meeting, Denver, may, 2017.
- Weyand, P. The mechanical basis of sprint running performance, Keynote address, International Conference of Biomechanics in Sports, Cologne, Germany, June, 2017.

CONCLUSIONS

In the past year of the award, we have largely finished testing and have continued to analyze data, develop models and algorithms. Our primary efforts have been focused upon analysis and manuscript writing, particularly on our field test for predicting walking metabolism across a broad range of speed, grade and loading conditions using our minimum mechanics model. We are also moving forward with analysis and writing on sprint acceleration with and without loads.

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APPENDICES

Please see submitted manuscripts.

RESEARCH ARTICLE

Walking economy is predictably determined by speed, grade, and gravitational load

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Submitted 7 June 2017; accepted in final form 18 July 2017

Ludlow LW, Weyand PG. Walking economy is predictably determined by speed, grade, and gravitational load. *J Appl Physiol* 123: 1288–1302, 2017. First published July 20, 2017; doi:10.1152/jappphysiol.00504.2017.—The metabolic energy that human walking requires can vary by more than 10-fold, depending on the speed, surface gradient, and load carried. Although the mechanical factors determining economy are generally considered to be numerous and complex, we tested a minimum mechanics hypothesis that only three variables are needed for broad, accurate prediction: speed, surface grade, and total gravitational load. We first measured steady-state rates of oxygen uptake in 20 healthy adult subjects during unloaded treadmill trials from 0.4 to 1.6 m/s on six gradients: -6° , -3° , 0° , 3° , 6° , and 9° . Next, we tested a second set of 20 subjects under three torso-loading conditions (no-load, +18, and +31% body weight) at speeds from 0.6 to 1.4 m/s on the same six gradients. Metabolic rates spanned a 14-fold range from supine rest to the greatest single-trial walking mean (3.1 ± 0.1 to 43.3 ± 0.5 ml $\text{O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$, respectively). As theorized, the walking portion ($\dot{V}\text{O}_{2\text{-walk}} = \dot{V}\text{O}_{2\text{-gross}} - \dot{V}\text{O}_{2\text{-supine-rest}}$) of the body's gross metabolic rate increased in direct proportion to load and largely in accordance with support force requirements across both speed and grade. Consequently, a single minimum-mechanics equation was derived from the data of 10 unloaded-condition subjects to predict the pooled mass-specific economy ($\dot{V}\text{O}_{2\text{-gross}}$, ml $\text{O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$) of all the remaining loaded and unloaded trials combined ($n = 1,412$ trials from 90 speed/grade/load conditions). The accuracy of prediction achieved ($r^2 = 0.99$, SEE = 1.06 ml $\text{O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$) leads us to conclude that human walking economy is predictably determined by the minimum mechanical requirements present across a broad range of conditions.

NEW & NOTEWORTHY Introduced is a “minimum mechanics” model that predicts human walking economy across a broad range of conditions from only three variables: speed, surface grade, and body-plus-load mass. The derivation/validation data set includes steady-state loaded and unloaded walking trials ($n = 3,414$) that span a fourfold range of walking speeds on each of six different surface gradients (-6° to $+9^\circ$). The accuracy of our minimum mechanics model ($r^2 = 0.99$; SEE = 1.06 ml $\text{O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$) appreciably exceeds that of currently used standards.

metabolism; locomotion; generalized equation; load carriage; algorithm; wearable sensors

THE METABOLIC ENERGY that human walking requires can vary considerably, depending on mechanical and muscular de-

mands. Slow walking on level and declined surfaces elevates metabolism only marginally above the body's basal or resting rates. Fast walking on inclines can elevate the body's resting metabolic rate by an order of magnitude or more. Inclined walking with loads can require metabolic rates that exceed the aerobic maximums of even the fittest human endurance athletes. Because metabolism is a fundamental determinant of the body's physiological state and walking is the most common form of human physical activity, hundreds of studies have examined the metabolic requirements of walking since formal investigation began more than a century ago (78).

Despite extensive and ongoing scientific attention, a generalized understanding of walking metabolism across the full range of conditions humans typically walk remains unavailable. Scores of predictive equations have been developed, but the vast majority have been limited to level surface conditions (10, 46, 59, 71, 73, 77). The two predictive equations with greatest conditional breadth, those of Pandolf et al. (56) and the American College of Sports Medicine (ACSM) (3), are the most widely used. However, both were formulated using very small sample sizes, have somewhat unclear scientific foundations, do not include declined conditions, and generally underpredict walking metabolic rates under the predominantly level conditions under which they have been thus far evaluated (46).

A primary difficulty in identifying the determinants of the metabolic cost, or economy of human walking is isolating the limited metabolic signal present under typical experimental conditions. The large majority of investigations have understandably been limited to level surface conditions. However, long periods of ground force application to support the body's weight (12, 36) and conservative, pendulum-like gait mechanics that minimize muscular work (11, 12) constrain gait-induced elevations in whole body metabolism two to four times the body's supine resting rate across the level walking speeds typically used. Additionally, quantitative approaches to isolating and predicting the walking, or nonresting, portion of the body's total metabolic rate have been inconsistent and are potentially confounding (1, 75). Some studies analyze the body's gross metabolic rates without implementing a baseline subtraction (15, 33, 38, 44), some subtract supine resting metabolic rate (46, 47, 76), and some subtract a measured rate of sitting metabolism (32), whereas many subtract a preexercise standing metabolic rate (13, 14, 16, 19, 20, 27–29, 65, 72). The rationale for standing metabolic rate subtractions is unclear because standing, like walking, includes a nonresting metabolic cost of supporting the body's weight against gravity (75).

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Signal size and isolation issues have undoubtedly contributed to the lack of consensus regarding the determinants of human walking economy. At present, a substantial portion of the metabolic cost has been attributed to each of the following mechanical factors: gravitational support force requirements (29, 45, 46, 74), the mechanical work of lifting and accelerating the body's mass (29), the pushing and braking that the trailing and leading limbs perform, respectively, against one another during double contact (19, 43), swinging of the limbs (18, 27, 51), lateral stabilization of the body's center of mass (20), and others. Similarly unresolved is whether the per kilogram metabolic costs of body mass vs. external mass affixed to the torso are equal (6, 26, 30, 37, 45, 51, 58, 67). Finally, the validity of existing explanations for the substantial differences in walking economy observed across different surface gradients (3, 8, 49, 54, 56) is largely unknown.

Here, we used speed, grade, and torso loading as experimental tools to vary mechanical demands and maximize the range of gait-induced metabolic signals obtained. We reasoned that conservative gait mechanics should effectively reduce metabolic demands to those required to satisfy the gross mechanical requirements across these broad test conditions. This approach has previously been applied successfully to gaits such as running and bipedal hopping that provide large, easily isolated metabolic signals (41, 62). Analytically, we approached this question by building upon our prior work that successfully predicted both speed and body size-related variability under level conditions by using a two-component description of walking metabolism (46, 76): a first component that is constant across speed and a second that increases as a function of the velocity of walking squared (2, 76).

We hypothesize that the walking economy of adult humans can be predicted across a broad range of conditions from three basic mechanical variables: speed, surface grade, and the total weight (i.e., body plus load) supported against gravity. Successful test outcomes would provide a predictive and analytical tool with broad application. Potential uses include exercise prescription, physiological monitoring, performance prediction, and modeling of rates of heat production and fatigue. The rapid advancement of wearable sensing technologies capable of incorporating the three basic inputs in our model could avail broad, nearly immediate use to the general public during daily living.

METHODS

Experimental Design and Overview

We adopted a two-step approach to testing the hypothesis that the economy of human walking across a broad range of conditions can be predicted from three basic mechanical requirements: speed, grade, and total gravitational load. The two-step sequence was implemented to facilitate the acquisition of the large volume of data needed to develop a robust, multiconditional model. The data set ultimately compiled includes 3,414 steady-state walking trials acquired from 32 subjects over a period spanning 2 yr.

In *part I*, we measured walking economy across a broad range of walking speeds on six different grades in 20 subjects. In *part II*, we measured walking economy across a slightly narrower range of speeds on the same six grades under three different load conditions: unloaded (1.0 W_b), +18% added torso weight (1.18 W_b), and +31% added torso weight (1.31 W_b).

In contrast to our prior investigations of walking on level surfaces only (46, 76), height was not included in the present model for both scientific and pragmatic reasons. Scientifically, our objective of developing a generalized equation for predicting human walking metabolism in an adult population across a broad range of conditions did not require an age- or height-stratified sample. Pragmatically, the volume and intensity of the testing protocol was too rigorous to reasonably include children.

Minimum Mechanics Model of Walking Metabolism

For predictive purposes, our minimum mechanics model partitions the body's total metabolic rate into one resting and two walking components. In the original, level-only formulations (45, 76), the model was expressed as

$$\dot{V}O_{2\text{-gross}} = \dot{V}O_{2\text{-rest}} + \underbrace{C_1 \times \dot{V}O_{2\text{-rest}}}_{\text{MWMR}} + \underbrace{C_2 \times V^2/Ht}_{\text{SDWMR}} \quad (1)$$

where $\dot{V}O_{2\text{-gross}}$ is the body's gross, or total, metabolic rate; $\dot{V}O_{2\text{-rest}}$ is supine, resting metabolic rate; C_1 is the coefficient describing the model's first walking metabolic component, the minimum walking metabolic rate (MWMR) as a multiple of the resting metabolic rate; C_2 is the coefficient describing the model's second metabolic component, speed-dependent walking metabolic rate (SDWMR), V is the velocity of walking in meters/seconds, and Ht is height in meters. Above and throughout this article, all the metabolic terms are expressed in mass-specific units of oxygen uptake ($\text{ml } O_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$), in keeping with physiological convention for weight-bearing exercise and the scientific rationale for the model.

Multiconditional Formulation of the Minimum Mechanics Model

We expanded the prior level-only version of the model to the multiconditional purposes examined here by incorporating grade as follows:

$$\begin{aligned} \dot{V}O_{2\text{-gross}} = & \underbrace{\dot{V}O_{2\text{-rest}}}_{\text{Rest}} \\ & + \underbrace{(C_1 \times G) + \dot{V}O_{2\text{-walk min}}}_{\text{Minimum Walking}} + \underbrace{(1 + (C_2 \times G)) \times (C_3 \times V^2)}_{\text{Speed-dependent}} \\ & \text{Walking Metabolism} \end{aligned} \quad (2)$$

where $\dot{V}O_{2\text{-gross}}$, $\dot{V}O_{2\text{-rest}}$, and V are as defined above, $\dot{V}O_{2\text{-walk min}}$ is a constant, G is the positive surface inclination expressed in percent grade, C_1 is a coefficient describing the minimum walking metabolic rate in conjunction with grade, C_2 is a coefficient describing the influence of grade on speed-dependent walking metabolism, and C_3 is a coefficient that describes the influence of velocity on speed-dependent walking metabolism regardless of grade. The number 1 is included in the speed-dependent walking metabolism term to prevent this portion of walking metabolic rate from equaling zero at 0% grade. A C_{decline} coefficient was also derived to quantify walking, or non-resting, metabolic rates on negative grades as a fraction of the level values provided by the final equation.

The specific values of four coefficients, C_1 , C_2 , C_3 , and C_{decline} , and one constant, $\dot{V}O_{2\text{walk-min}}$, were determined empirically. All $\dot{V}O_2$ terms are expressed in $\text{ml } O_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$, whereas V has the units of meters per second. The physiological basis of the model is provided below.

Model Formulaic and Scientific Rationale

The model assumes that elevations in the body's metabolic rate above supine resting rates due to walking 1) result entirely from the activity of skeletal muscle, 2) are attributable primarily to the activity of the limb muscles to support the weight of the body, or body plus load, against gravity (69, 70), and 3) vary across grade in accordance with muscular contractions that elevate, maintain, or lower the body's center of mass during each step (34, 35, 49, 50).

