Swansea University
Prifysgol Abertawe

A comparison of measured and modelled energetics, estimated from global positioning systems (GPS) velocity

Robert Owen

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Abstract

Introduction. Traditionally in laboratory settings, indirect calorimetry and blood lactate B[La] analysis provide a criterion measure of bioenergetics, although it is not feasible within a multitude of competitive sports. Mathematical modelling provides a solution to estimate metabolic power during competitive sport, whereby a sprint running model was proposed, using global positioning systems (GPS) velocity data and the known energy cost of the equivalent slope running. Now a novel mechanical approach has been presented as an alternative model to estimate metabolic power from GPS velocity data and principles of the work-energy theorem. The purpose of this study was to compare metabolic power as produced from the sprint running model, the mechanical model and indirect calorimetry. **Methods.** Thirteen participants performed a maximal effort 400 m- and a repeated 40 m- sprint and sub-maximal continuous running and repeated 20 m shuttle running test. The tests were completed across two testing sessions a week apart. In all tests, through exercise and recovery periods, $\dot{V}O_2$ was measured by single breath analysis and B[La] was sampled during the recovery. The sum of $\dot{V}O_2$ and B[La] determined the energy cost. GPS velocity data collected throughout each test was processed through the sprint running and mechanical models to estimate energy cost. **Results.** Indirect calorimetry determined significantly greater values of overall metabolic power than sprint running ($P < 0.001$) and mechanical ($P < 0.001$) models across all exercise tests, and the mechanical model estimated larger overall metabolic power values than the sprint running model. **Conclusion.** This study urges sports scientists to understand the constructs of modelling bioenergetics and the inherent limitations of modelled energetics before implementing them within professional practice. Modelled bioenergetics may provide an estimation of the aerobic energy demand of overground running during exercise but is unable to account for the increased metabolic supply post-exercise.

Keywords. Energy Cost, GPS, Indirect Calorimetry, Energetic Modelling, Mechanical Modelling.

Declaration and Statements

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed...[redacted]..........

Date..07/10/2021..

This thesis is the result of my own investigations, except where otherwise stated. Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

Signed. [redacted]....

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Due to the COVID – 19 pandemic, the data collection for this thesis was performed by a secondary party and my role was to perform statistical analysis and write up of the investigation.

Signed...[redacted]..

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The University's ethical procedures have been followed and, where appropriate, that ethical approval has been granted.

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List of Abbreviations

$^{+ve}\eta$ Positive work efficiency

a_f Forward horizontal acceleration

A_p Frontal surface area

C Energy cost

C_d Drag coefficient

COM Centre of mass

CP Critical power

C_r Energy cost of running

C_r Energy cost of running

C_{sr} Energy cost of sprint running

d Distance

d Duty factor

D_{limbs} Work performed mechanically to swing the limbs

EE Energy expenditure

EM Equivalent normalised body mass

EPOC Excess post-exercise oxygen consumption

ES Equivalent slope

F Force

F′ Force equivalent to body weight

f Stride frequency

F_{air} Air resistance

g Gravity

g' Initial acceleration acting on a runner's body

GPS Global positioning systems

h Vertical displacement of the centre of mass

ht Standing height

J Joules

KT Terrain constant

LMS Local positioning measurement system

M Body mass

P Metabolic power

RER Respiratory exchange ratio

RPE Rate of perceived exertion

s Modelled running velocity

S^2 Relative air speed squared

t Time

v Velocity

VCO2 Volume of carbon dioxide exhaled

VE Ventilation (total volume of air inhaled and exhaled in a minute)

${}^{-ve}\eta$ Negative work efficiency

v_{max} Maximal velocity

VO_2 Volume of oxygen consumed

$\dot{V}O_{2max}$ Maximal volume of oxygen consumption

W' W-Prime – finite work capacity above critical power

W_{air} Mechanical work to overcome air resistance

W_{ext} External work

W_{hor}- Negative horizontal work

W_{hor}+ Positive horizontal work

W_{int} Internal work

W_{limbs} Internal work done to move the limbs

W_{limbs} Work performed by the limbs

W_{total} Sum of internal and external work

W_{vert}- Negative vertical work

W_{vert} Total vertical work

W_{vert}^{+} Positive vertical work

α An angle

ρ Ambient air density

τ Time constant

η Work efficiency

Chapter 1.0 Introduction

The fundamental role of sports scientists is to mitigate injury risk and improve the athletic performance of their athletes. As such, practitioners must record relevant information to be able to assess an athlete's readiness to perform by monitoring training and competition load. Training load can be described as internal or external, depending on whether the measured outcomes are acting internally or externally to the athlete (Impellizzeri, et al., 2019; Bourdon, et al., 2017; Vanrenterghem, et al., 2017; Halson, 2014). Internal load describes the physiological, psychological, and biochemical responses of the athlete (Bourdon, et al., 2017; Vanrenterghem, et al., 2017; Halson, 2014), whereas external load refers to quantification of external kinematic outputs of gross movement (Gray, et al, 2018; Bourdon, et al., 2017; Vanrenterghem, et al., 2017; Halson, 2014). Coaches will draw upon training load data, whether internal or external, to inform the prescription of training interventions to elicit a desired physiological adaptation. The most widely adopted practice prioritises external load (Impellizzeri, et al., 2019; Gray, et al, 2018) and whilst this is effective for prescribing training, it does not directly correlate to positive training adaptations. However, it is important to understand the internal load associated with training because improved athletic performance occurs from physiological adaptations, such as in cardiovascular and skeletal muscle, which is largely dependent on the magnitude of the metabolic disruption from homeostasis (Buchheit, et al., 2015; Iaia, et al, 2009; Holloszy & Coyle, 1984; Blomqvist & Saltin, 1983).

While internal load can be measured in several ways, such as using heart rate telemetry (Vanrenterghem, et al., 2017; Halson, 2014) or rating of perceived exertion (RPE) (Vanrenterghem, et al., 2017; Halson, 2014), these metrics are often indirect correlates of metabolic 'energy' (Gray, et al., 2018) and are unable to thoroughly describe exercise demands, particularly during intermittent activities. Given the limitations of these rudimentary approaches, metrics that provide a global understanding of metabolic cost might be more appropriate and are often used in laboratory environments but are seldom adopted in the field. Indeed, based on thermodynamic principles, all metabolic processes produce an equivalent heat, which is the basis of 'gold standard' direct calorimetry (Kenny, et al, 2017). Direct calorimetry measures the temperature exchange between the body and the environment in the chamber. Heat production is directly related to energy expenditure (EE), therefore being the quantification of aerobic and anaerobic metabolism. However, the requirement of an insulated chamber means this is not viable for competitive sport. Thus, indirect calorimetry has become more commonly adopted in laboratory settings, providing estimates of EE from the chemical process of metabolism based on the respiratory gas exchange of oxygen and carbon dioxide, alongside known caloric equivalents (Kenny, et al, 2017). However, the use of a portable metabolic cart is also impractical and prohibited in most competitive sports.

To circumvent these problems, one such method that can be effectively implemented to indirectly monitor training load in competitive sport is the mathematical modelling of bioenergetics, and thus EE (Clarke & Skiba, 2013). Such models provide estimations of internal load, based on energetic equivalents from measures of external load. Nevertheless, they appear to be a viable method of globally quantifying physiological responses to athletic training due to being non-invasive and producing reliable estimations of metabolic power (Gray, et al., 2018). Furusawa and Hill (1927) initiated the concepts of modelling overground locomotion and, in more recent years, this has been adapted and advanced by di Prampero and collaborators (di Pramero, et al., 2015; Buglione & di Prampero, 2013; di Prampero, et al., 2005; di Prampero & Ferretti, 1999; di Prampero, et al.,1986), as well as Péronnet and Thibault, (1989). Notably, these developments identified a relationship between metabolic power and the mechanical cost of running (di Prampero, et al., 1986), the time maximal aerobic power can be sustained, and the capacity of anaerobic metabolism (Péronnet & Thibault, 1989). Fundamentally, these models are based on maximal aerobic power or the maximal theoretical velocity set by the maximal volume of oxygen consumption ($\dot{V}O_{2max}$) and equivalent energy cost, which were accurate in determining power outputs in distances from 60 m to marathon length (Péronnet & Thibault, 1989; di Prampero, et al., 1986).

While the former research had been focused on endurance forms of locomotion, di Prampero et al. (2005) took a novel approach to sprint running by comparing it to running on an inclined surface. Using the instantaneous velocity, collected from a radar gun, and equivalent slope, the instantaneous cost of sprint running can be estimated. di Prampero's model was utilised to estimate metabolic power and EE of football using, time-motion analysis, semi-automated multi-camera systems to be able to estimate instantaneous velocity (Osgnach, et al., 2010). The benefit of using the multi-camera system was it is non-invasive and can monitor the fluctuations in metabolic load throughout a match (Osgnach, et al., 2010). Osgnach et al. (2010) proposed the use of global positioning systems (GPS) as an alternative method to collect instantaneous velocity for the estimation of metabolic power and EE.

Methodological limitations have been identified in the model, primarily due to the assumptions the models are based upon. One such assumption is that all locomotion is horizontal forward in direction. This can lead to modelling errors when, in sports such as football, players have possession of the ball causing a deviation in running gait (Buchheit, et al., 2015), as di Prampero's model likens these movements to sloped running and not the greater muscular work done in these actions. Furthermore, previous research has indicated the model underestimates EE when performing rapid changes of direction (Oxendale, et al., 2017; Stevens, et al., 2015). This may be attributed to regression equations and acceleration data from maximal testing, which does not account for an increased EE with excess post-exercise oxygen consumption (EPOC) during intermittent exercise (Lyons, et al., 2006). Gray et al. (2018, 2020) proposed an alternative method to improve the collection of energetic data from GPS devices. This unique approach was proposed to model mechanical energetics in overground locomotion (Gray, et al., 2020). This model was developed to quantify mechanical demands of both continuous and intermittent forms of locomotion, with metabolic power estimated based on the known efficiency of positive and negative work done during gait (Vassallo, et al., 2021; Vassallo, et al., 2020; Cummins, et al., 2016; Furlan, et al., 2015).

Whilst EE can be a useful measure to monitor global training load, the theoretical basis of each model are not the same and it is unclear whether they will produce the same energetic values. The di Prampero model (2005) which estimates the bioenergetics of sprint running is underpinned by a single-stage method employing energetic equivalents between the energy cost of uphill running at a constant velocity to sprint running at a corresponding equivalent slope. As opposed to the Gray model (2020) which consists of a two-stage method to estimate bioenergetics. Firstly the model considers the runner as a multisegmented system, of stature and mass, that uses chemical energy to increase kinematic energy and/or potential energy of the body segments (positive work done) or conversely decrease kinematic and/or potential of segments (negative work done) (Gray, et al., 2020). The sum of negative and positive work performed produces the overall work done by an athlete. In the second stage, once overall total work done has been calculated, by use of efficiency values of performing positive and negative work estimations of metabolic power and EE can be produced.

The models, therefore, rely on accurate and reliable data to be able to estimate mechanical and metabolic power. To apply the use of radar guns, as per di Prampero et al. (2005), would be unachievable in live sport. Osgnach et al. (2010) used multi-camera systems, from which intentions velocity data can be derived to use within the modelling but comes at a great economic cost. GPS devices are one of the most popular microtechnologies employed within professional sport (Bourdon, et al., 2017; Malone, et al., 2017; Scott, et al., 2016). From the instantaneous velocity data recorded by GPS devices, sports scientist can gain a comprehensive understanding of external load on an athlete (Impellizzeri, et al., 2019; Bourdon, et al., 2017). Furthermore they are more financially accessible to sports teams and so was proposed as means to collect instantaneous velocity data (Osgnach, et al., 2010). An extensive review of GPS microtechnology has suggested that velocity data acquired from the devices are valid for all devices with a sampling rate of ≥10 Hz (Scott, et al., 2016).

The comparison of the energetic models to gas analysis systems has been questioned (Buchheit, et al., 2015; Stevens, et al., 2014). Indirect calorimetry yields EE from expired gas analysis, which can be likened to the direct '*supply'* of energy metabolised. In contrast to this, EE estimated via energetic modelling utilises velocity-time data from GPS, which is akin to the '*demand*' of the exercise (Gray, 2011). There are discrepancies in these values produced, dependent on the supply or demand. For example, this is notable during an on-transient (transition from a state of rest to exercise) (Sousa, et al., 2015), where modelled data will estimate instantaneous energy cost (the demand). However, as identified by breath-by-breath gas analysis, during the initiation of exercise, the metabolic rate (the supply) increases curvilinearly until it reaches a plateau to meet energy requirement and a steady state is reached (Whipp, et al. 2005; Bangsbo, et al., 2000; Wasserman, et al., 1975; Wasserman, et al., 1967). The initial energy requirement is predominantly produced anaerobically, and an oxygen debt is incurred (Whipp, et al., 2005; Bangsbo, et al., 2000), which is somewhat replenished by the increased metabolic rate associated with EPOC (Buchheit, et al., 2015; Lyons, et al., 2006). Thus, there is a temporal dissociation between energy supply and demand, as well as the theoretical source of energy across the exercise transition (aerobic or anaerobic).

During steady-state, sub-maximal, on-kinetics (exercise) (Sousa, et al., 2015), the supply and the demand is theoretically equivalent and predominantly met using aerobic pathways (James, et al., 2009; Busso & Chatagnon, 2006; Alvarez-Ramirez, 2002; Lacour, et al., 1990). Therefore, modelled metabolic values are predicted to provide similar values to those derived from breath-by-breath gas analysis. As with on-kinetics, during off-transient (transition from exercise to resting) and off-kinetics (recovery) (Sousa, et al., 2015), temporal dissociations between supply and demand are apparent. This is due to the cessation of locomotion, resulting in no modelled EE, as per the constraints of energetic models designed to capture the instantaneous demand of exercise. During the recovery period, the supply of energy will persist, such that measured VO_2 is inversely related to the phosphocreatine repletion (i.e. EPOC) (Cleuziou, et al., 2004; Perrey, et al., 2002; Paterson & Whipp, 1991; Maehlum, et al., 1986). Therefore, it is possible that both energetic models, compared with indirect calorimetry, might not equally account for all work performed, particularly during high-intensity intermittent exercise, owing to the fluctuation in exercise supply and demand during repeated bouts (Buchheit & Laursen, 2013). Furthermore, the detailed analysis of the recovery period, and modelled aerobic/anaerobic contributions, might also provide further insight into the underestimation of EE identified in previous literature (Highton, et al., 2017; Oxendale, et al., 2017; Stevens, et al., 2015).

This study aimed to compare methods of indirect calorimetry and two separate energetic modelling approaches (di Prampero and Gray models) for estimation of EE during outdoor overground running exercise. Specifically, the current study compared the EE values during exercise, recovery and combined segments during overground locomotive exercise tests that replicated common actions during team field sports, including continuous sub-maximal running, 400 m sprinting, repeated shuttle running, and repeated sprint running. It was hypothesised that overall, across the whole protocol, the di Prampero model and the Gray model would underestimate total overall EE and the aerobic contribution to EE compared with indirect calorimetry as reported elsewhere (Buchheit, et al., 2015), as there is no exercise demand during the recovery but there is an increased metabolic rate due to EPOC. However, it was hypothesised that the di Prampero model and the Gray model would produce similar estimations of EE related to anaerobic contribution to exercise. Furthermore, it is hypothesised that the di Prampero model and the Gray model would estimate similar values for EE across all measures.

Chapter 2.0 Theoretical Framework

Modelling metabolic power stems from the work of di Prampero (1985) investigating the limiting factors to maximal oxygen consumption (VO_{2max}) during two- and one-legged exercise, providing insight on how to develop oxygen transportation. This paved the way for estimating EE of energy demands of human locomotion on land (di Prampero, 1986). This chapter will present the progression of the models for estimating metabolic power and work, with the addition of the proposed adjusted method to model metabolic power and work utilising mechanical modelling to calculate the demand of the exercise from GPS-derived velocity data.

2.1 Model to estimate metabolic load by di Prampero (2005)

di Prampero et al. (2005) took a novel approach to model metabolic power based on the energy cost of sprint running and the equivalence of accelerating the runners' centre of mass (COM) with the Earth's gravitational field. Sprint running on flat terrains was likened to uphill running at a constant speed, where the uphill slope was determined by the forward acceleration (di Prampero, et al., 2002). Therefore, forward acceleration could be measured and translated into the corresponding energy cost as the energy cost of uphill running is well documented (Minetti, et al., 2002; Minetti, et al., 1994; Margaria, et al., 1963). Combining this information with instantaneous velocity data allowed the calculation of metabolic power.

Underpinning theory

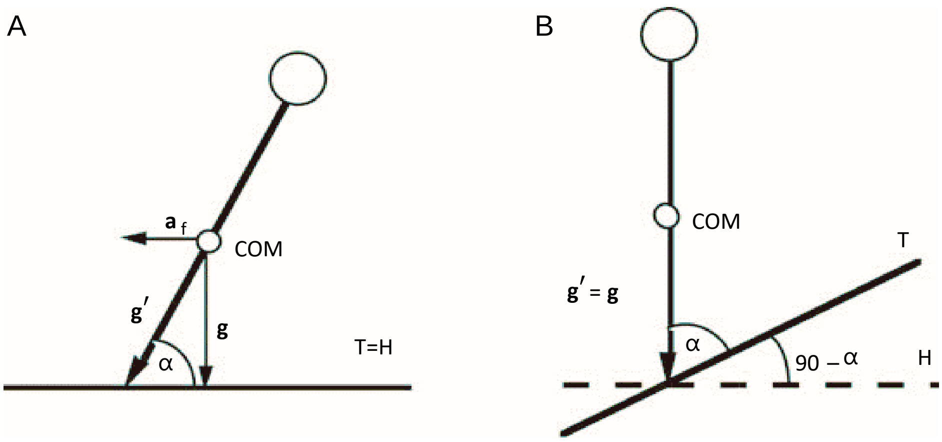

Figure 1 A simplified view of the forces acting on a runner. The subject is accelerating forward while running on flat terrain (A) or running uphill at constant speed (B). The subject's body mass is assumed to be located at the centre of mass (COM); a_f=forward acceleration; g=acceleration of gravity; $g'=(a_f^2+g^2)^{0.5}$ is the acceleration resulting from the vectorial sum of a_f plus g; T=terrain; H=horizontal; α (=arctan g/a_f) is the angle between runner's body and T; the angle between T and H is α′=90–α**.** Reproduced from di Prampero et al. (2005)

During sprint running the initial acceleration acting on the runner's body (g′) is a vectoral sum of forward horizontal acceleration (a_f) and gravity (g). Both forces are assumed to be applied to the runner COM as seen in figure 1A and given as:

(1)

$$g' = \left(a_f^2 + g^2\right)^{0.5}$$

An angle (α) between g′ is applied by generating a line through the foot-terrain contact with the runners COM to maintain an equilibrium, this is expressed as:

(2)

$$\alpha = \arctan g \ / \ a_f$$

Similar to if the runner were running uphill at a constant speed, where the average acceleration (g') is assumed to be applied vertically as seen in figure 1B. As g' was tilted upward to make it vertical, so must the latter with the horizontal to maintain a constant angle with the terrain (α). The angle between the horizontal and terrain (α') is created by forward acceleration giving the angle α between g' and the terrain as:

(3)

$$\alpha' = 90 - \alpha = 90 - \arctan \mathrm{g} \;/\; \mathrm{a_f}$$

The equivalent slope (ES) to the angle α' is given as the tangent of itself:

(4)

$$\mathrm{ES} = \tan\,(90 - \arctan \mathrm{g} \;/\; \mathrm{a_f}\,)$$

In sprint running the average force (F) exerted by active muscle groups in a stride cycle (F' = equivalent to body weight) is expressed:

(5)

$$\mathrm{F}' = M_\mathrm{b} \cdot \mathrm{g}'$$

When running at a constant velocity the average force F equates to the runner's body weight, thus:

(6)

$$\mathrm{F} = M_\mathrm{b} \cdot \mathrm{g}$$

The ratio of equations 5 and 6

(7)

$$\mathrm{F}'/\mathrm{F} = \mathrm{g}'/\,\mathrm{g}$$

reveals the equivalent bodyweight (F' = the average force generated by active muscle groups), during sprint running, is equal to maintaining a constant velocity with the same mass multiplied by the ratio g'/g on the Earth's surface. This ratio was called equivalent normalised body mass (EM) and given:

(8)

$$\mathrm{EM} = g'/g = (a_f^2 / g^2 + 1)^{0.5}$$

Therefore, sprint running is considered as constant speed running on the Earth's surface, on an ES whilst transporting additional mass $\Delta M = M_b\,(g'/g-1)$, meaning total EM becomes $\mathrm{EM} = \Delta M + M_b$. Both ES and EM are determined from forward acceleration as seen in equations 4 and 8, thus can be calculated once forward acceleration is known. Using ES and EM values, energy cost can be determined provided that the energy cost of sprint running uphill at a constant velocity per unit of body mass is known.