Our third assumption deviates from the long-standing practice of modeling walking and running metabolic rates on positive grades as a separate, supplemental metabolic component to level metabolic rates. Although a distinguished tradition for this practice exists from the pioneering work of Zuntz (78) and Dill (17) forward (3, 8, 25, 56), a physiological justification for doing so is lacking. Contemporary observations document progressive alterations in the contractile activity (24, 61) and neuromuscular activation (65) across different grades in accordance with our assumption.

Added Load: Modeling Validation and Signal Isolation Analysis

The walking portion of the body's metabolic rate was isolated by subtracting each subject's measured supine resting metabolic rate from the total or gross metabolic rate measured during exercise ($\dot{V}O_{2\text{-walk}} = \dot{V}O_{2\text{-gross}} - \dot{V}O_{2\text{-rest}}$). In the event that each kilogram of added torso weight incurred an equal metabolic cost to each kilogram of body weight as postulated, load-induced increases in the walking portion of the body's total metabolic rate should be directly proportional to the additional load carried; thus

$$\dot{V}O_{2\text{walk-L}}/\dot{V}O_{2\text{walk-UL}} = W_{\text{body+load}}/W_{\text{body}} \quad (3)$$

where $\dot{V}O_{2\text{walk-L}}$ and $\dot{V}O_{2\text{walk-UL}}$ are walking metabolic rates under loaded and unloaded conditions, respectively, $W_{\text{body+load}}$ is the total weight of the body plus load and W_{body} is body weight only. Accordingly, our model predicts that the ratio of loaded to unloaded walking metabolic rate ($\dot{V}O_{2\text{walk-L}}/\dot{V}O_{2\text{walk-UL}}$) will equal the ratio of loaded to unloaded walking weight, which here equaled 1.18 and 1.31, respectively, across all of the speed and grade trials administered for the respective load conditions.

Signal Isolation Analysis

We also used the loaded walking data acquired to evaluate the effectiveness of signal isolation via resting metabolic rate subtractions. We did so by repeating the above analysis with two methods for quantifying walking metabolic rates that were expected to be inaccurate. The first was to examine load-induced increases in metabolic rates without implementing a baseline subtraction, thereby making the untenable assumption that the body's resting or basal metabolic requirement becomes zero during exercise (i.e., $\dot{V}O_{2\text{-walk}} = \dot{V}O_{2\text{-gross}}$). The second was to subtract a preexercise standing metabolic rate ($\dot{V}O_{2\text{-walk}} = \dot{V}O_{2\text{-total}} - \dot{V}O_{2\text{-stand}}$) that likely overestimates the body's baseline metabolic rate requirements that are present during walking. This second approach ignores the elevations above supine resting metabolic rates that result from standing (68, 75). The error introduced from these two alternative approaches is expected to skew the ratios of $\dot{V}O_{2\text{walk-L}}/\dot{V}O_{2\text{walk-UL}}$ on the left side of Eq. 3: negatively for the zero under-subtraction treatment and positively for the standing over-subtraction treatment. In both cases, ratio skewing is expected to be signal size dependent, affecting trials with the lowest gross metabolic rates most and trials with the greatest gross metabolic rates least.

Because of the considerable variability present in the literature for standing metabolic rate values, we compiled values reported from those laboratories and investigators who have frequently subtracted measured standing rates from gross exercise rates to isolate walking metabolism. A representative literature average was used to assess the error potentially introduced.

Experimental Protocol and Measurements

Subjects. Twenty subjects each participated in *parts I* (males, $n = 13$; females, $n = 7$) and *II* (males, $n = 12$; females, $n = 8$) of the study (Table 1). Because eight subjects participated in both *parts I* and *II*, the total number of participating subjects was 32. All subjects were physically active and without contraindications for exercise according to the cardiovascular guidelines set forth by the American College of Sports Medicine. Each provided written, informed consent before

Table 1. Subject characteristics by group

Group	<i>n</i> (Males)	Age, yr	Mass, kg	Height, cm
Experimental	10 (6)	28.1 ± 2.3	73.6 ± 4.7	170.9 ± 3.5
Validation	10 (7)	26.4 ± 1.6	75.2 ± 6.0	170.5 ± 2.7
Load	20 (12)	30.2 ± 1.1	73.9 ± 2.7	171.8 ± 1.8

Values are means ± SE.

testing in accordance with the protocol approved by the Institutional Review Board of Southern Methodist University.

Treadmill testing protocol: part I. The 20 subjects in *part I* completed 5-min walking trials at five treadmill speeds (0.4, 0.7, 1.0, 1.3, and 1.6 m/s) on each of six different grades (−6, −3, 0, 3, 6, and 9°). Subjects reported to the laboratory for one session for measurement of resting, sitting, and standing metabolic rates, one session for measuring maximal aerobic rates, and a minimum of five sessions for measurement of walking economy at different speeds and grades without added weight. For the resting, sitting, and standing test session, subjects were asked to arrive at the laboratory as close to waking as possible, to refrain from exercise on the morning of the test, and to avoid caffeine and food consumption for a minimum of 8 h before testing. For the five walking sessions, each combination of grade and speed was tested on separate days to acquire two steady-state metabolic rates for each trial condition. Each subject was equipped with Brooks (Cascade Trail model) shoes.

Treadmill testing protocol: part II. The 20 subjects in *part II* completed 5-min treadmill walking trials at three speeds (0.6, 1.0, and 1.4 m/s) at six different grades (−6, −3, 0, 3, 6, and 9°) under three load conditions: unloaded (1.0 W_b), +18% added body mass (1.18 W_b), and +31% of added body mass (1.31 W_b). Nine of the 20 subjects completed an additional speed of 1.8 m/s for the two declined conditions. Each of the 20 *part II* subjects reported to the laboratory on a minimum of 8 different days for test sessions. As for the *part I* subjects, one early morning session was devoted to measuring post-absorptive resting, sitting, and standing metabolic rates. Maximal aerobic rates were measured in a single separate test session. The other six sessions were devoted to steady-state walking at the speeds, grades, and loads required. For each of the walking sessions, data from two grades, and all three load and speed conditions were acquired. Six sessions were required to acquire duplicate, separate-day walking metabolic measurements at each combination of grade, speed, and load. Within sessions, breaks occurred when it was necessary to change the treadmill grade and load or upon subject request. A subset of the data from 10 subjects has been reported previously (45).

Loads were added based on each subject's body weight rounded to the nearest 10-lb. increment. The exact percentage of body mass carried by each subject varied, with the group average values being 18 and 31%, respectively, for the two loaded conditions. Loads were added using vacuum-sealed steel shot packaged in 0.5, 1.0, and 2.0-lb. pouches. The weight added was distributed symmetrically about the torso by placing the blocks with shot into a military style backpack (5.11 Rush72; 5.11, Irvine, CA) posteriorly and vest (5.11 TacTec plate carrier) anteriorly. Seven blocks were fit into a tightly fitting backpack configuration to minimize or eliminate bouncing and load shifting. Vest blocks of equal weight were inserted into 14 tightly attached MOLLE pouches (5.11 C5 case).

The duplicate-trial walking metabolic rates acquired in *part I* and *part II* ($n = 3,414$) were averaged to obtain single trial-specific means for the modeling analysis. Trials were not administered above 85% of the subject's measured maximum rate of aerobic metabolism to avoid fatigue and nonsteady-state conditions.

Metabolic Measurements. Metabolic rates were determined by indirect calorimetry using a computerized metabolic system (TrueOne 2400; Parvo Medics, Sandy, UT). Samples of expired gases were collected during walking, supine resting, sitting, and standing. Col-

lection occurred through a one-way breathing valve and tubing that directed flow first through a pneumotach for measurement of volume flow rates and then into a mixing chamber. Expired air was sampled from the mixing chamber with O₂ and CO₂ fractions analyzed using paramagnetic and infrared gas analyzers, respectively. Rates of oxygen uptake ($\dot{V}O_2$) were determined from the average value during the last 2 min of each 5-minute trial.

Resting, sitting, and standing rates of oxygen uptake were acquired in the early morning with the subjects in a postabsorptive state. In each of these nonwalking measurement conditions, subjects were instructed to remain awake and refrain from fidgeting or any unnecessary motion. Resting rates were determined from the lowest, consecutive-segment, 10-min average over a 30-min test period. Sitting and standing metabolic rates were determined from the lowest, consecutive-segment, 5-min average during the 15-min test period. Maximum aerobic rates were determined using a continuous, grade-incremented, treadmill-running protocol to failure. Resting metabolic rates were also estimated using the population equation of Schofield (64).

Throughout this article, metabolic rates are reported in units of oxygen uptake. In all cases, mass-specific units denoting either body mass only (kg_{body}), or body-plus-load mass (kg_{total}) are reported per the widespread conventions for expressing weight-bearing exercise rates and per the scientific foundation of our model.

Minimum Mechanics Model Formula Derivation and Validation

Hypothesis evaluation relied upon a cross-validation design that match-paired and split the 20 *part I* subjects into experimental and validation groups of 10 subjects each. Subjects were randomly assigned to experimental and validation groups after being match-paired by stature and body mass. Empirical values for our three-input, minimum mechanics model of walking metabolism were determined using the data from the 10 experimental group subjects only. In accordance with prior procedures (45, 76), the optimizer function in Excel was used for the empirical derivation of the values, providing the best overall fits to the experimental group data while holding all other values constant (23). Here, the values of four coefficients, C₁, C₂, C₃, and C_{decline}, and one constant, $\dot{V}O_{2\text{walk-min}}$, were optimized empirically using the data of the experimental group subjects. The predictive accuracy of the model across speed and grade without loads was then evaluated on 10 validation group subjects, whose data were not used in the model's empirical formulation.

Subsequently, the walking economy values of all 20 *part II* subjects were predicted using the model formulated from the data of the experimental group subjects in *part I*. Model predictions across load conditions assumed equal per kilogram metabolic requirements for body vs. added weight. This assumption allowed the model formulated in *part I* to be used without modification to predict walking economy across the load conditions examined in *part II*. The body weight term in the model equation was modified to include the total weight supported against gravity (i.e., body plus load) under loaded conditions. A one-way ANOVA ($\alpha = 0.05$) was used to test the effect of load condition on walking economy per total body-plus-load mass (ml O₂·kg_{total}⁻¹·min⁻¹).

Model Accuracy Comparisons

The predictive accuracy of our optimized minimum mechanics model of walking metabolism was directly compared with the two most commonly used predictive standards, those of the American College of Sports Medicine (ACSM) and Pandolf et al. (56), using the equations provided in Table 2. Because the ACSM equation was not formulated to include declined or added load conditions, negative grade predictions for this model were generated here by using the level condition equation, whereas load carriage predictions were generated by incorporating added load weight into body weight. The one quantitative addition needed to generate predic-

Table 2. ACSM and Pandolf et al. (56) prediction equations

Equation	Reference
$\dot{V}O_2$ (ml O ₂ ·kg ⁻¹ ·min ⁻¹) = (0.1·V) + (1.8·V × G) + 3.5 ml·kg ⁻¹ ·min ⁻¹	ACSM (3)
$\dot{V}O_2$ -equiv (watts) = 1.5·M + 2.0·(M + L) (L/M) ² + η (M + L) [1.5·V ² + 0.35·V × G]	Pandolf et al. (56)
Decline CF = η [G·(W + L)·V]/3.5 - {(W + L)·(G + 6) ² }/W + (25 - v ²)	Santee et al. (63)

ACSM, American College of Sports Medicine; V, velocity; M, body mass (kg); L, load (body weight units); G, grade (%); η , terrain factor, (arbitrary units). For V, units are reference specific: ACSM, m/min; Pandolf et al. (56) and decline CF [Santee et al. (63)], m/s.

tions using Pandolf et al. (56) for all conditions here was the utilization of the declined extension for Pandolf et al.'s (56) equation developed by Santee et al. (63). The predictions derived from the ACSM and Pandolf et al. (56) model equations were compared with those obtained from our minimum mechanics model for both the validation group subjects from *part I* and the load group subjects in *part II*. The agreement between measured and predicted values was evaluated primarily via the standard error of the estimate (SEE) and secondarily using the *r*² statistic. A first modified Bland-Altman (42) analysis of the performance of our two-component model, ACSM, and Pandolf et al. (56) across speed and grade was conducted on the data acquired from validation group subjects in *part I*. A second modified Bland-Altman analysis was conducted using the data acquired across all the speeds, grades, and load conditions completed by the 20 subjects who participated in *part II* of the study.