Calculations

Running velocities were recorded by a radar gun and speed-time curves were fitted by an exponential functional (Chelly & Denis, 2001; Volkov & Lapin, 1979; Henry, 1954):

(9)

$$s(t) = v_{\max} \cdot \left(1 - e^{-t/\tau}\right)$$

(s is modelled running velocity, t is time, v_{max} is maximal velocity, τ is time constant)

As the modelled velocity accurately describes the actual running velocities (di Prampero, et al., 2005), instantaneous forward acceleration was given as a derivative of equation 9:

(10)

$$a_f^{(t)} = ds/dt = \left[v_{\max} - v_{\max} \cdot (1 - e^{-t/\tau})\right]/\tau$$

From equation 9, using the time derivative a function of distance (d, m) can be expressed as:

(11)

$$d(t) = v_{\max} \cdot t - \left[v_{\max} \cdot \left(1 - e^{-t/\tau}\right)\right] \cdot \tau$$

Using individualised ES (equation 4) and EM (equation 5) are obtained from forward acceleration which allows for the calculation of energy cost of sprint running. Energy cost as presented by Minetti et al. (2002) for slopes from -0.45 to +0.45 is expressed as:

(12)

$$C = 155.4_{x^5} - 30.4_{x^4} - 43.3_{x^3} + 46.3_{x^2} + 19.5_{x} + 3.6$$

The incline of the terrain is represented as *x* as given by the tangent of the angle α' to the horizontal (Figure 1B). The energy cost of sprint running (C_{sr}) was estimated by replacing *x* with ES and the overall cost is multiplied by EM:

(13)

$$C_{sr} = (155.4\mathrm{ES}^5 - 30.4\mathrm{ES}^4 - 43.3\mathrm{ES}^2 + 46.3\mathrm{ES}^3 + 46.3\mathrm{ES}^2 + 19.5ES + 3.6)\mathrm{EM}$$

di Prampero et al. (2005) noted that when ES = 0 and EM = 1, C_{sr} reduces to that applying at a constant velocity on flat terrain to 3.6 $J \cdot kg^{-1}$ as per Minetti et al. (2002).

2.2 Energy cost and metabolic power derived from GPS (Osgnach, et al., 2010)

Osgnach et al. (2010) first adapted the model detailed in section 2.1 (di Prampero, et al, 2005) to derive instantaneous velocity data from a multi-camera system in soccer compared to previously used radar guns and camera devices. It was in this research that the suggestion to utilise GPS technology to attain the instantaneous velocity data was proposed.

Once velocity and acceleration are known, metabolic power (P) can be estimated by multiplying that with the energy cost of sprint running, given as:

$$P = C_{\mathrm{sr}} \cdot v \tag{14}$$

This equation (14) indicated that running velocity can generate different metabolic demands based upon the given acceleration (Osgnach, et al., 2010).

As di Prampero et al. (2005) considered the terrain to be firm as in on a treadmill, Osgnach et al. (2010) adjusted the terrain constant (KT = 1.29) in equation 12 to account for the 30% greater energy cost of running on a football field (Pinnington & Dawson, 2001) and given as:

$$C = 155.4_{x^5} - 30.4_{x^4} - 43.3_{x^3} + 46.3_{x^2} + 19.5_{x} + 1.29 \tag{15}$$

The amendment is carried to equation (13) and expressed as:

$$C_{\mathrm{sr}} = (155.4\mathrm{ES}^5 - 30.4\mathrm{ES}^4 - 43.3\mathrm{ES}^2 + 46.3\mathrm{ES}^3 + 46.3\mathrm{ES}^2 + 19.5\mathrm{ES} + 1.29)\mathrm{EM} \tag{16}$$

2.3 Model to calculate mechanical work of overground running by Gray et al. (2020)

The velocity-time curve used in the model is based upon the assumption that; the predominant purposeful locomotive motion is forward horizontal acceleration of the COM (Bloomfield, et al., 2007), overground running is performed on a hard (non-deforming) level horizontal surface orthogonal to the Earth’s gravitational field, the runner adopts a fixed vertical position, perpendicular to the ground surface (Grey, et al., 2020). Total mechanical work (W_{total}) can be divided into external work (W_{ext}) and internal work (W_{int}). Whereby, W_{ext} is the work performed to accelerate or decelerate the COM and W_{int} is the work performed by the limbs about the COM. Therefore, W_{total} is expressed as:

$$W_{total} = W_{ext} + W_{int} \tag{17}$$

Moreover, W_{ext} can describe locomotion in greater detail as elements of positive and negative work performed. Where positive (W_{hor}+) and negative (W_{hor}-) work (J/kg) in the horizontal plane are associated with accelerations and decelerations of the COM. The model accounts for the mechanical work performed by the athlete to overcome air resistance (W_{air}) (J/kg). Furthermore, positive (W_{vert}+) and negative (W_{vert}-) work done (J/kg) in the vertical plane is associated with the oscillation of the COM in each step. W_{int} is depicted by the work done to move the body's limbs (W_{limbs}) (J/kg).

$$W_{ext} = W_{hor}+ + W_{hor}- + W_{vert}+ + W_{vert}- + W_{air} \tag{18}$$

$$W_{int} = W_{limbs} \tag{19}$$

Calculations

To obtain mechanical work, power and demand from a GPS receiver, velocity data during overground running is modelled on the time-velocity curve. The model summarised follows a four-step framework to determine W_{total} (analysis over a limited number of samples (n) from a GPS receiver over a fixed time interval (t_i)).

1. Prediction of the COM and limb kinematics
2. Calculating external work performed (W_{ext})
3. Calculating internal work performed (W_{int})
4. Summation to calculate total mechanical work and power

Prediction of COM and limb kinematics

During overground running, COM and limb kinematics are closely linked with running speed. When running the COM will rise and fall across the gait cycle, being at its lowest point in the mid support phase and highest in the mid-flight phase (Segers, et al., 2007; Farley & Ferris, 1998). The vertical displacement of COM (Δh, from lowest to highest point) has been demonstrated to alter linearly with movement velocity(v) (r^2= 0.444, p= 0.034, n= 90) (Lee & Farley, 1998; Ito, et al., 1983) given as:

$$\Delta h = 0.080 + 0.004 \cdot v \tag{20}$$

(Δh is in m, and v is in $m \cdot s^{-1}$)

Likewise, limb kinematics are indicated to vary during a continuous running velocity. The support phase in the gait cycle decreases and the swing duration is maintained or fractionally decreased at higher velocities (Nilsson et al., 1985). When a single limb is in the support phase of the gait cycle it is known as the duty factor. As steady-state running velocity increases, so does stride frequency (f) and duty factor decreases (d). f and d have been established as determinants of metabolic power during locomotion (Nardello, et al., 2011) and regressions had been determined (Gray, et al., 2019):

$$f = 0.026 \cdot v^2 - \mathit{0.111} \cdot v + 1.398 \tag{21}$$

$$d = 0.0004 \cdot v^2 - 0.061 \cdot v + 0.50 \tag{22}$$

(f is in Hz, d is in decimal form percentage, and v is in $m \cdot s^{-1}$)

Calculating external work

Cavagna et al., (1964) identified external work as the changes in potential and kinetic energy in the COM. The kinetic energy of the COM is the vectoral summation of the horizontal and vertical components giving W_{hor}, which is given as:

(23)

$$w^{j}_{hor} \sum_{j=1}^{n} 0.5\left(v^{2}_{j+1} - v^{2}_{j-1}\right)$$

W_{hor} is divided into positive (accelerating) horizontal work (W_{hor}^{+}) and negative (decelerating) horizontal work (W_{hor}^{-}). Where v_{J+1} is greater than v_{J-1} W_{hor}^{+} is being done and conversely when v_{J-1} is greater than v_{J+1} W_{hor}^{-} is done in the units of J/kg.

The vertical displacement of COM is in continuous motion (Δh), rising and falling, throughout the phases of running gait. This indicated a state of constant fluctuation of vertical kinematic and potential energy. Laws of thermodynamics were used, implying Δpotential energy = Δkinetic energy meaning either measure can be used to estimate W_{vert}. Gray et al. (2019) used Δpotential energy for this model to provide the Δh using the equation (20). Δpotential energy of the COM from its lowest to highest point correlates to the positive work done (W_{vert}^{+}) and contrariwise attributes to negative work done (W_{vert}^{-}). This model assumes that the rise and fall of the COM are equal $\left| W_{vert}^{+} \right| = \left| W_{vert}^{-} \right|$. Therefore, is given as:

(24)

$$\left|W^{j}_{vert^{+}}\right| = \left|W^{j}_{vert^{-}}\right| = \left| \sum_{j=1}^{n} \left(2 \cdot g \cdot \Delta h_{j} \cdot f_{j}\right)\right.$$

Δh_{J} and f_{J} are calculated from velocity through equations (20) and (21) respectively.

Air resistance (F_{air}) has been accounted for in this model as an external force acting against the surface area of the body. Using ambient air density (ρ), projected frontal surface area (A_{p}), relative air speed squared (S^{2}) and drag coefficient (C_{d}), F_{air} can be calculated:

(25)

$$F_{air} = 0.5 \cdot \rho \cdot Ap \cdot S^{2} \cdot C_{d}$$

Air density is known to vary with temperature (T) and barometric pressure (BP). Air density is expressed as kg/m^3 when BP is in mmHg and T is in °C and ρ_o = 1.293 kg/m^3 as at sea level. Air density was approximated accordingly:

(26)

$$\rho = \frac{273 \cdot \rho_o \cdot BP}{760 \cdot T}$$

The surface area of bipedal running locomotion was set as ~26% of total body surface area as evidenced in earlier research (Davies,1980; Pugh, 1976; Shanebrook & Jaszczak, 1976) and calculated with previously established calculations (Shuter & Aslani, 2000; DuBois & DuBois, 1916) using standing height (*ht*) (measured in m) and body mass (*M*) (measured in kg) producing units in m^2. Participant surface area can be calculated as:

(27)

$$\mathrm{A}_\rho = 0.26(94.9 \cdot ht^{0.655} \cdot M^{0.441}$$

Drag coefficient (C_d) was determined as 1 in the model, extracted from prior research which presented values of 0.7 – 1.1 in human locomotion (Walpert & Kyle, 1989; Davies,1980; Shanebrook & Jaszczak, 1976).

Mechanical work to overcome air resistance ($\mathrm{W}_{\mathrm{air}}$) is proportional to the forward horizontal velocity cubed (v^3). Established from findings of di Prampero (1986) where the runners movement velocity deduces relative air speed, v = S. Overcoming $\mathrm{W}_{\mathrm{air}}$ is presented in units' J/kg and expressed as:

(28)

$$\mathrm{W}_{\mathrm{air}}^{\mathrm{j}} = \sum_{\mathrm{j}=1}^{n} \left(\frac{0.5 \cdot \rho \cdot A_\rho \cdot \mathrm{v}_{\mathrm{j}}^3 \cdot C_{d\mathrm{j}} \cdot t_i}{M} \right)$$

Calculating internal work

Internal work is comprised predominantly of work done to move the limbs (W_{limbs}) which Minetti (1998) devised to predict work performed mechanically to swing the limbs (D_{limbs}). q represents the inertial properties of the limbs and is valued as a constant of 0.1 (units J/kg·m).

(29)

$$D_{limbs} = q \cdot \mathrm{v}^2 \cdot \mathrm{f}\left(1 + \left(\frac{d}{1-d}\right)^2\right)$$

The original equation (29) allowed for both within and between segment energy transfer and so the absolute summation of negative and positive work done by the limbs. Meaning work done by the limbs was able to be calculated as:

(30)

$$W^{\mathrm{j}}_{limbs} \sum_{\mathrm{j}=1}^{n} \left(q \cdot \mathrm{v}_{\mathrm{j}}^3 \cdot \mathrm{f}_{\mathrm{j}} \left(1 + \left(\frac{d_{\mathrm{j}}}{1-d_{\mathrm{j}}}\right)^2\right) \cdot t_t\right)$$

f_{j} and d_{j} are calculated from equations (21) and (22) respectively.

Summation of total mechanical work, power and demand

The model estimates total work done (W_{total}) (units J/kg) by summing the values of equations (18) and (19) which are determined by equations (23), (24), (28), and (30). This is expressed as:

(31)

$$W^{\mathrm{j}}_{total} = \sum_{\mathrm{j}=1}^{n} \left(\left|\mathrm{W}^{\mathrm{j}}_{vert^+}\right| + \left|\mathrm{W}^{\mathrm{j}}_{vert^-}\right| + \left|\mathrm{W}^{\mathrm{j}}_{hor^+}\right| + \left|\mathrm{W}^{\mathrm{j}}_{hor^-}\right| + \left|\mathrm{W}^{\mathrm{j}}_{air}\right|\right)$$

Total mechanical power (P_{total}) is derived from dividing the W_{total} by the time interval and units are W/kg:

(32)

$$P^{\mathrm{j}}_{total} = \frac{W^{\mathrm{j}}_{total}}{t_i}$$

Total mechanical demand is established through division of the mechanical power by the running velocity and units are presented in J/kg·m, in correspondence with the work of Minetti (1998). Total mechanical demand is given as:

(33)

$$D^{\mathrm{j}}_{total} = \frac{P^{\mathrm{j}}_{total}}{\mathrm{v}^{j}}$$

2.4 Gray's model to estimate metabolic load via mechanical modelling from GPS derived velocity data

Utilising the mechanical model (Grey et al. 2020) determines mechanical work done as seen in equation (31), which dictates the energy cost of running (C_r). To be able to estimate energy cost, the efficiency (η) of executing the mechanical work is determined on the understanding that:

(34)

$$\mathrm{C_r} = \frac{\mathrm{W_{tot}}}{\eta}$$

As presented by Minetti et al. (2002) locomotion on uphill slopes >0.15 the COM only performs positive work and thus, locomotion on downhill slopes >0.15 the COM performs negative work. The work efficiency is then compared with a likeness of the muscle contraction type to the work performed. Slow speed positive work efficiency ($^{+ve}\eta$) compares with concentric muscle contractions (~0.25) and slow speed negative work efficiency ($^{-ve}\eta$) compares with eccentric muscle contractions (~1.20) (Minetti, et al., 2002; Whipp & Wasserman, 1969; Abbott, et al., 1952; Margaria, 1938; Dickinson, 1929). At higher speeds efficiency of positive work is reported to increase to ~0.5 (Willems, et al., 1995; Cavagna, et al., 1977; Cavagna, et al., 1964) due to the utilisation of elastic energy from musculotendinous structures (Zamparo, et al., 2019; Cavagna, et al., 1977; di Prampero, et al., 1993; Ito, et al., 1983). Arsac and Locatelli (2002) proposed a model to portray the performance of positive work of running varied linearly dependant on velocity given as:

(35)

$$^{+ve}\eta = 0.25 + \left(\frac{0.25}{v_{max}}\right) \cdot v$$

Meaning positive work efficiency at the j^{th} GPS sample will be defined as:

(36)

$$^{+ve}\eta_j = 0.25 + \left(\frac{0.25}{v_{max}}\right) \cdot v_j$$

Negative speed efficiency was considered constant at 0.8 as in previous research changes in negative work efficiency at higher speeds are not well defined and often use constant values of negative work efficiency ranging from 0.8 to 1.2 (Minetti, et al., 1994; Ito, et al., 1983). EE for positive and negative mechanical work performed by the body at the j^{th} sample is given by:

(37)

$$C_j^+ = \frac{W_{hor^+}^j + W_{vert^+}^j + W_{air}^j + W_{limbs}^j}{^{+ve}\eta_j}$$

(38)

$$C_j^- = \frac{W_{hor^-}^j + W_{vert^-}^j}{^{-ve}\eta_j}$$

Consideration of work to overcome air resistance and its metabolic cost was noted before generating total EE. During acceleration air resistance gradually increases with velocity requiring energy to overcome this. During deceleration, it is assumed air resistance assists the reduction of COM velocity, and so has no metabolic cost.

3.0 Literature Review

3.1 '*Supply*' and '*demand*' principle of measuring energy expenditure

Methods of estimating EE have progressed from directly measuring heat dissipation, quantifying inspired and expired air, to mathematically modelling from instantaneous GPS velocity data. Whilst the two approaches have the same aim of producing metabolic power, they attain this information by different means. The current 'gold standard' method of generating EE, indirect calorimetry, measures respiratory gases during exercise using a mask and portable metabolic cart. As oxygen consumption and carbon dioxide production are directly related to aerobic and anaerobic metabolism, it is determined that indirect calorimetry measures the *supply* of energy production. Vice versa, modelled EE and mechanical work, determined from instantaneous velocity data from GPS devices, can quantify the locomotive movements of exercise. This provides the classification that the modelled metabolic power is calculating EE based on the energy *demand* of the task. Some commercial systems offer a method to quantify 'player load' from the use of tri-axial acceleration data from GPS devices. However, the results are presented in arbitrary units and therefore possess no physiological or mechanical significance.

3.2 Calorimetry

3.2.1 History of calorimetry

Metabolic processes occur within all living organisms and a by-product is heat, therefore all living beings are in a continuous open cycle of heat exchange with the environment (bioenergetics). The measurement of heat exchange between animal and environment is known as direct calorimetry. Antoine Lavoisier and Pierre Simone Laplace (1780) are recognised as the creators of the first animal calorimeter for measuring animal heat generation during winter (Lodwig & Smeaton, 1974). This calorimeter was comprised of two layers, an outer layer of snow and an inner layer of ice. Heat transferred from the animal into the surroundings melted the ice, and the water was weighed to provide a metric to calculate the energy transferred to melt the ice (Kenny, et al., 2017). This initial calorimeter was limited in the size of the chamber that could be created and limited all tests to be performed in the winter. The first human calorimeter was developed in the 19th century which concurrently measured heat from both aerobic and anaerobic metabolism whilst measuring the gas exchange in the atmosphere (Atwater, 1905). This was the empirical evidence to demonstrate the law of conservation via an equivalency relationship between fuel consumption of oxygen and heat production (Mtaweh, et al., 2018; Kenny, et al., 2017). As a result, EE could be calculated from heat exchange measurements (direct calorimetry) or could be estimated from oxygen consumption converting it into an energy equivalent (indirect calorimetry).

Initially, indirect calorimetry methods required the connection of participants to static apparatus such as a spirometer and Douglas bags (Mtaweh, et al., 2018; McLean & Tobin, 2007). The innovation of portable metabolic carts came in the late 19th century (Gunga & Kirsch, 1995), revolutionising how scientists were able to measure physiological demands across sports performed in a variety of settings. The original portable metabolic cart was designed to measure the physiological effects of altitude in mountain climbing (McLean & Tobin, 2007). Portable metabolic carts have progressed and are fully automated and able to perform open-circuit spirometry (Valanou, et al., 2006; Macfarlane, 2001), meaning that the subject breathes air from the surrounding environment (Valanou, et al., 2006). Automated, open circuit calorimetry has become the most common method of quantifying EE (Kenny, et al., 2017). The metabolic carts can quantify oxygen consumption and carbon dioxide production by measuring inspired and expired air and using minute ventilation (Kenny, et al., 2017). Additionally, oxygen consumption and carbon dioxide production are used to calculate the respiratory exchange ratio. This provides an estimate for substrate utilisation and allows for a further breakdown of EE using the caloric equivalents for macronutrients.