Data are reported as means ± SE throughout unless otherwise specified.

RESULTS

Metabolic Rates: Resting, Sitting, Standing, and Aerobic Maximums

The mean measured supine resting metabolic rate for all 32 subjects was 3.13 ± 0.07 ml O₂·kg⁻¹·min⁻¹ (range: 2.34–3.82 ml O₂·kg⁻¹·min⁻¹). The corresponding mean for sitting metabolic rates was 3.16 ± 0.08 ml O₂·kg⁻¹·min⁻¹ (range: 2.22–4.24 ml O₂·kg⁻¹·min⁻¹), whereas the mean measured standing rate was 3.51 ± 0.08 ml O₂·kg⁻¹·min⁻¹ (range: 2.62–4.55 ml O₂·kg⁻¹·min⁻¹).

The mean overall supine resting value measured for the 20 *part I* subjects of 3.05 ml O₂·kg⁻¹·min⁻¹ was used to generate our minimum mechanics model predictions for both *part I* and *part II*. The supine resting values predicted for all 32 subjects using the population equations of Schofield et al. (64) based on height, weight, and sex of 3.21 ± 0.05 ml O₂·kg⁻¹·min⁻¹ agreed to within <0.1 ml O₂·kg⁻¹·min⁻¹ of the mean measured value provided above.

The mean maximum rates of aerobic metabolism for the male and female participants were 53.2 ± 1.6 and 45.7 ± 3.0 ml O₂·kg⁻¹·min⁻¹, respectively.

Standing Metabolic Rates: Literature Values

The mean standing metabolic rate compiled from the subject test population means in 12 literature sources (Table 3) of 4.5 ± 0.19 ml O₂·kg⁻¹·min⁻¹ was 1.4 times greater than the mean supine resting metabolic rate measured of the 32 subjects tested here.

Table 3. Standing metabolic rates from the walking metabolism literature

Reported Stand Value, ml O ₂ ·kg ⁻¹ ·min ⁻¹	Author(s)	Year
5.6	Bastien et al. (6)	2005
3.9	Browning et al. (9)	2006
4.5	Collins and Kuo (13)	2010
4.4	Collins et al. (14)	2015
5.8	DeJaeger et al. (16)	2001
4.4	Farley and McMahon (21)	1992
4.9	Gottschall and Kram (27)	2005
4.6	Grabowski et al. (29)	2005
4.5	Martin et al. (48)	1992
3.9	Silder et al. (65)	2012
4.1	Silder et al. (66)	2013
3.4	Vanderpool et al. (72)	2008
Average	4.5	
Minimum	3.4	
Maximum	5.8	

Walking Economy: Individual Variability

Individual variability in walking economy was limited, with the mean standard deviation from each of the 90 different trial conditions averaging <0.8 ml O₂·kg⁻¹·min⁻¹. When individual variability was quantified in relation to each trial mean as a coefficient of variation (= standard deviation/trial mean), values ranged from a minimum of 0.034 to a maximum of 0.122. In general, coefficient of variation values tended to be greater for trials eliciting lower metabolic rates.

Walking Economy Across Speed, Grade, and Load

The grand mean for all walking metabolic rates measured across the 90 different speed, grade, and load trial conditions administered was 14.4 ± 0.21 ml O₂·kg⁻¹·min⁻¹, representing a 4.7-fold elevation on average of the body's supine, resting metabolic rate. Across these 90 different trial conditions, individual walking metabolic rates spanned a nearly 10-fold range from a minimum of 4.8 ml O₂·kg⁻¹·min⁻¹ to a maximum of 45.4 ml O₂·kg⁻¹·min⁻¹.

The gross metabolic rates measured, expressed in relation to body mass (i.e., per kg_{body}) across all the speed, grade, and load conditions administered appear in Fig. 1. The same gross, or total, metabolic rates measured, expressed per kilogram

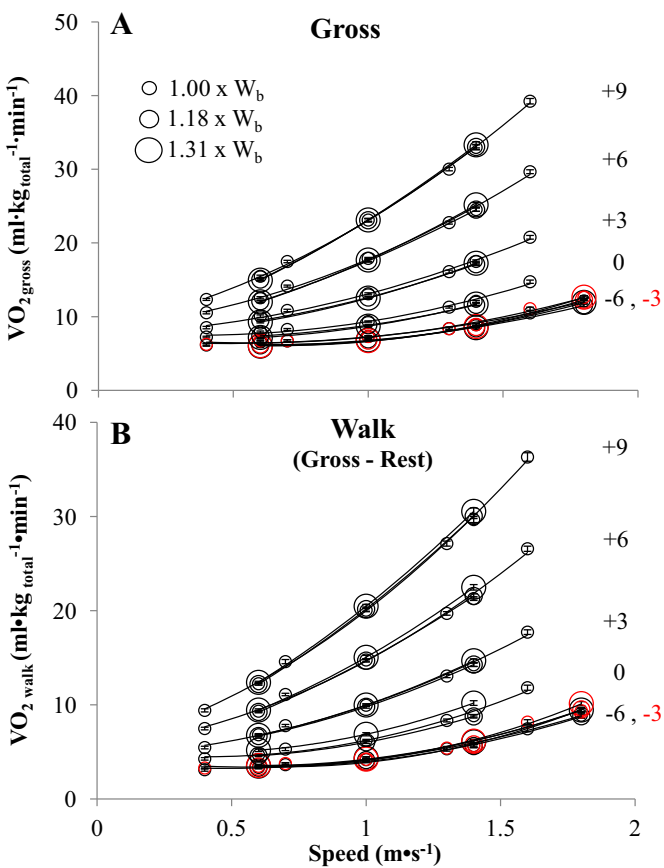


Fig. 2. Gross metabolic rates per total mass (body + load) vs. walking speed for all 3 load and 6 grade conditions tested. Data are presented as gross metabolic rates (A) and walking metabolic rates determined from gross – supine resting metabolic rate (B). Means for the –3° condition are illustrated in red.

total, or load plus body mass (i.e., per kg_{total}), appear in Fig. 2A. The corresponding rates due to walking (i.e., net rates = $\dot{V}O_{2\text{-gross}} - \dot{V}O_{2\text{-rest}}$), expressed per kg_{total} appear in Fig. 2B. Across each of the six different grades examined, walking metabolic rates increased from roughly two to four times across the fourfold range of test speeds administered from 0.4 to 1.6 m/s, with greater increases being observed on

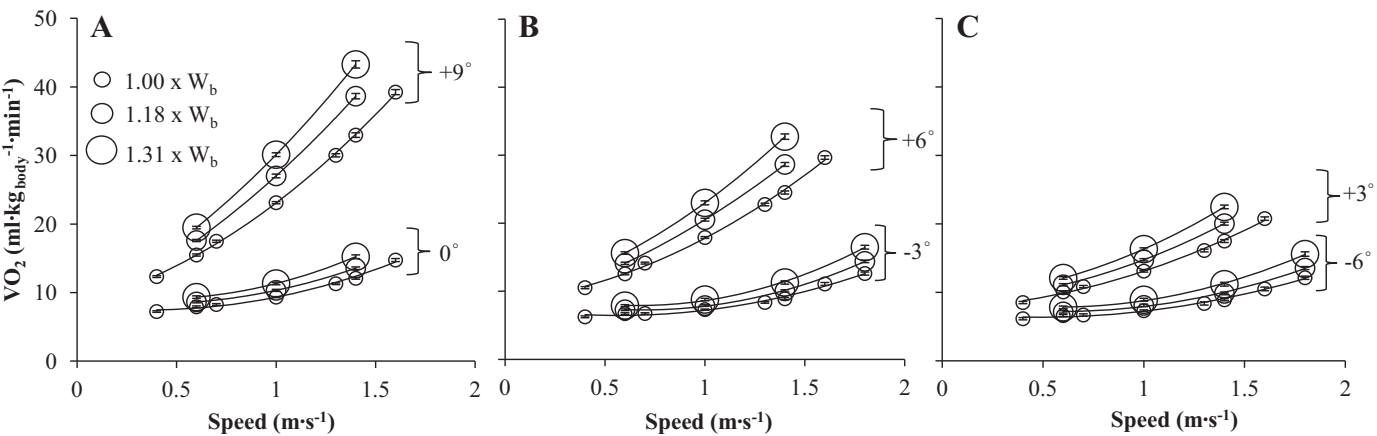


Fig. 1. Mass specific gross metabolic rates calculated/kg body mass and expressed as a function of walking speed for all 3 load and 6 grade conditions tested [0 and 9 (A), –3 and 6 (B), and –6 and 3° (C), separated for clarity]. Error bars represent the standard error of the mean in all figures. W_b, body weight.

the steeper positive grades. At all grades, speed-induced increases in walking metabolic rates were slightly curvilinear.

The influence of grade on walking economy was larger than that of speed (Figs. 1 and 2). At any given speed in the protocol, walking metabolic rates spanned a minimum range of fourfold and as much as sevenfold range from the -6 to $+9^\circ$ grade conditions examined. The grade-induced differences present at any speed were an approximately linear function of grade across positive grades from 0 to 9° . In contrast, grade-induced differences in walking metabolic rates from 0 to -6° were not linear. The differences observed between the 0 and -3° conditions were relatively small, and there were essentially no differences between the -3 and -6° conditions.

The addition of either 18 or 31% of the body's weight resulted in proportional increases in walking metabolic rates regardless of the speed or grade of the walking trial (Fig. 1). Consequently, when the load-induced increases in the body's mass-specific (i.e., per kg_{body}) walking metabolic rates were expressed in relation to the total load carried, or per kg_{total} , there were no discernable differences across any of the 20 speed and grade conditions for which each of the three load conditions were administered (Fig. 2). There was no effect

Table 4. Empirically derived minimum mechanics model equation values

Experimental group	<i>n</i>	<i>C</i> ₁	<i>V</i> O _{2-walk-min}	<i>C</i> ₂	<i>C</i> ₃	<i>C</i> _{decline}	<i>r</i> ²	SEE
Value	10	0.32	3.28	0.19	2.66	0.73	0.98	1.12

SEE, standard error of estimate.

of load condition on walking economy per kilogram total load ($\text{ml O}_2 \cdot \text{kg}_{\text{total}}^{-1} \cdot \text{min}^{-1}$; ANOVA, $\alpha = 0.05$).