3.2.2 Use of indirect calorimetry in medicine and sport performance

The primary use of indirect calorimetry is for interpretation of EE and respiratory analysis in medicine (Delsoglio, et al., 2019; Mtaweh, et al., 2018; Reeves, et al., 2004) and sport and exercise science (Mtaweh, et al., 2018; Robergs, et al., 2010; Macfarlane, 2001). Indirect calorimetry is based on the understanding that food is oxidised within the body and produces heat. Using oxygen inhalation and carbon dioxide exhalation, the laws of conservation can be expressed as (Kang, 2008):

$$\text{Substrate} + O_2 \rightarrow \text{heat} + CO_2 + H_2O \tag{39}$$

Inspired and expired air measurements can provide an accurate estimate of EE (Macfarlane, 2001). This has been applied in medical settings to estimate the resting daily EE of critical patients in intensive care (Smyrnios, et al., 1997). Smyrnios et al. (1997) conducted a 30-minute test during the middle of the day (11 am to 3 pm) measuring minute ventilation, respiratory rate and heart rate which were found to be representative of daily average EE values. Despite the estimation being representative of a daily average, the values should not be used to predict expenditure on subsequent days due to patient condition fluctuation greatly varying resting EE values by up to 46% (Weissman, et al., 1989). Understanding the EE of patients is predominantly utilised for the prescription of nutritional therapy as a treatment or to stabilise a patients condition (Achamrah, et al., 2021; Psota & Chen, 2013). In addition, physical activity has been used as a tool to prevent and manage a variety of chronic diseases, where EE was used as a method of global monitoring in these small populations (Psota & Chen, 2013; Valanou, et al., 2006). Wherein the use of indirect calorimetry was evaluated as an accurate method to estimating EE but not without the pitfalls of being inhibititory to normal behaviour patterns and costly to perform across large populations.

Sport and exercise scientists use indirect calorimetry as a gold standard approach to understanding physiological demands by a global measure of metabolic power (Oxendale, et al., 2017; Buchheit, et al., 2015; Koehler, et al., 2010). The quality of modern flow sensors and gas analysers have been shown to produce highly valid and reliable results (Macfarlane, 2001). The Jager ‘Oxycon Pro’ is compared with the Douglas bag method, during a graded exercise test to validate the device for use at low- and high-intensity exercise (Rietjens, et al., 2001). No statistical differences were identified in $\dot{V}E$ (r^2 0.996), $\dot{V}O_2$ (r^2 0.957) and $\dot{V}CO_2$ (r^2 0.980) between the two methods (Rietjens, et al., 2001). Bland-Altman validity analysis revealed minimal bias and low standard deviations in gas measurement between the Oxycon Pro and Douglas bag method. The use of mobile metabolic carts has been questioned and has been shown to underestimate $\dot{V}O_2$ during steady-state and graded incremental endurance exercise at high cycle ergo workloads, > 200 W, and so must be considered when using the device to calculate EE (Perret & Mueller, 2006).

3.3 Modelling energy expenditure

3.3.1 Overview of the di Prampero et al. (2005) sprint running model

di Prampero et al. (2005) first formulated a model (detailed in section 2.1) to estimate metabolic power from video analysis. This development had the benefit that athletes were able to move naturally and unimpeded by equipment. The model required a minimum of four camera systems strategically placed to determine the location of the athlete on the pitch. Through the use of video analysis, the athletes’ movements could be tracked and so the velocity at which the athlete moved. The movements were subcategorised depending on their velocity as a means to quantify and evaluate an athletes performance. The EE of the athlete is calculated via the measured cumulative distance covered by the athlete and the assumed energy cost of running. This assumed energy cost was determined based on the angle of torso lean during acceleration and deceleration which has been compared to inclined and declined running and is like running at constant speed on an equivalent slope (di Prampero, et al., 2005). During this study, instantaneous velocity was recorded using a radar gun. di Prampero et al. (2005) identified a strong relationship between modelled and measured instantaneous speed recorded by radar gun (r^2 > 0.98). This method proved advantageous being non-invasive and grants sports scientists the ability to profile fluctuations of metabolic load during play. GPS technology was suggested as an alternative method to video analysis to capture instantaneous velocity measures where video analysis may be unavailable due to cost or location such as a training venue (Osgnach, et al., 2010).

Osgnach et al. (2010) proposed alternative parameters to interpret metabolic power. Equivalent distance (ED), is the distance covered by the player if run at an aerobic steady pace. This is calculated by dividing EE by the energy cost of running (C_r) per unit of distance:

$$\mathrm{ED} = \frac{\mathrm{EE}}{\mathrm{C_r}} \tag{40}$$

Anaerobic index (AI), is the ratio of EE above a metabolic power threshold ($EE_{>TP}$) to overall EE:

$$\mathrm{AI} = \frac{\mathrm{EE_{>TP}}}{\mathrm{EE}} \tag{41}$$

The metabolic threshold is aligned with VO_{2max}. This assumes that energy delivered above this rate is generated from an anaerobic source.

The method proposed by Osgnach et al. (2010) produced comparable estimates of EE to that estimated from video analysis during a football match. The total distance was only a partial indication of overall EE as the energy demand of accelerations and decelerations could increase the EE for the total distance by 15 % (Osgnach, et al., 2010). Osgnach et al. (2010) proposed the measure of equivalent distance as a more appropriate means to measure overall EE. Furthermore, individualised thresholds can be identified based on VO_{2max} to determine energy contribution from aerobic or anaerobic sources (Osgnach, et al., 2010).

3.3.2 Application of di Prampero model

As Osgnach et al. (2010) identified, the metabolic player load can be greater from an increased number of accelerations/decelerations which demonstrates that traditional kinematic methods to quantify training load may not be representative of the demand of the exercise such as in small-sided games. This popular training tool monitored by traditional kinematic methods underestimates player load as players do not reach high-speed thresholds or accrue large total distances and so estimations of metabolic power provide a more valid method to represent the demands of small-sided games (Gaudino, et al., 2014). Furthermore, Gaudino et al. (2013) drew attention that not only in training protocols would there be discrepancies but also between positional requirements during a match. High-speed efforts (> 14.4 $km \cdot h^{-1}$) were compared with high-power efforts (> 20 W kg^{-1}) during football training sessions. This comparison is made plausible as the metabolic cost of consistent running at 14.4 $km \cdot h^{-1}$ is approximately 20 W kg^{-1} (Osgnach, et al., 2010). Results show that the demands of positions that are associated with fewer high-intensity actions, like central defenders and central midfielders, are underestimated by traditional forms of kinematic measurements with high power distance being 62 to 84 % greater than high-speed running distance (Gaudino, et al., 2013). This therefore indicates the value of prescribing individualised training load based on the metabolic requirement of players based on position. However, it does not imply that specific drills or exercises must be programmed solely on internal descriptors and negate the use of kinematic measurements.

Positional differences in physical demands have been explored across a variety of team field sports (Coutts, et al, 2015; Kempton, et al., 2015; Gaudino, et al., 2014; Gaudino, et al., 2013; Osgnach, et al., 2010). Coutts et al. (2015) explored the energetic cost of professional athletes in the Australian Football League (AFL). Data from 19 matches were retrieved from GPS devices and metabolic measurements were estimated using the di Prampero model detailed in section 2.1. This study reported higher values of metabolic power in AFL compared to other field sports of football (Gaudino, et al., 2013) and rugby league (Kempton, et al., 2015) during match play. Although using the equivalent distance index presented by Osgnach et al. (2010), AFL presented lower values than football training (Osgnach, et al., 2010) and rugby league match play (Kempton, et al., 2015). These findings were contributed to AFL matches being played on larger pitch sizes than the other sports, therefore, allowing players to run greater distances between accelerations/ decelerations or collisions. The overall EE during AFL matches was similar to that reported by Osgnach et al. (2010) in football match play (Coutts, et al, 2015). Kempton et al. (2015) presented results akin to those of previously mentioned studies whereby traditional kinematic measures of high-speed running could underestimate match-play demands in comparison to energetic measures in rugby league. Additionally, the equivalent distance ratio by Osgnach et al. (2010), provided value when evaluating the contribution of accelerating distance to overall distance. Total distance in this study was approximately 25 to 30 % lower than the equivalent distance, demonstrating the importance of measuring dynamic actions when quantifying the demands of sport (Kempton, et al., 2015).

The model proposed by di Prampero et al. (2005) has been applied in theoretical settings to explore the reliability of the model. Stevens et al. (2015) conducted a study with adult semi-professional footballers, whereby the energy cost was determined from the use of a local positioning measurement system (LMS) and compared to values from a portable metabolic cart. A continuous running and shuttle running test was completed for a total of 18 minutes, with a starting average velocity of 7.5 $km.h^{-1}$, increasing by 0.5 $km.h^{-1}$ every 3 minutes until a velocity of 10 $km.h^{-1}$ was achieved. Stevens et al. (2015) identified the energy cost of continuous running, calculated from LMS data to overestimate EE by approximately 8 % when applied with the di Prampero model. This overestimation may be attributed to human error in pacing when trying to maintain a constant velocity, whilst not on a treadmill. The subjects would be performing small accelerations and decelerations to maintain a steady-state pace which would be included in the averaged data for processing, and the LMS device has been identified to incorrectly measure low-velocity accelerations as they can be misinterpreted for noise (Stevens, et al., 2014). Shuttle running was performed over 10 m with a 180° turn; the EE for this test was underestimated by about 15 % compared to respiratory gas analysis, although the overall EE for shuttle running was greater than continuous running (Stevens, et al., 2015). Factors to consider for the underestimation are 1) the equivalent slope estimation is based on research conducted with elite mountain racers, and the energy cost of elite runners is lower at constant velocities compared to professional footballers (Sassi, et al., 2011), and 2) the method using LMS underestimates actions such as 180° changes of direction by 5 %, so a multiplication of 1.05 could reduce the error to approximately 10 % (Stevens, et al., 2014).

EE values historically have been hard to quantify during intermittent running tests, such as the yo-yo intermittent running test. This is because the athletes’ repeated changes in direction and continuous cycles of accelerations and decelerations mean a constant steady-state velocity cannot quite be attained (Buglione & di Prampero, 2013). Buglione and di Prampero (2013) used mathematical modelling (di Prampero, et al., 2005), from multi-camera system analysis, to estimate the energy cost of shuttle running modes between 8.5 and 22 m, as corresponds with commonly used testing protocols. The data was compared with a kinetic approach, by combining kinetic energy, estimated from max velocity, and the energy cost of steady-state running and indirect calorimetry combined with blood lactate concentration (B[La]). The results of the study found the two modelled approaches, the kinetic approach and the di Prampero model, yield similar values for EE with no significant differences in the outcomes. For shorter shuttle distances (8.5 to 10 m), both models underestimated the energy cost of shuttle running at an average speed of 4 m/s producing an estimate of 9.5 J/(kg·m) compared to indirect calorimetry, 14 J/(kg m). This was because the indirect calorimetry exhibited greater energy cost at faster average velocities. As for the longer distance shuttle runs (18.5 to 22 m), all three methods generated similar estimations of energy cost for shuttle running. Buglione and di Prampero (2013) highlighted a greater energy demand (approx. 3.5 times) of shuttle running compared with steady-state running as seen in previous research (Minetti, et al., 2002; Margaria, et al., 1963). This could be attributed to the greater energetic demand of continual acceleration and deceleration actions that in turn increase the angle of the equivalent slope (di Prampero, et al., 2005) being more comparable to uphill and downhill running than to constant velocity flat terrain running.

Zamparo et al. (2014) conducted a similar investigation around the energetics of shuttle running, within male junior basketball players, intending to identify the energy cost of running with different turning angles (0 - 180° change of direction) and across different distances (5 – 25 m). Results at shorter distances (10 m) indicated a significantly larger energy cost when the change of direction increased from 90 to 180°, $P < 0.05$. The cost of shuttle running across the 10 m was 5 times larger than that of the steady-state continuous running on flat terrain (Zamparo, et al., 2014). Although, across conditions with changes of direction < 180°, no significant difference in energy cost was identified in shuttle runs with an effect size of 0.33. This would indicate that for changes in direction < 180° there is minimal change in physiological demand, but this would not negate the significant changes in biomechanical actions such as decelerating and accelerating forces, joint force loading and change of momentum (Schot, et al., 1995). Furthermore, significant differences were noticed between distances of 5, 10 and 25 m at a 180° change of direction. It is worth noting that players were unable to able to maintain the same average velocity during 5 m shuttles which may have contributed to the metabolic differences. Zamparo et al. (2014) found that the energetic cost for a 180° turn, for all distances, was 2.5 to 7 times larger than that of running on flat terrain at constant velocity. Overall cardiorespiratory data and B[La] increase with shuttle distance but the energy cost decrease. In agreement with the findings of Buglione and di Prampero (2013), the higher energy cost was identified to be at shorter shuttle distances, but across all distances, the energy cost of shuttle running was greater than that of flat terrain steady-state running. Using this insight, practitioners need only adjust shuttle distance dependant to increase or decrease the metabolic demand on the athlete dependent on the training outcome.

Buchheit et al. (2015) implemented the di Prampero model, collecting instantaneous velocity data from a 4 Hz GPS device. The study aimed to compare estimations of the di Prampero model with indirect calorimetry during football-specific circuits. The circuits included slalom running with a ball and sport-specific actions such as receiving and passing a ball as well as shooting. The author reported significant underestimations of metabolic power from the di Prampero model and presented an argument of the effectiveness of modelling metabolic power. However, Buchheit et al. (2015) does acknowledge that the findings require further support from future research within match simulation and in an adult cohort to confirm them. The di Prampero model was reported to underestimate metabolic demands, compared with indirect calorimetry, by up to 4 times during recovery phases (Buchheit et al., 2015). Although, this is to be expected as there is little-to-no metabolic demand during this time as there is minimal velocity data recorded during rest. However, there will be a metabolic supply increase in VO_2 kinetics, to replenish the phosphocreatine system from its depletion at the onset of exercise (Cleuziou, et al., 2004; Perrey, et al., 2002;

Paterson & Whipp, 1991; Maehlum, et al., 1986). Additionally, Buchheit et al. (2015) stated moderate reliability for the di Prampero model in calculating average metabolic power during the football-specific circuit, however the distance at high metabolic power (> 20 $W \cdot kg^{-1}$) revealed a very large typical error (CV 73.6%). The accuracy of GPS devices with < 10 Hz sampling rate have been questioned in research and may underestimate instantaneous velocity and distance measures (Osgnach, et al., 2016; Varley, et al., 2012; Waldron, et al., 2011). Osgnach et al. (2016) wrote a response to the research presented by Buchheit et al. (2015), in which physiological principles and modelling assumptions were set forth to offer an explanation for the findings and provide clarification on applying the model.

Initially, Osgnach et al. (2016) clarified key differences between the energy supply and metabolic demand. To that end, the energy cost of an exercise does not always equal the metabolic demand, especially in intermittent bouts of high- and low-intensity work such as in football training or match play. For instance, the energy cost at the onset of exercise is greater than the $\dot{V}O_2$ supply until a steady state is reached where the $\dot{V}O_2$ supply meets the energetic cost. On the contrary in recovery periods the $\dot{V}O_2$ supply is greater than the energy cost (Osgnach, et al., 2016). Figure 2 in Buchheit et al.'s (2015) (reproduced as Figure 2) article showed the $\dot{V}O_2$ included the measure at rest, but was compared to the net metabolic power, which is the work performed above rest, not providing a true comparison (Figure 2, yellow arrow) (Osgnach, et al., 2016). Additionally in Figure 2, metabolic power was seen to surpass 30 $W \cdot kg^{-1}$ (approximately, 85 ml $O_2 \cdot kg^{-1} \cdot min^{-1}$ above rest values) eliciting a significant contribution from the anaerobic lactate system to fulfil the energy requirement, which raises concerns with a direct comparison between measured $\dot{V}O_2$ and modelled metabolic power (Figure 2, green arrows) (Osgnach, et al., 2016). Finally, when metabolic power is zero, the measured $\dot{V}O_2$ begins to increase indicative of the onset of exercise (Figure 2, red arrows) (Osgnach, et al., 2016). Osgnach et al. predict if these concerns are met, to estimate metabolic power and measure $\dot{V}O_2$, the yields from both methods will produce more meaningful results.

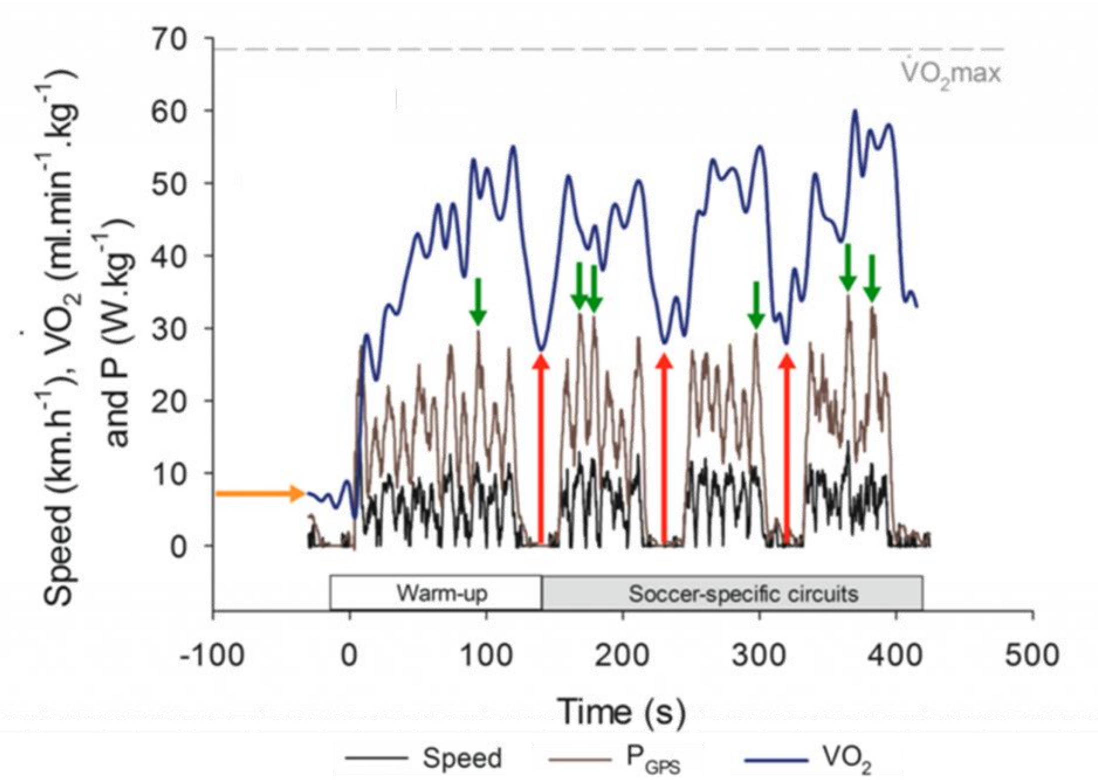

Figure 2 Oxygen uptake (VO_2), speed and metabolic power estimated from locomotor demands (P_{GPS}) during warm-up and the 3 exercise bouts in a representative player. VO_{2max}: maximal oxygen uptake reached during the incremental test to exhaustion. This figure is reproduced from Figure 2 of Buchheit et al. 2015. Refer to the text for the meaning of the arrows.