Added Load: Modeling Validation and Signal Isolation Analysis

The ratios of loaded to unloaded walking economy ($\dot{V}\text{O}_{2-L}/\dot{V}\text{O}_{2-UL}$) observed across all speeds and grades for the two respective load conditions appear in Fig. 3, A and B, (+18 and +31%, respectively), where they are plotted in relation to the gross metabolic rates ($\dot{V}\text{O}_{2\text{-gross}}$) measured. When walking metabolic rates were determined by subtracting supine resting rates from the gross rates measured (i.e., $\dot{V}\text{O}_{2\text{-walk}} = \dot{V}\text{O}_{2\text{-gross}} - \dot{V}\text{O}_{2\text{-rest}}$), load-induced increases in walking metabolism were a close function of the load added regardless of the speed, grade, and gross metabolic rate elicited by the trial (Fig. 3, blue open circles and curve fits, and Table 3). The mean value for the ratio of $\dot{V}\text{O}_{2-L}$ to $\dot{V}\text{O}_{2-UL}$ across the 20 common speeds and grades administered with the lighter load was 1.17 ± 0.004 . The mean overall ratio for the heavier load from these 20 speeds and grades was 1.35 ± 0.006 . There was no discernable trend across the gross metabolic rates measured under either load condition.

Both alternative data treatments of the gross metabolic rates measured during walking were signal size dependent. When no baseline quantity was subtracted (Fig. 3, red open squares and curve fits), the ratio of loaded to unloaded walking metabolic rates ($\dot{V}\text{O}_{2-L}/\dot{V}\text{O}_{2-UL}$) was appreciably less than the relative increase in load. For both the +18 and +31% added load conditions, ratios were lowest at low metabolic rates and greatest at the highest ones. For both load conditions, the ratios progressively approached a value directly proportional to the relative load added as the measured gross metabolic rates increased.

The opposite pattern was observed when the literature standing value of $4.5 \text{ ml O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$ was subtracted from the $\dot{V}\text{O}_{2\text{-gross}}$ values measured (where $\dot{V}\text{O}_{2\text{-walk}} = \dot{V}\text{O}_{2\text{-gross}} - \dot{V}\text{O}_{2\text{-stand}}$; Fig. 3, green open triangles and curve fits). Subtraction of the literature standing values from measured rates resulted in ratios of loaded to unloaded walking metabolic rates ($\dot{V}\text{O}_{2-L}/\dot{V}\text{O}_{2-UL}$) that were appreciably greater than the respective relative increase in load for both conditions. For both the +18 and +31% added load conditions, the ratios observed were greatest at low metabolic rates and least at the highest ones. In both cases, the ratios progressively decreased toward a value proportional to the relative load added as the measured gross metabolic rates increased.

Predictive Accuracy of the Minimum Mechanics Model

Part I. The optimized coefficients for our minimum mechanics model of walking metabolism derived from the experimental group subjects appear in Table 4. The accuracy of the model equation predictions on the validation group subject's data is provided in Fig. 4, A and B. Equation-predicted curves and the

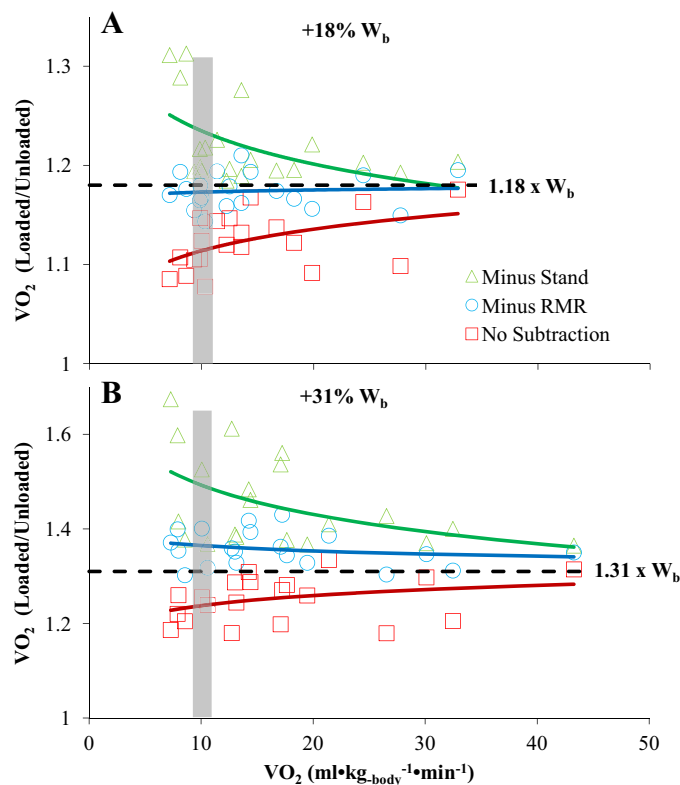


Fig. 3. The ratio of loaded to unloaded metabolic rates for the +18 (A) and +31% load conditions (B) vs. the body's gross metabolic rate during loaded walking. Ratios were determined using 3 different baseline subtraction methods: no subtraction (red squares and curve fits), gross metabolic rate — supine resting metabolic rate (blue circles and curve fits), and gross metabolic rate — average standing metabolic rate reported in the literature (green triangles and curve fits). Dashed horizontal lines represent the relative $\dot{V}\text{O}_2$ increases predicted for respective conditions: 1.18 (A) and 1.31 (B). Logarithmic trend lines are included for each baseline subtraction method. Shaded gray vertical bars highlight the metabolic rates for level walking at the speeds typically self-selected (1.0–1.3 m/s).

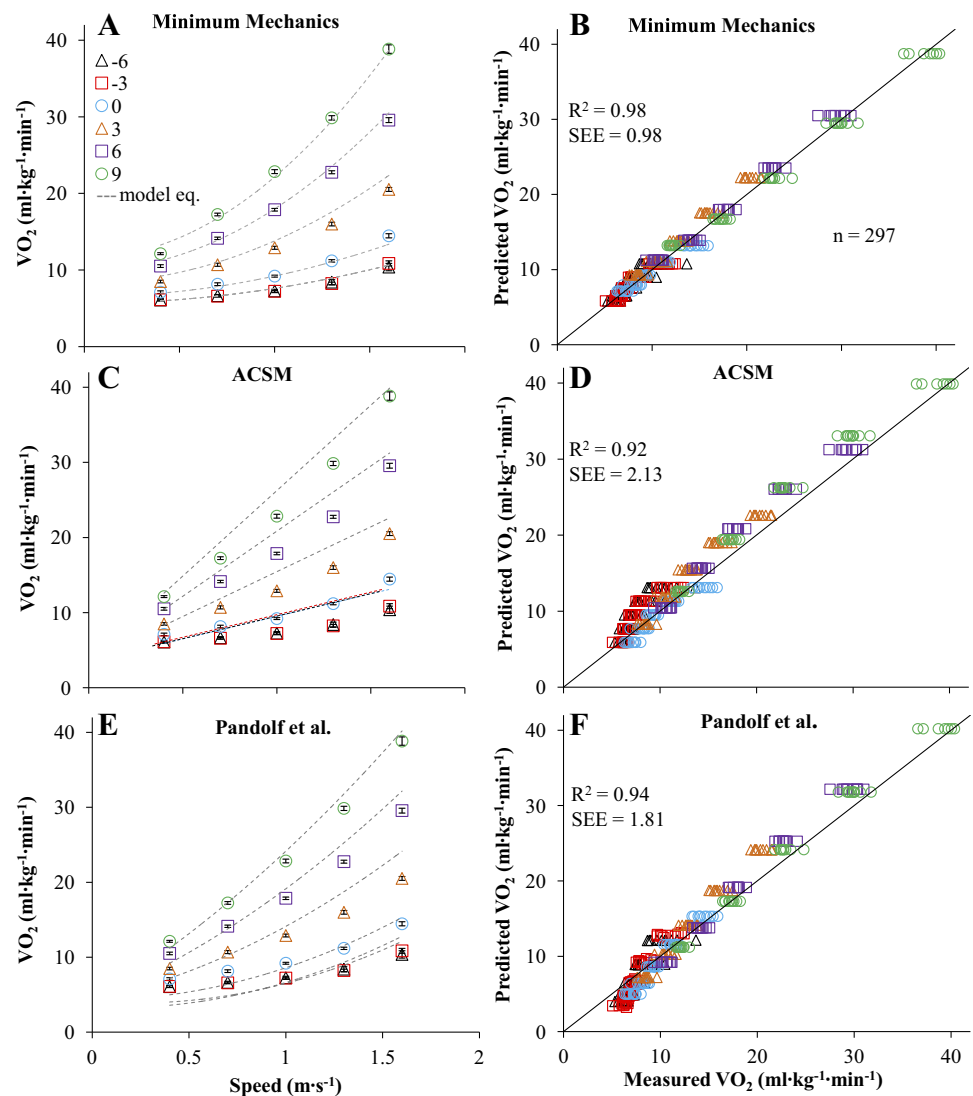


Fig. 4. Measured metabolic rate means during unloaded walking for the experimental group subjects vs. walking speed (all symbols in A, C, and E) in relation to the metabolic rates predicted (dashed lines) by our minimum-mechanics model (A), the American College of Sports Medicine (ACSM) equation (C), and the Pandolf et al. (56) equation (E) on each of the 6 surface grades investigated. Measured metabolic rates for each of the walking trials completed by validation group subjects vs. those predicted by our minimum mechanics model (B), the ACSM equation (D), and the Pandolf et al. (56) equation (F). Diagonal lines in B, D, and F represent the lines of identity. Declined gradient predictions were calculated using the level equation for ACSM and the declined extension of the Pandolf et al. (56) equation by Santee et al. (63).

experimental group mean values measured for each unloaded speed and grade appear in Fig. 4A, whereas the measured vs. equation-predicted values for each of the individual subjects in the validation group are plotted in Fig. 4B. The overall error of individual prediction, or SEE value, for the individual measured metabolic rates for the validation group subjects of <1.0 ml $\text{O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ corresponded to 7.4% of overall mean measured. The proportion of the total variance in the 297 measured metabolic rates for the validation group subjects accounted for by the minimum-mechanics model was $>98\%$.

The overall error of individual prediction of our minimum mechanics model was roughly one-half that of the ACSM and Pandolf et al. equations on average when evaluated with the SEE statistic. The equivalent evaluations of the ACSM and Pandolf et al. equations are presented in relation to speed and grade means for the validation group subjects (Fig. 4, C and E) and measured vs. equation-predicted values (Fig. 4, D and F). The ACSM equation generally overpredicted declined and inclined values while slightly underpredicting level values. The Pandolf et al. (56) equations tended to underpredict level and declined values while also overpredicting the values obtained on positive grades. Consequently, the respective SEE values for the ACSM

and Pandolf et al. (56) equations corresponded to 15.8 and 13.4%, respectively, of the overall mean measured for the validation group subjects across all of the trials completed ($2.13/13.5 = 15.8$ and $1.81/13.5 = 13.4\%$).

Part II. Both economy vs. speed and actual vs. predicted model accuracies for the minimum mechanics model, ACSM and Pandolf et al. (56) across the three load conditions administered for *part II* appear in Fig. 5. Because of the close relationship between increases in mass-specific metabolic rates and added gravitational loads relative to body weight, the accuracy of the minimum mechanics model under loaded conditions was almost the same as under unloaded conditions (Fig. 5, A and B). The absolute accuracy of the ACSM equation also declined marginally vs. the prediction of the unloaded values in *part I*, whereas that of the Pandolf et al. (56) equation improved marginally by 0.1 ml $\text{O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$.

Modified Bland-Altman Analysis

The difference between measured and model-predicted values in ml $\text{O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ for the three predictive models evaluated, minimum mechanics, ACSM, and Pandolf et al.

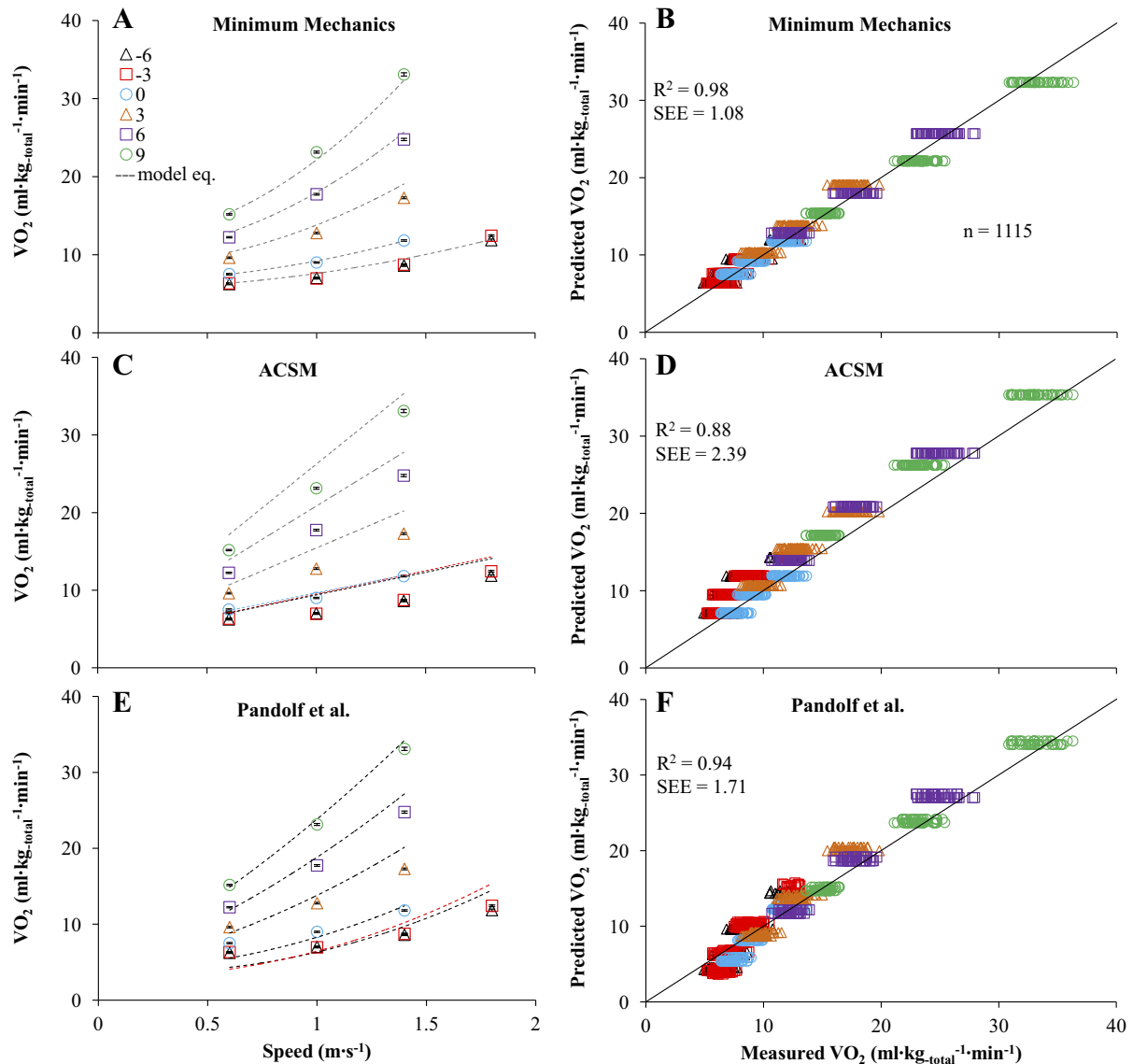


Fig. 5. Measured metabolic rate means during loaded walking for load group subjects vs. walking speed (all symbols in A, C, and E) in relation to the metabolic rates predicted (dashed lines) by our minimum-mechanics model (A), the ACSM equation (C), and the Pandolf et al. (56) equation (E) on each of the 6 surface grades investigated. Measured metabolic rates for each of the walking trials completed by load group subjects vs. those predicted by our minimum-mechanics model (B), the ACSM equation (D), and the Pandolf et al. (56) equation (F). Diagonal lines in B, D, and F represent the lines of identity. Declined gradient predictions were determined using the level equation for the ACSM and the declined extension of the Pandolf et al. (56) equation by Santee et al. (63).

(56), appear for the unloaded trials completed by validation group subjects in *part I* in Fig. 6, A, C, and E, respectively. For the minimum mechanics model, the mean overall difference was nearly equal to zero per the ideal ($-0.36 \text{ ml O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$), the standard deviation of the prediction was relatively small, and little speed- or grade-dependent bias in the accuracy of the predictions was evident. For both the ACSM and Pandolf et al. (56) equations, the standard errors of estimate were nearly twice as large and exhibited bias predominantly across grade. In both cases, the established standardized equations tended to underpredict metabolic rates at lower grades and lower metabolic rates and overpredict at higher ones. The overall predictive error for ACSM was larger, as was the zero error baseline vs. the equation of Pandolf et al. (56). The same error analysis for the three loaded conditions using the three predictive equa-

tions appears in Fig. 6, B, D, and F. The grade- and signal size-dependent predictive bias patterns of the loaded conditions were similar to those in the unloaded trials in *part I*.

DISCUSSION

Per our minimum mechanics hypothesis, we were able to predict walking economy accurately across a broad range of conditions from only three mechanical variables: speed, grade, and the total weight supported against gravity. Across more than 1,400 individual values from 90 different speed, grade, and load trial conditions and gross metabolic rates that ranged from two to 14 times the body's resting rate, our model predicted the rates we measured with a standard error of estimate of just $>1.0 \text{ ml O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$ out of an overall mean nearly 14 times larger ($14.6 \pm 0.2 \text{ ml O}_2 \cdot \text{kg}_{\text{body}}^{-1} \cdot \text{min}^{-1}$; $n =$

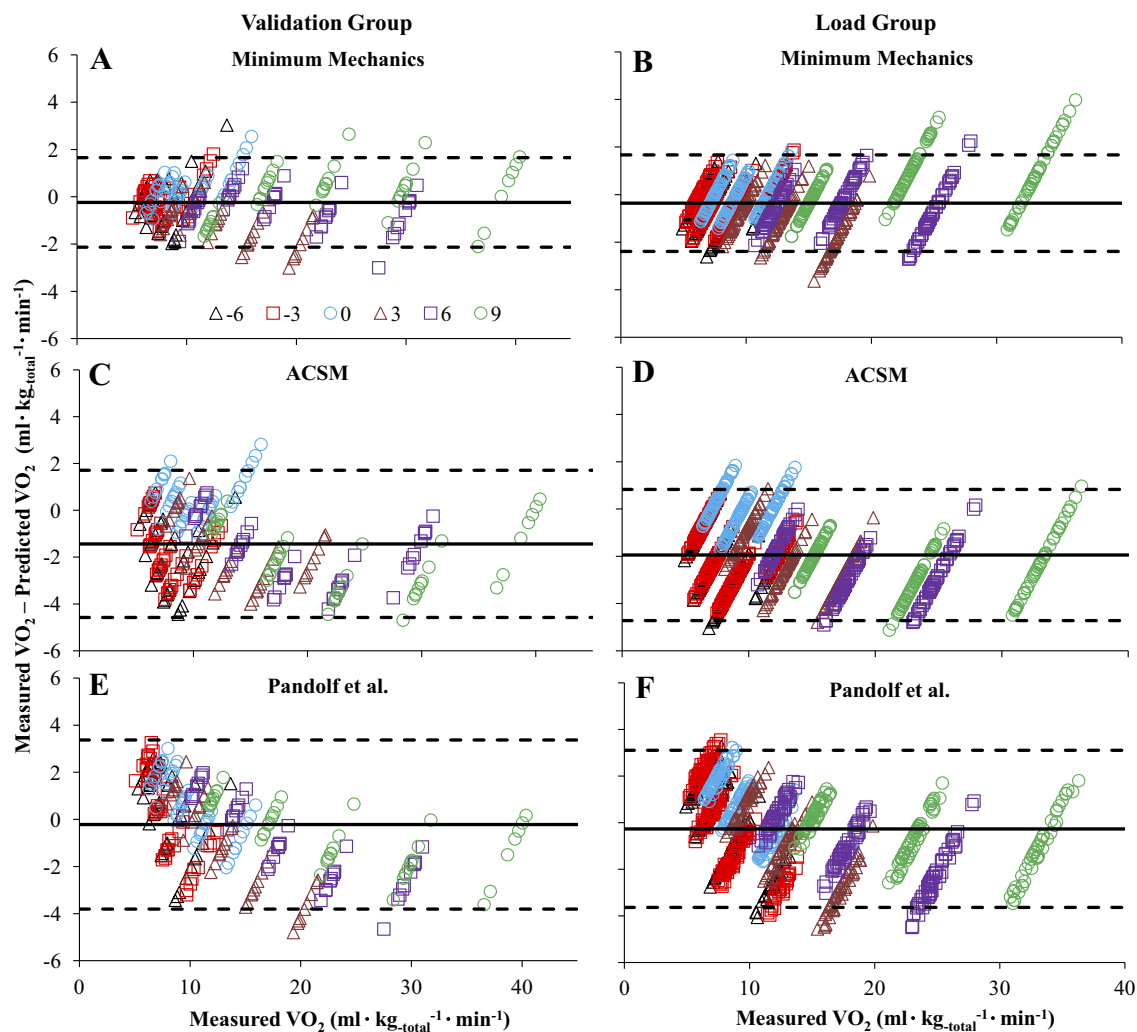


Fig. 6. Validation and load group modified Bland-Altman plots for our minimum mechanics model (A and B), the ACSM model equation (C and D), and the Pandolf et al. (56) model equation (E and F), illustrating the difference between measured and equation-predicted gross metabolic rates during walking. Horizontal black lines represent the average predictive error of the respective equations. Dashed horizontal lines correspond to the average error ± 2 SD.

1,412). The relative agreement between the model-predicted and measured values across nearly 300 speed and grade values in *part I* and across $>1,100$ speed, grade, and load values in *part II* was $>98\%$ in each case (Figs. 4B and 5B). Before specifically considering the economy influences of each of the three mechanical variables we altered, we note that our outcomes offer capabilities and scientific insights not previously available. Practically, the extension of generalized predictive capabilities to declined gradients that are equally present in the natural world, but not included in earlier predictive equations, offers a more comprehensive field tool than previously available. Scientifically, if support forces were not the fundamental determinant of walking economy as modeled, accurate metabolic predictions across the 90 different speed, grade, and load conditions investigated here would have been unlikely, if not impossible.

Loaded Walking Economy Is Determined by the Total Mass Supported Against Gravity

Many investigations under level-only conditions have reported that, on a per kilogram basis, each unit of additional

torso mass incurs a relatively greater metabolic cost than each kilogram of body mass (6, 29–31, 37). However, our 738 individual loaded walking trials spanning a 2.5-fold range of speeds on six different grades consistently supported the alternative conclusion that each kilogram of body and load mass incurs the same metabolic cost (Figs. 2 and 3 and Table 5). This is evident from the agreement between the ratios of loaded to unloaded walking economy ($\dot{V}O_{2\text{-walk-L}}/\dot{V}O_{2\text{-walk-UL}}$; Eq. 3) and loaded to unloaded walking weight ($W_{\text{body} + \text{load}}/W_{\text{body}}$) to within $<1\%$ for the lighter load (+17.4% with +17.6% added weight), 5% for the heavier load (+35.8% with +31.0% added weight), and $<3\%$ ($+2.5 \pm 0.4\%$; $n = 40$) overall for the speed and grade means acquired from both added-load conditions.