3.3.3 Overview of Gray et al. (2020) mechanical model

Gray et al. (2018) proposed a novel approach to assessing energetics by modelling mechanical load. The Gray model (detailed in section 2.3), through the use of GPS velocity data and running kinematics, estimates the mechanical work performed by an individual during overground locomotive exercise to provide estimations of EE through the application of the energy-work theorem (Gray, et al., 2018). The total mechanical work is calculated from the sum of work performed to propel the COM horizontally, vertically, to overcome air resistance, and to move the limbs (Gray, et al., 2020). The model demonstrated the ability to produce estimates from absolute- and acceleration-running velocities and can attribute different mechanical loads to the individual during varied walking and running patterns. Like the model presented by di Prampero et al. (2005) advantages of this alternative mechanical model is attributed to the non-invasive method of data retrieval which will not impact the performance of an athlete in field sports. Sports scientists can quantify the metabolic load of the athletes and in turn, identify metabolic and mechanically demanding bouts which may have attributed to performance outcomes. Progressive work utilising the mathematical model of Gray et al. (2020) has permitted the estimation of exercise tolerance from modelling overground power in exhaustive running (Vassallo, et al., 2020) and the assessment of the power-duration relationship in overground running (Vassallo, et al., 2021).

3.3.4 Application of Gray et al. (2020) mechanical model

Vassallo et al. (2020) utilised the mechanical model by Gray et al. (2020) (detailed in section 2.3) to obtain instantaneous power output and mechanical work from raw velocity data retrieved from a 10 Hz GPS receiver. This enabled Vassallo et al. (2020) to calculate an individual's time to exercise intolerance (T_{LIM}) and calculation of W-prime (W') balance using a differential method ($W'_{BALdiff}$). The $W'_{BALdiff}$ provided a close estimation (~ 9 s difference) of T_{LIM} to the over-ground W'_{BAL} derived from a locomotor-specific regression equation, which provides validity to the differential method. Furthermore, the mechanical model (Gray, et al. 2020) has been employed to estimate bioenergetics to assess power-duration relationships during over-ground running (Vassallo, et al., 2021). Vassallo et al. (2021) ran a comparison of power- and speed-duration relationships during a 3 minute all-out over-ground running test. The results demonstrated reliable power-duration indices comparative to speed-duration, critical power coefficient of variation (CV) 2.6% had similar error to critical speed CV 2.0% and W' measured CV 8.1% and D-prime CV 5.6%. This concurs with previous research, in which W' and D-prime produce great variability than critical power and critical speed (Johnson, et al., 2011; Gaesser & Wilson, 1988). As the Gray et al. (2020) mechanical model has been able to enable further mathematical models, by accurately estimating mechanical work and power, to determine valid estimations of exercise tolerance (Vassallo, et al., 2020) and reliable estimations of power-duration relationships (Vassallo, et al., 2021), by extension, it is predicted that the mechanical model (Gray, et al. 2020) will facilitate accurate estimations of metabolic power in the Gray model.

3.4 Global positioning systems (GPS)

GPS technology has become common practice for sports scientists to monitor external load (Bourdon, et al., 2017; Malone, et al., 2017; Scott, et al., 2016; Cummins, et al., 2013). The GPS devices must obtain a high level of intra- and inter-device validity and reliability to produce consistent accurate data between units (Heale & Twycross, 2015). These commercially available devices can calculate athlete velocity by use of the Doppler shift (Scott, et al., 2016), by examining changes in frequency of the satellite signal due to the movement of the receiver (Larsson, 2003). GPS has been advantageous over other movement tracking technologies by being economically viable, producing real-time feedback, and ability to track multiple athletes at once (Scott, et al., 2016; Aughey, 2010). Commercial GPS devices are classified by their rate of sampling and originally had a sampling rate of 1 Hz. Through continuous advancements in technology, commercial GPS devices normally sample at rates of up to 20 Hz (Polglaze, et al., 2021; Scott, et al., 2016) and are located between the shoulder blades. Increased sampling speeds were accompanied by the integration of triaxial accelerometers to be able to sum the accelerations in the X, Y, and Z-axis, as seen in Figure 3, to generate composite vector magnitudes (G-force).

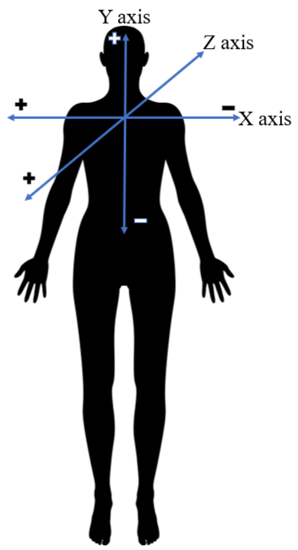

Figure 3 Representation of location and orientation of triaxial accelerometer axes direction. (The figure outlined is facing forward – out of the page).

3.4.1 Reliability and validity of GPS

1 Hz GPS devices

Reliability of intra-unit refers to the consistency of a single device across several sessions (Coutts & Duffield, 2010). It is paramount that devices have good intra-unit reliability as this allows for comparisons of an athletes activity between sessions. Devices that sample at 1 Hz have been identified to have good reliability in linear and curvilinear running tasks (Gray, et al., 2010; Portas, et al., 2010 Petersen, et al., 2009; Edgecomb & Norton, 2006). Edgecomb and Norton (2006) reported a relative technical error measurement (TEM) of 4.8% for distance measurements across distances between 128 to 1386 m compared with that measured by calibrated trundle wheel and intra-device reliability with a TEM of 5.5%. In more recent studies the values for intra-device reliability were improved, reporting CV < 5% during linear and non-linear locomotive tasks of walking, jogging, and running of up to 8800 m (Gray, et al., 2010; Portas, et al., 2010 Petersen, et al., 2009). Petersen et al. (2009) found that for velocities between 2 to 5 $m.s^{-1}$, 1 Hz GPS devices had valid measures compared with the standardised distance, standard error estimate (SEE) ≤ 2.1%. Gray et al. (2010) stated CV between and within devices was 2.8% and 2.6% although reduced validity was seen in increased movement intensities in non-linear locomotion, underestimating distance travelled.

Minimal research has been performed on the validity of velocity data obtained from 1 Hz devices (Scott, et al., 2016). Barbero-Álvarez et al. (2010) determined that GPS velocity data produced valid measures to estimate peak velocity during a 30 m sprint with a significant Pearson correlation between GPS devices and timing gates for peak velocity (r^2 -0.93)and total sprint time (r^2 -0.96). Furthermore, intra-device reliability was acceptable with CV 1.2% at max velocity and CV 1.7% for summed max velocity. MacLeod et al. (2009) compared the velocity of 1 Hz GPS devices to that from timing gates during hockey-related circuits. Pearsons correlation ($r^2 \geq 0.99$) identified that the 1 Hz produced valid measurement of speed across shuttle, linear, and T-drills performed at a variety of velocities. Coutts and Duffield (2010) compared the velocity reliability across 3 1 Hz GPS devices and the inter-device reliability was identified as good (CV 2.3 to 5.8%) during a circuit comprising of varying forms of locomotion (walking, jogging, and sprinting) with agility and rest components.

5 Hz GPS devices

Across the literature, a consensus has been drawn that 5 Hz devices can accurately measure athlete distances (Scott, et al., 2016). During linear walks and low velocity running, Portas et al. (2010) reported high velocity (SEE 3.1% and 2.9%) over distances from 50 to 60 m. Similarly, Petersen et al. (2009) reported the validity of distance quantification for 5 Hz devices in curvilinear walking and running distances between 600 to 8,800 m (SEE 0.4 to 3.8%). Rampinini et al. (2015) observed differences when performing high velocity shuttles (CV 7.8%) and even larger discrepancies when performing at very high velocity running (CV 23.2%). Intra-device reliability has generally been identified as good when measuring distance during walking, jogging, and running in linear or curvilinear patterns (CV < 5%) (Portas, et al., 2010; Petersen, et al., 2009). In concurrence with the former research, Waldron et al. (2011) reported 5 Hz GPS to be reliable when quantifying distance and speed (CV 1.62% to 2.3%). Although the devices underestimate both distance measured by tape, and velocity measures, compared with timing gates, so the validity was questioned. Furthermore, moderate levels of validity of the velocity measures (CV

< 10%) were observed in linear running and seemed to improve as distance increased. Varley and colleagues (2012) had similar results whereby measurements of instantaneous velocity were valid at moderate or high initial velocities (between 3 to 8 $m \cdot s^{-1}$) of acceleration (CV ≥ 9.5%) and for high-velocity (5 to 8 $m \cdot s^{-1}$) constant speed running (CV 3.6%). Although, accelerations with initial low speeds and decelerations had poor validity for instantaneous velocity (Varley, et al., 2012). Inter-device reliability has been questioned, during simulated multi-directional protocols replicating field sports movements, for mean velocity (CV 19.8 to 33.4%) and peak velocity (CV 14.2 to 31.5%) (Vickery, et al., 2014).

10 Hz GPS devices

Early results of 10 Hz GPS devices demonstrated an acceptable measure of validity for sprint distances of 15 m and 30m with mean standard error of measurement (SEM) respectively 10.9% and 5.1% (Castellano, et al., 2011). Despite the SEM of 15 m sprinting being over 10% (indicative of poor validity), 8 of the 9 GPS devices used produced SEM < 6%. Furthermore, Castellano et al. (2011) found 10 Hz devices to have good inter-device reliability for distance performing sprints across 15 and 30 m (CV 1.3% and 0.7%). Vickery et al. (2014) found that 10 Hz devices provided reliable measures of distance during simulated cricket protocols, for fielding and sprinting (fast bowling), which were similar to values of the criterion data recorded by the 22 multi-camera VICON system (P > 0.05). 10 Hz GPS devices across literature, exhibit moderate and good levels of validity of instantaneous velocity measures when performing constant speed running and accelerations, irrespective of the initial velocity, and improved when the velocity of actions increase (Scott, et al., 2016). In contradiction to this, poor validity from 10 Hz devices was seen during deceleration actions (Varley, et al., 2012). Likewise, Akenhead et al. (2014) produced similar results, reporting instantaneous velocity measures were valid for accelerated running up to 4 $m \cdot s^{-1}$ (SEE 0.12 – 0.19) but may be compromised above this threshold (SEE 0.32). Vickery et al. (2014), similarly found no significant differences (P >0.05) between peak speed measures of 10 Hz GPS devices and that of the VICON camera system across cricket fast bowling and fielding protocols, such as 5-m sprint acceleration, a 5-m sprint with a walking start, a run-a-three protocol, change of direction circuits, and random 10 s task of field-based sports movements. Furthermore, in the same study, mean velocity measures were not significantly different from that measured by VICON in all tasks except during the change of direction circuit and a random 10 s task of field-based sports movements. Johnston et al. (2014), found 10 Hz GPS to estimate valid ($P > 0.05$) and reliable measure (TEM 1.3%) of total distance and provided improved measures of devices that sample at a lower frequency.