Although load-induced increases in walking metabolism might have been greater than our model predictions for the trials inducing greater elevations in the body's metabolic rate (51), no discernable pattern was present. Deviations from the relative increases expected based upon the weight added ($W_{\text{body} + \text{load}}/W_{\text{body}}$; Eq. 3) were negligible across speed and either absent or inconsistent across the -6 to $+9^\circ$ slopes tested

Table 5. Ratios of loaded to unloaded walking economy for all load trials

Grade (°)	Load ($\times W_b$)	Speed, m/s				Average
		0.6	1.0	1.4	1.8	
−6	1.176	1.170	1.193	1.165	1.16	1.173
−3	1.176	1.176	1.143	1.210	1.19	1.181
0	1.176	1.156	1.150	1.166	NA	1.157
3	1.176	1.155	1.159	1.179	NA	1.164
6	1.176	1.167	1.179	1.193	NA	1.180
9	1.176	1.174	1.190	1.195	NA	1.186
−6	1.310	1.371	1.399	1.401	1.393	1.391
−3	1.310	1.359	1.362	1.430	1.417	1.392
0	1.310	1.303	1.312	1.354	NA	1.323
3	1.310	1.302	1.318	1.352	NA	1.324
6	1.310	1.328	1.344	1.386	NA	1.353
9	1.310	1.328	1.346	1.350	NA	1.342
Average						
$1.18 \times W_b$		1.166	1.169	1.185	1.178	
$1.31 \times W_b$		1.332	1.347	1.379	1.405	

NA, not available.

(Table 5). The possibility of load-related deviation being responsible for marginally greater relative increases for the heavier vs. lighter load condition as suggested by several investigators (25, 26, 38, 51, 58) to occur for loads >0.3 body weights cannot be completely ruled out. However, evaluation is difficult in our data because our heaviest load corresponded to the load threshold suggested (51). Evaluation of this possibility more broadly in the existing literature is difficult for several other reasons. First, the data available from loads >0.3 times body weight are limited and include unbalanced loading schemes that compromise economy regardless of load mass (40, 44). Second, the most informative heavy-load study available (67), which involved balanced torso loads of ≤ 1.0 times body mass, concluded that there is little and perhaps no difference in per kilogram costs between body and load mass. Third, the apparently poor mass-specific economy reported for both lighter (29–31, 37) and heavier load masses (6) from level-only investigations appears to be an analytic artifact introduced by resting metabolism oversubtractions (see APPENDIX).

Mechanistically, our load results are consistent with the manner in which our model incorporates the mechanical consequences of added mass, with each kilogram of body or load mass supported requiring the application of the same ground support force ($= 1.0 \text{ kg} \times \text{gravitational acceleration}$) over the course of each stride. Assuming the limb's leverage is not altered by balanced loading, the volume of limb extensor muscle activated, and, therefore, the rate at which chemical energy is used, to provide the requisite support forces should be a direct function of the total body-plus-load mass supported. This interpretation is fully consistent with the neuromuscular activation data available from the tissue level under different load conditions (52, 66).

Isolating Walking Metabolism Requires a Valid Resting Baseline Subtraction

The close agreement between the ratio of loaded to unloaded economy and the ratio of loaded to unloaded walking weight across the four- to fivefold range of gross metabolic rates measured under two load conditions (Fig. 3) indicates that two factors almost certainly remained essentially constant as as-

sumed: 1) the metabolic requirements per kilogram added load ($\dot{V}O_{2\text{-kg-total}}$, Figs. 2B and 3), as noted above, and 2) the basal metabolic requirements of the body's nonlocomotor tissues as implied by earlier studies examining O_2 delivery to these tissues across rest and exercise conditions (4). Accordingly, the constant ratios for each load condition allow us to infer that the measured supine resting rates we subtracted ($3.1 \pm 0.1 \text{ ml } O_{2\text{-kg-body}}^{-1} \cdot \text{min}^{-1}$) from the gross bodily rates measured during walking (i.e., $\dot{V}O_{2\text{-gross}} - \dot{V}O_{2\text{-rest}}$) accurately isolated the non-resting fraction of bodily metabolism for which walking was responsible.

Alternatively, if a resting rate that was either too low or too high had been subtracted, positive or negative trends, respectively, would have been observed as the body's gross metabolic rate increased and the fractional contributions of resting to gross metabolic rate decreased. Analysis of the positive and negative trends illustrated in Fig. 3 for the "no-subtraction" and "minus-stand" ratios vs. the body's gross metabolic rate appears in the APPENDIX.

Grade Walking Economy Varies with Muscular Support Force Dynamics

The walking economy data we acquired with and without loads on six different grades support our model's theoretical foundation while extending the grade-walking insights offered by Margaria (49) eight decades ago. This pioneering investigator recognized that the rate at which metabolic energy was expended to support and displace the body on steep positive and steep negative grades matched the metabolic cost of generating force during concentric and eccentric muscular contractions in isolated skeletal muscle. The quantitative agreement between tissue and whole body levels allowed Margaria (49) to deduce that essentially all of the metabolic energy being expended to walk on steep gradients was attributable to supporting and displacing the body's mass either positively via concentric contractions on steep inclines or negatively via eccentric contractions on steep declines. The constant metabolic rates per total kilogram supported across three load conditions on all six inclines (Fig. 2B) investigated here reveal that Margaria's support and displacement conclusions from unloaded walking on very steep positive and negative grades also apply to the moderate and intermediate grades we examined here.

The alternative suggestions that significant metabolic requirements exist for factors other than supporting and displacing the body's mass, such as repositioning the limbs between steps (18, 27) and the trailing and leading limbs pushing against one another during double support (19, 43), do not explain our results. The torso loads added here increased ground support force requirements in a direct 1:1 ratio, with no direct effect on limb-repositioning requirements. Thus, if limb repositioning accounted for an appreciable portion of the total walking metabolic rate at any given speed and grade, then load-induced increases in economy should have been substantially less than the 1:1 relationship that consistently resulted across different speeds and grades (Figs. 2B and 3). Similarly, the double-stance limb antagonism suggested by some to be a major metabolic requirement during level walking does not occur on inclines and declines of 3° and greater (22). Rather, single-limb data importantly demonstrate (22) that leading and

trailing limbs operate synergistically to simultaneously support and displace the body on positive and negative gradients, respectively, largely in accordance with Margaria and colleagues' (49, 50) insights from very steep grades.

The nearly universal approach to considering graded walking economy by investigators other than Margaria (49) and Minetti et al. (54) has been to do so 1) only for positive gradients and 2) to model inclined-only walking metabolic rates as a supplement to a level baseline rate that remains constant across all grades. However, neither the muscular activity present during level walking nor the metabolic requirement of this activity remain as constants across different grades. If this were the case, the extension of this theoretical framework to declined conditions would then logically require subtracting a bodily energy savings accrued during downhill walking from the level baseline requirements rate held constant by these model equations (8, 17, 25, 56). The inability of skeletal muscle to convert lost gravitational potential energy into accumulated chemical energy reveals the physiologically unsound foundation of this prevailing approach (3, 8, 17, 25, 56, 78).

Our formulaic avoidance of modeling inclined and declined walking economy by supplementing or subtracting from a constant level metabolism baseline simplified the quantitative treatment of both (Eq. 2) while reducing the number of model terms required. This is most evident from our negative gradient modeling solution, which fractionally reduced all of the body's walking or nonresting metabolism (Eq. 2) to describe economy differences vs. nonnegative gradients. The empirically derived decline coefficient of 0.73 (Table 4) is consistent with the metabolic reductions suggested by the slope of the force-velocity curve for eccentric muscular contractions in vivo (60).

Our results, the foundational context provided by Margaria and colleagues (49, 50), and the muscle activation and length-change data now available from the tissue level (24, 61) all support the same mechanistic explanation for differences in walking economy across grade. A small portion of the fivefold range in walking economy values observed across grade at each protocol speed tested here (Fig. 2B) can be attributed to within-fiber rates of ATP utilization being greater during concentric uphill vs. eccentric downhill contractions (34, 35, 39, 70). However, the majority is explained by the different per-fiber muscular forces generated under the different grade conditions. Relatively greater volumes of muscle must be activated during the relatively low-force concentric contractions that simultaneously support and elevate the body's weight on positive grades. Relatively smaller muscle volumes are activated during the relatively high-force eccentric contractions that simultaneously support and lower the body on negative grades (24, 61).

Speed-Dependent Walking Economy Is Predicted Accurately by a Two-Component Model

The modeling of our third independent variable partially followed the widely accepted literature convention of describing speed-induced increases in walking metabolic rates as a square function of walking velocity. However, here, as previously (46, 76), we deviated from widespread convention in doing so for only a portion of the body's walking metabolism; a separate portion was modeled as a constant across speed.

This approach, although more mathematically descriptive than physiologically mechanistic, ultimately provided highly accurate descriptions of the two- to fourfold increases in walking metabolic rates observed across the fourfold range of speeds investigated on the six different grades (Figs. 2, 3, 4, and 5). The somewhat larger relative increases on the more positive grades and smaller ones on the level and declined gradients were described equally well by our two-component approach.

The relatively small departure of walking metabolic rates from linearity across speed on each of the six grades tested (Figs. 1 and 2), in conjunction with our velocity-squared description of only a portion of walking metabolism, made the high degree of predictive accuracy possible (Figs. 4 and 5, A and B). The nearly linear relationship may perhaps be explained by a mechanistic relationship between the duration of the foot-contact time when ground force is applied and the rate of ATP utilization in the muscle fibers recruited to apply support forces, as suggested by Taylor (70). The approach was successfully applied to level human walking by Hoyt et al. (36), who expressed rate of ground force application in terms of body weight and time of foot-ground contact (W_b/t_c), but has been explored only limitedly since (31). Our earlier efforts employing body size stratification and stride frequency variation as experimental tools (74) support the possibility that the W_b/t_c approach may provide a general mechanistic explanation for human walking economy across speed that we report for the different grades investigated here.

Predictive Accuracy of Existing Standard Models

A primary factor enabling us to develop a model with greater conditional breadth and roughly one-half the predictive error of the two leading standards was the singly-focused nature of our effort. In contrast, both the ACSM (3); and Pandolf et al. (56) model equations are amalgams of a series of smaller studies and data sets (for ACSM, see Refs 17 and 55; for Pandolf et al, see Refs. 25 and 26). The piecemeal formulation of these older standards, although impressive in terms of the accuracy achieved, also has intrinsic limitations. The intrinsic strengths and weaknesses that resulted explain the patterns of agreement between actual and predicted values that appear in Figs. 4 and 5 for the loaded and unloaded data sets and in Fig. 6 from the modified Bland-Altman mean difference plots. These patterns also reflect the formulaic differences resulting from the distinct intellectual legacies of the three models.

For the ACSM model equation, a minor weakness (Figs. 4, C and D, 5, C and D, and 6, C and D), given the broad purpose served, is the inability to fully describe the walking metabolic rate speed using a linear relationship. This understandable simplification is responsible for a small portion of the scatter above and below the lines of identity in Figs. 4D and 5D. However, the more significant limitation of the ACSM model equation is the overprediction of walking metabolic rates on all nonzero grades. For the declined gradients, overprediction resulted from the need to use the level condition predictions because the model equation does not extend to negative gradients. This conditional limitation and the consistent overprediction of inclined walking metabolic rates resulted in most of the predicted values falling above the line of identity (Figs. 4D and 5D) and a mean predictive error that was roughly 2 ml O_2 ·kg_{body}⁻¹·min⁻¹ too low for both the loaded and

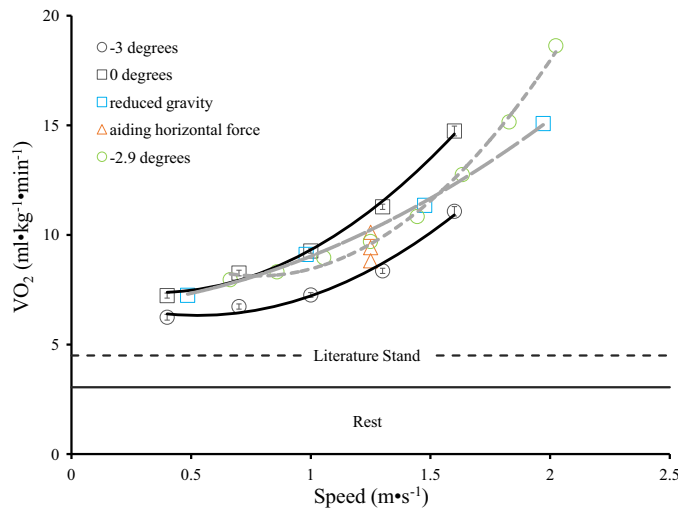


Fig. 7. Mean measured gross metabolic rates vs. walking speed for our unloaded subjects walking on 0 (squares) and -3° (circles) surface gradients. Horizontal lines correspond to the resting metabolic rate mean measured for our subjects (solid line) and the average standing metabolic rates (dashed line) reported from the 12 literature studies appearing in Table 3. Literature data from walking downhill (1), with assisted pulling (27) and under reduced gravity (21), are also illustrated.

unloaded conditions (black horizontal lines in Figs. 6C and 6D).

The greater conditional breadth of the Pandolf et al. (56) model equation resulted in slightly better overall performance (Figs. 4, E and F, 5, E and F, and 6, E and F) vs. the ACSM model equation. The considerable length of the Pandolf et al. (56) equation resulted in part from the more complex incorporation of load compared with our model as well as the arduous work required of Santee et al. (63) to extend the original model to negative grades. The elaborate final equation that incorporates at least four identifiable components of walking metabolism was able to predict the multiconditional variation present in both of our data sets reasonably well, resulting in a mean overall error near zero (black horizontal lines in Fig. 6, E and F). Predictive error was most pronounced across slower speeds and at lower metabolic rates for two reasons. The first is a conflation of resting metabolism with unloaded and loaded standing metabolic terms. These modeling choices do not seem scientifically well justified in terms of either the tight economy-load linkage we report (Figs. 2B and 3, Table 5, and APPENDIX) or differences in standing vs. walking posture (7) that likely decouple the metabolic requirements of supporting body weight across these different conditions. These factors in combination with a description that slightly overestimates the slope of the walking metabolic rate vs. speed relationship resulted in consistent underpredictions at slower walking speeds and a tendency toward overprediction at faster ones. These limitations are responsible for the pattern of predictive error in the modified Bland-Altman plots (Fig. 6, E and F) that are most evident at lower metabolic rates.

Concluding Remarks

Given the ubiquity of human walking and general availability of the basic inputs our model requires to predict walking metabolic rates, broad potential for application exists. Tradi-

tional uses such as exercise prescription, energy balance and weight management, and metabolic rate assessments from walking speeds and grades are directly computational. However, new applications may also be enabled by the accuracy of our minimum mechanics model. A half century ago, Astrand and Rhyning (5) were able to develop a submaximal test for estimating maximal aerobic power in part because of the accuracy with which they were able to predict cycling metabolic rates from mechanical work rates. In their original work, these authors reported being able to do so with an accuracy of $\pm 6.0\%$ for 67% of their cycling trials. The accuracy of our walking predictions here approached that of Astrand and Rhyning's (5) cycling predictions. Here, 63% of our unloaded level and inclined walking trials fell within the $\pm 6.0\%$ standard.

Finally, we note that new technological tools, like wearable sensors and digital topographical maps, expand potential usage well beyond traditional realms. These and other contemporary tools may allow our minimum mechanics model to be used to determine hiking route transport costs, sustainable walking speeds with and without loads, and instantaneous rates of metabolism and bodily heat production in the field. If the total supported load is known, these capabilities are potentially available from any technology that can provide speed and grade data in the field.

APPENDIX

The agreement between the ratios of loaded to unloaded walking economy and loaded to unloaded walking weight (Eq. 3) across two load conditions with 20 specific trial speed and grade conditions each (Fig. 3, A and B, blue circles and line fits) enables an informative analysis. Specifically, deviation from economy ratios specified a priori on the basis of load weight can be used to detect resting baseline under- and oversubtractions. At lower metabolic rates particularly, the relatively greater influence of incorrect subtractions on the smaller unloaded values in the denominator vs. the loaded values of the numerator ($\dot{V}O_{2\text{-walk-L}}/\dot{V}O_{2\text{-walk-UL}}$) introduces inequality with the respective walking weight ratios ($W_{\text{body} + \text{load}}/W_{\text{body}}$).

First, we consider an undersubtraction that incorrectly assumes that the body's basal metabolic requirement during walking is zero (i.e., $\dot{V}O_{2\text{-gross}} = \dot{V}O_{2\text{-walk}}$). Not removing any contribution of resting to the gross metabolic rate signal measured during walking disproportionately inflates the metabolic requirements of walking in the unloaded condition. Accordingly, ratios of loaded to unloaded walking economy that are smaller than the ratios of loaded to unloaded walking weight should result from doing so. Indeed, this is precisely what we observed, as nearly all the zero-subtraction economy ratios from 40 different load condition trials administered were lower than the ratio of loaded to unloaded walking weight (Fig. 3, A and B, red squares and line fits).

Next, we consider an oversubtraction that results from using a measured preexercise standing metabolic rate, or equivalent, as a surrogate for the body's resting metabolic rate. The average literature value of $4.5 \text{ ml O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$ in Table 3 exceeds the supine resting values measured for our subjects here (mean = $3.1 \text{ ml O}_2 \cdot \text{kg}_{\text{body}}^{-1} \cdot \text{min}^{-1}$; $n = 32$) by $1.4 \text{ ml O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$. Removing a quantity larger than the actual contributions of resting to the gross metabolic rates measured disproportionately deflates the metabolic requirements of walking in the unloaded condition. Therefore, this data treatment should result in economy ratios that are greater than the respective condition/weight ratios. As illustrated (Fig. 3, A and B, green triangles and curve fits), this is precisely what we observed.

For both the under- and oversubtraction data treatments, economy ratio deviation from respective condition weight ratios was signal size

dependent. In each case, economy ratios progressively approached the condition weight ratios as the body's gross metabolic rates increased. At the greatest metabolic rates for which the resting subtraction quantities have the least influence, the economy ratios from all three subtraction methods converged at or very near the values of the weight ratios from the respective conditions: 1.18 for the lighter load and 1.31 for the heavier one (Figs. 3A and 3B, respectively). Convergence at the greatest metabolic rates where economy ratio values are minimally affected by the subtracted quantity results from the direct influence of balanced torso loads on walking economy. These observations allow the error potentially introduced by incorrect baseline oversubtractions to be reasonably quantified.

The error potentially introduced by an oversubtraction of $1.4 \text{ ml O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ is substantial because the metabolic rates measured under typical walking conditions are quite small (Fig. 7). For example, on a level surface at an intermediate walking speed of 1.0 m/s in the unloaded condition, $1.4 \text{ ml O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ constitutes 15.1% of the body's gross metabolic rate and 22.7% of the walking rates based on our data. For our level walking economy data illustrated in Fig. 7, the resulting underestimations of walking metabolic rates range from a maximum of 33.9% at 0.4 m/s to a minimum of 12.0% at 1.6 m/s. Accordingly, across-speed analyses and other scientific assessments are directly affected and potentially confounded by the baseline quantity subtracted. The recent analysis of the most economical walking speed ($\text{ml O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$) by Abe et al. (1) illustrates this phenomenon. These authors reported that the speed identified as most economical differed over a 20% range, depending upon the baseline quantity subtracted from their gross metabolic rates. Potential effects for those conditions and interventions that elicit relatively low walking metabolic rates, such as walking downhill, in simulated reduced gravity, and with assistive pulling, will be most heavily influenced by the specific value of the baseline quantity subtracted. As Fig. 7 illustrates, in many of these cases, the literature standing subtraction eliminates most of the originally measured metabolic signal.

The factors responsible for the common usage of preexercise, or in some cases postexercise, standing metabolic rates as a resting baseline subtraction quantity are less clear than the difficulties potentially introduced. Scientifically, the justification for subtracting a baseline rate that includes a metabolic cost of supporting the body's weight against gravity is questionable since gravitational support is the primary determinant of walking metabolism. Conceivably, a standing subtraction would be justified if one wanted to assess a difference between the metabolic requirements of supporting the body while stationary vs. doing so while walking. However, the scientific objective that would be served by doing so is unclear. More generally, a rationale for subtracting any quantity greater than the body's supine resting rate is difficult to identify, particularly since doing so eliminates a portion of the body's walking metabolism that the subtraction is meant to isolate.

A basic quantitative issue with preexercise standing metabolic rates in Table 3 also exists. These measures are substantially greater on average than the values reported in the literature from those studies for which measuring standing metabolic rate was a primary rather than a secondary objective. The mean standing metabolic rate we measured under postabsorptive conditions here of $3.53 \pm 0.08 \text{ ml O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ is representative of this difference. Our mean is nearly $1.0 \text{ ml}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ lower than the literature mean in Table 3 but in good agreement with the dedicated standing values appearing in the classic (68) and more recent literature (53). The factors responsible for the greater mean and considerable between-study variability in the standing values in Table 3 are difficult to identify from the limited measurement information available in many of these studies. Possible elevating factors include the preexercise condition, brief measurement period durations, and perhaps other factors.

Because advances in exoskeletons (14, 57), prosthetics (33), and other assistive devices continue to bring about reductions in walking

metabolism, valid baseline subtractions are necessary if the effect sizes resulting from these and other interventions are to be accurately quantified. More generally, these results identify resting supine metabolic rates as a sound standard for quantifying exercise metabolic rates more broadly.

Practical Baseline Subtraction Suggestions for Isolating Walking Metabolism

For circumstances in which resting supine metabolic rate measurements are impractical or impossible, the literature identifies one, and perhaps two, viable alternatives. First, the extensively validated population equations of Schofield et al. (64) provide accurate resting metabolic rate estimates from only sex, height, and weight. For our subjects here, these equations predicted a mean resting metabolic rate ($3.21 \pm 0.05 \text{ ml O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$) that was within $0.08 \text{ ml O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ of the measured mean, with an average individual error of $0.26 \pm 0.04 \text{ ml O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$. Second, our measurements suggest that sitting metabolism may be able to serve as a reasonable supine resting rate surrogate. The postabsorptive sitting metabolic rates of our subjects were essentially identical to their supine resting rates (3.13 ± 0.07 vs. $3.16 \pm 0.08 \text{ ml O}_2\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$, respectively; $n = 32$).

ACKNOWLEDGMENTS

Jen Nollkamper is acknowledged for extensive efforts that made successful completion of this work possible. We thank Bill Santee for scientific project guidance throughout and Laurence Ryan, Kenneth Clark, and Andrew Udofa for general support, consultation, and input. We also thank our subjects for the quality, and extent of their efforts.

GRANTS

This work was supported by US Army Medical and Materiel Command Award W81XWH-12-2-0013 to P. G. Weyand.

DISCLOSURES

The authors declare competing financial interests. L. W. Ludlow and P. G. Weyand are the inventors of a method for determining walking energy expenditure, which is owned by Southern Methodist University, includes information directly related to the contents of the manuscript, and is in preparation for submission to the US Patent Office.

AUTHOR CONTRIBUTIONS

L.W.L. and P.G.W. conceived and designed research; L.W.L. performed experiments; L.W.L. and P.G.W. analyzed data; L.W.L. and P.G.W. interpreted results of experiments; L.W.L. and P.G.W. prepared figures; L.W.L. and P.G.W. drafted manuscript; L.W.L. and P.G.W. edited and revised manuscript; L.W.L. and P.G.W. approved final version of manuscript.

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Running impact forces: from half a leg to holistic understanding – comment on Nigg et al.

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COMMENTARY

Article History:

Submitted 7th February 2018

Accepted 1st March 2018

Published 18th April 2018

Handling Editor:

Markus Tilp

Karl-Franzens-University Graz, Austria

Editor-in-Chief:

Martin Kopp

University of Innsbruck, Austria

ABSTRACT

Running impact forces have immediate relevance for the muscle tuning paradigm proposed here and broader relevance for overuse injuries, shoe design and running performance. Here, we consider their mechanical basis. Several studies demonstrate that the vertical ground reaction force-time (vGRFT) impulse, from touchdown to toe-off, corresponds to the instantaneous accelerations of the body's entire mass (M_b) divided into two or more portions. The simplest, a two-mass partitioning of the body (lower-limb, $M_1=0.08 \cdot M_b$; remaining mass, $M_2=0.92 \cdot M_b$) can account for the full vGRFT waveform under virtually all constant-speed, level-running conditions. Model validation data indicate that: 1) the non-contacting mass, M_2 , often accounts for one-third or more of the early "impact" portion of the vGRFT, and 2) extracting a valid impact impulse from measured force waveforms requires only lower-limb motion data and the fixed body mass fraction of 0.08 for M_1 .

Keywords:

Two-mass model – effective mass – ground reaction forces – running performance – spring-mass model

Citation:

Clark, K. P., Udofa A. B., Ryan, L. J. & Weyand, P. G. (2018): Running impact forces: from half a leg to holistic understanding – comment on Nigg et al. *Current Issues in Sport Science*, 3:107. doi: 10.15203/CISS_2018.107

This is a commentary on a CISS report article authored by Nigg, B. M., Mohr, M. & Nigg, S. R. (2017). Muscle tuning and preferred movement path – a paradigm shift. *Current Issues in Sport Science*, 2:007. doi: 10.15203/CISS_2017.007

Impact Forces Revisited

Dr. Nigg and colleagues deserve commendation for efforts that have endowed the area of running biomechanics with a sizeable body of empirical observations. These observations have, and undoubtedly will, continue to inform work on a broad range of topics that include running injuries, running shoes and the relationship between the two. Their willingness to confront the experimental challenges involved in studying a largely unpredictable phenomenon like running injuries deserves particular praise.

Here, we focus on the impact force conclusions offered by Nigg, Mohr and Nigg (2017) in their target article. While their contribution purports a lack of importance in overuse injury etiology, there are compelling scientific reasons to consider

their basis and importance from an independent, contemporary perspective. These are: 1) the existence of credible evidence supporting a running impact force-overuse injury link (Daoud, Geissler, Wang, Saretsky, Daoud, & Liebermann, 2012; Milner, Ferber, Pollard, Hamill, & Davis, 2006), 2) the direct effect of impact forces on bodily motion and performance (Clark & Weyand, 2014), and 3) the need for valid quantification to advance general understanding and inform specific applications. One noteworthy application is the input signal required by the muscle-tuning paradigm Nigg *et al.* advance in their target article here. More broadly, the inability to quantify running impact forces recently noted by Nigg and colleagues elsewhere (Baltich, Maurer & Nigg, 2015) is obviously a direct impediment to reaching firm conclusions regarding their importance.

From our perspective, the development of a quantitative understanding has been at least partially impeded by two assumptions that have framed the study of running impact forces for decades. These are: 1) assuming that the early portion of the vertical ground reaction force-time waveform can be attributed to a small fraction (i.e. an “effective mass”) of the body’s total mass (M_b) while ignoring the rest (Chi & Schmitt, 2005; Denoth, 1986; Derrick, 2004; Lieberman, Venkadesan, Werbel, Daoud, D’Andrea, Davis, Mang’eni & Pitsilades, 2010; Nigg, 2010; Nigg, Mohr, Nigg, 2017), and 2) assuming that the impact impulse can be quantified using the localized force peak often visible on the rising edge of the measured waveform (Figure 1). Three studies indicate that these assumptions obscure the mechanics of the impact event.

The first study was provided by Bobbert, Schamhardt and Nigg (1991) more than 25 years ago. These investigators demonstrated that the instantaneous accelerations of seven body mass components (comprising 100% of M_b : right and left foot, shank, and upper leg components plus a combined head-arms-torso mass) acquired from motion data, can be summed to provide a close match to the measured total vertical ground reaction force-time (vGRFT) waveform during slow and moderate speed running (i.e. $F_{z1} + F_{z2} + F_{z3} + F_{z4} + F_{z5} + F_{z6} + F_{z7} = F_{z-total}$, where z designates the vertical component of the ground reaction force). This noteworthy experimental accomplishment was based on Newton’s 2nd Law including the first-principle recognition that the measured vGRFT waveform must somehow correspond to the instantaneous accelerations of 100% of the body’s mass. The second insightful study was the detailed temporal and spatial analysis of the rising edge of the vGRFT undertaken by Shorten and Mientjes (2011). From pressure mapping data on the sole of the foot and frequency analyses of measured waveforms, these investigators also concluded that the body’s entire mass contributed to the rising edge of the waveform. Per their title, they concluded that the localized, rising-edge waveform force peak widely attributed to heel impact, is in fact, “neither heel, nor impact” during heel-toe running.

The most recent of the three studies involved an experimental effort from our laboratory (Clark, Ryan & Weyand, 2017) that, like Bobbert *et al.* adopted a Newtonian approach. We did so with the goal of identifying the simplest partitioning of the body that might account for the vGRFT waveform in full. Our efforts led to the two body-mass component, two-impulse waveform explanation illustrated in Figure 1. Ultimately, this approach was able to predict 500 measured vGRFT waveforms acquired at speeds from 3.0 to 11.0 m/s regardless of the runner’s foot-strike mechanics. Due to the model’s conciseness, only three inputs are required to generate the waveforms from a runner’s gait mechanics: contact time, aerial time, and the vertical acceleration of the lower limb. The close agreement between model-generated and measured vGRFT waveforms ($R^2=0.95$) supports the general validity of the two-mass, two-impulse explanation for their mechanical basis.

The Rising Edge of the vGRFT Waveform: Impact Is Not Enough

Clearly, additional experimental work remains to test and refine the existing Newtonian explanations for running vGRFT waveforms. However, the two studies that have successfully linked bodily motion to running ground reaction forces share the foundational recognition that the waveform represents the summed acceleration of 100% of body mass.

The holistic Newtonian view that emerges for the rising-edge of the total vGRFT waveform, broadly conceived elsewhere as an “impact-only” event, is illustrated in Figure 1. The data appearing in the figure have been adapted from original vGRFT data acquired at a speed of 5.0 meters per second from a runner with heel-strike mechanics. As illustrated, the body’s full mass contributes to the rising edge of the waveform. Accurately predicting the magnitude and timing of the localized peak, for example, requires summing the impulse contributions of the model’s body mass components. Per the illustration, correct prediction of the overall impact mechanics using the two masses in our model relies heavily on the kinematic data used to determine Δt_1 from the period elapsing between the instant of initial foot-ground contact and subsequent time at which mass M_1 slows to a vertical velocity of zero. Correct identification of the localized rising-edge peaks for heel-strikers at all speeds and competitive sprinters at faster ones as previously reported would have been virtually impossible (Clark, Ryan & Weyand, 2017, Figures 5, 6 and 7) without both: 1) accurate

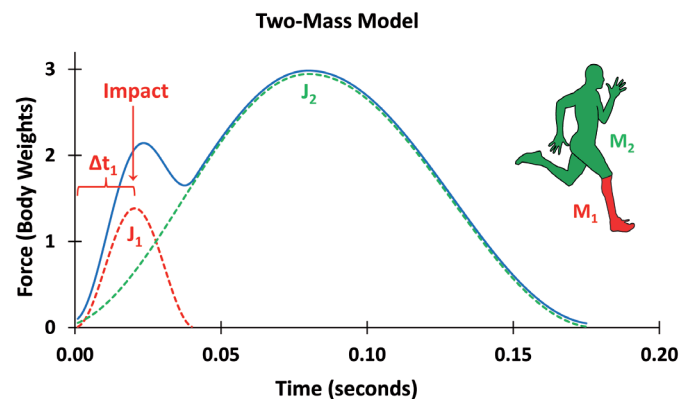


Figure 1: Running vertical ground reaction forces can be quantified as the sum of two impulses: a relatively brief impact impulse (J_1) that corresponds to the deceleration of the foot and shank ($M_1=0.08 \cdot M_b$), and a larger, longer-duration impulse (J_2) that corresponds to the acceleration of the remainder of the body’s mass ($M_2=0.92 \cdot M_b$) throughout the stance period. Both impulses begin at the instant of touchdown and contribute substantially to the rising-edge of the force-time waveform. Note that impact impulse, J_1 , is quantified from 8% of M_b and the time Δt_1 at which the ankle reaches its minimum vertical position.

kinematic data, and 2) a model capable of predicting the significant variability in the timing and magnitude of rising-edge force peaks across scores of different footfalls.

Figure 1 also reveals the specific manner in which the assumptions required by the effective mass techniques obscure the mechanical basis of the rising edge of the waveform. In the footfall illustrated, the effective mass approach assumes that mass M_2 would make little or no contribution to the rising-edge impulse up to the localized force peak. However, as illustrated, M_2 is actually responsible for roughly one-third of the total impulse over this early period of this illustrated waveform. During slow and moderate speed fore-foot strikes, the impulse contributions of mass M_2 actually exceed those of M_1 , primarily because the impact period Δt_i is relatively longer (Clark, Ryan & Weyand, 2017, Figures 5 and 6, Table 2). Also evident in the figure is that the localized peak on the total vGRFT waveform is not simultaneous with the peak of impact impulse J_i as implicitly assumed by effective mass quantification techniques. Rather, the time-dependent contributions of impulse J_2 cause the total waveform peak to occur at a later point in time than the J_i impulse peak. In the case of most forefoot strike waveforms, the longer Δt_i period results in the rising edge of the measured waveform lacking a localized force peak altogether (Clark, Ryan & Weyand, 2014; Clark, Ryan & Weyand, 2017, Figure 6, Table 2).

Impact Forces and New Paradigms: Retro- and Prospective Considerations

Intuitive appeal and computational simplicity may be responsible for the common conceptualization and quantification of the rising edge of human running vGRFT waveforms as an impact-only phenomenon. However, the works synthesized here: 1) provide a valid mechanical basis for the vGRFTs waveforms based on the body's entire mass, and 2) offer quantitative methods that apply over essentially all level-speed and foot-strike conditions. A two-mass partitioning of the human body allows the full running vGRFT waveform to be predicted from gait motion. The two-mass approach also allows the impact portion of the impulse to be extracted from measured vGRFT waveforms. Doing so requires only motion data from the ankle and the fixed lower-limb mass fraction identified for M_1 . Finally, we applaud Nigg, Mohr and Nigg for proposing muscle tuning and movement path paradigms in an effort to advance basic and applied understanding of running mechanics. We share their view that evaluating these paradigms will be a major and lengthy experimental undertaking. One useful tool for these efforts, directly in the case of muscle tuning and indirectly for preferred movement paths, is the holistic quantitative understanding of impact forces that is currently available.

Funding

This work was supported in part by a US Army Medical and Materiel Command award [W81XWH-12-2-0013] to PGW.

Competing Interests

The authors declare competing financial interests. Peter Weyand, Laurence Ryan and Kenneth Clark are the inventors of US Patent #8363891 which is owned by SMU and contains scientific content related to that presented in the manuscript. The patent is licensed to SoleForce LLC in which the three aforementioned individuals are equity partners.

Data Availability Statement

All relevant data are within the paper.

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