15 Hz GPS devices

Currently, there is limited literature on the reliability and validity of 15 Hz GPS devices. Vickery et al. (2014) found, when using two 15 Hz GPS devices, that both devices had meaningful differences of distance measurements, during change of direction circuits, compared to that from the VICON system. Additionally, Vickery et al. (2014), found both GPS devices to have similar distance results to VICON in the random 10 s task of field-based sports movements, 5-m sprint with a walking start, and a run-a-three protocol. Comparably, Johnston et al. (2014) found no meaningful difference ($P > 0.05$) between the criterion distance, measured by tape measure, and values recorded by the GPS device supporting the validity of distance measures from the 15 Hz units. Furthermore, they reported intra-device reliability for total distance (TEM 1.9%, ICC −0.20) and low velocity running distance (TEM 2.0%, ICC 0.98). Inversely when reporting high and very high-velocity running distance, Johnston et al. (2014) stated that the intra-device reliability decreases and becomes poor (TEM 7.6%, ICC 0.94, TEM 12.1 accordingly). Vickery et al. (2014) found 15Hz GPS devices to have moderate levels of intra-device reliability, when measuring distance, during the 15 m fast bowling protocol (CV 5.5%, intraclass correlation (ICC) 0.55), change of direction circuit, with shallow cutting angles, (CV 6.2%, ICC 0.46), and random 10 s task of field-based sports movements (CV 8.2%, ICC 0.10) and poor during high-intensity cricket fielding protocols and change of direction circuits with tight cutting angles (CV 12.5 to 17.9%). Whereas Rawstorn et al. (2014) observed 15 Hz GPS devices to have good intra-device reliability during a football shuttle test (CV 2.44%, ICC 0.99). This is similar to the findings of Buchhiet et al. (2014) where good to moderate levels of intra-device reliability was seen when reporting total distance (CV 3%), low velocity (CV 2%), and high velocity (CV 6%) running.

Suggestions have been made that increased sampling frequency may be detrimental to the validity of velocity measures from GPS devices (Scott, et al. 2016). Despite this, Vickery et al. (2014) found 15 Hz devices to be valid for both peak and mean velocity in simulated cricket fast bowling, fielding, and a run-a-three protocol. Although there were discrepancies during the shallow change of direction circuit for mean velocity measures and, during the tight angle change of direction circuit, one device substantially underestimated mean velocity and the other device overestimated the peak velocity measure (Vickery, et al., 2014). Johnston et al. (2014) studied simulated sports circuits; one GPS device was found to be significantly different to that of the criterion velocity measure (*P* 0.009), although Pearson correlations for the two devices were large (*r* 0.64) and very large (*r* 0.76) effects. The inter-device reliability was reported as moderate during cricket fast bowling (CV 8.8%, ICC 0.50), a random 10 s task of field-based sports (CV 7.5%, ICC 0.39), and a shallow change of direction task (CV 7.8%, ICC -0.14) when measuring mean velocity (Vickery, et al., 2014). Furthermore, the inter-device reliability for measuring mean velocity was found to be poor for the tight angle change of direction circuit, run-a-three, and cricket fielding protocols (CV 10.9 to 16.3%). In addition, the study revealed that inter-device reliability for peak velocity, across both change of direction circuits, run-a-three test, cricket fielding and the 10 s task of field-based sports movements protocols, to be poor (CV 11.9 to 20.0%), although the fast-bowling protocol to be moderate (CV 8.4%, ICC 0.36) (Vickery, et al., 2014). Inconsistent with these findings, Buchhiet et al. (2014) presented results of good intra-device reliability for measuring mean speed in a standardised running circuit (CV 1%) and moderate reliability (TEM 8.1%, ICC -0.14) during sport simulated circuits (Johnston, et al., 2014).

Whilst there has been conflicting reliability and validity measures reported on 15 Hz units for high velocity and change of direction tasks, the question arises whether a higher sampling rate is indicative of more accurate results. Johnston et al. (2014), when comparing 10 Hz and 15 Hz GPS devices, found the intra-device reliability measures to be more accurate, and suggested possible inconsistencies in reliability as the sampling rate is increased beyond 10 Hz but there was no empirical evidence to confirm this. In addition, the validity of velocity measures was stronger for 10 Hz devices (*r* 0.89 and 0.91) compared with the 15 Hz devices (*r* 0.64 and 0.76), indicating there may be no gain in increased sampling rate (Johnston, et al., 2014). This study suggests that practitioners should take precautions to understand that an increased sample rate may improve the validity or reliability of the data retrieved.

Chapter 4.0 Methods

4.1 Participants

Thirteen healthy male adults (see Table 1) volunteered to participate in the study. All volunteers were informed of the experimental procedures, the benefits of the research and risks associated with participation. Each participant provided written informed consent before undergoing pre-exercise health screening and only participated in the study if identified as low risk. Participants were provided pre-test instructions and informed to avoid heavy exertion or vigorous exercise 24-h before testing, to consume a carbohydrate-dense meal one to four hours before testing, to abstain from the consumption of stimulants or depressants three hours before testing, and to arrive in a euhydrated state. The study received ethical approval from the Human Research Ethics Committee of the University of New England, in accordance with the Declaration of Helsinki.

Table 1 Table of participant characteristics.

	Stature (cm)		Body mass (kg)		Age (years)		VO_{2max} (ml·kg·min)	
n	Mean	SD	Mean	SD	Mean	SD	Mean	SD
13	177.9	6.2	75.8	13.68	25	6	44.6	9.6

4.2 Experimental design

A randomised crossover design was implemented to compare the method of estimating EE from the demand of the exercise, through modelled velocity data, to measured EE from the supply of oxygen and B[La]. Each participant completed each test as outlined in Figure 4.

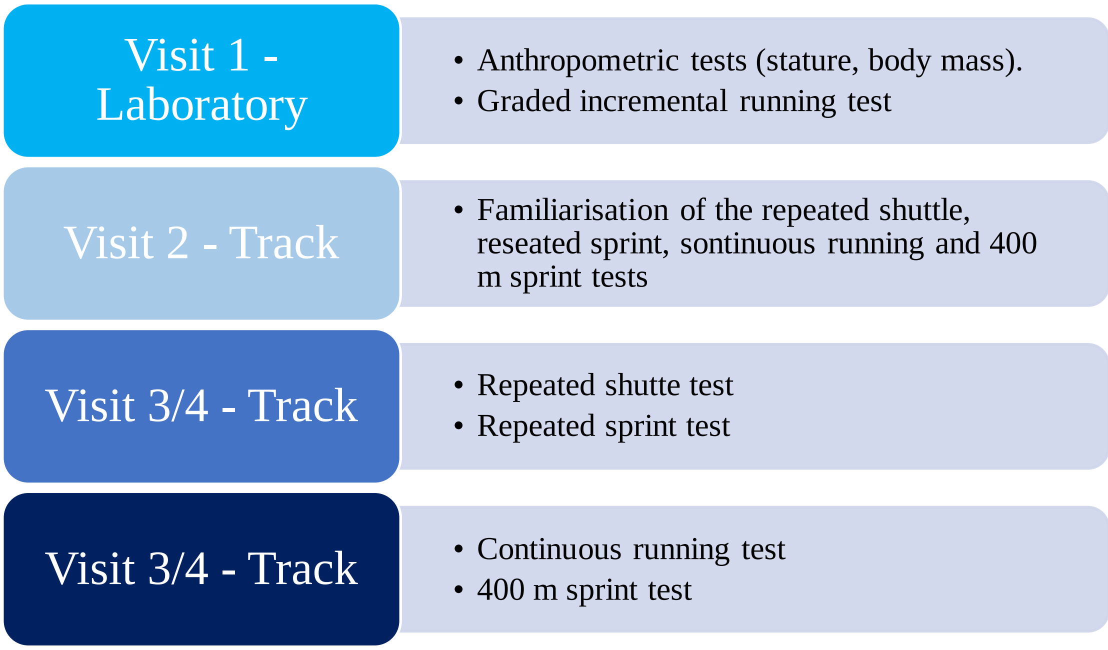

Figure 4 Participant testing schedule

Participants performed testing on four occasions, with each visit 1-h in duration, performed approximately 1-wk apart. The initial visit, consisting of the graded incremental running test and anthropometric measurements, was conducted in laboratory conditions and all subsequent visits were performed on a circular running track. On the second visit, the participants performed a familiarisation session, whereby the participants rehearsed the running tests. On the third and final visit, participants were randomly allocated and performed the repeated shuttle test over 20 m, the repeated sprint test over 40 m, the continuous running test (repeated laps the circumference of a 400 m athletics track), and a 400 m sprint (one complete lap of the athletics track). For each test, including during the familiarisation session, the participant wore a mobile metabolic cart for direct gas analysis, a GPS receiver, and B[La] was taken prior to exercise to measure homeostatic physiological markers and 2 min into the recovery of each test.

To mitigate the carryover effect, of one test impacting another, the participants performed a familiarisation session and were randomly allocated testing protocols to minimise the learning effect. Furthermore, participants would not start the next test until the physiological markers returned to homeostatic values and the participant verbally consented, that they felt fully recovered. Additionally, during the metabolic calculations, the energy contribution from lactate was fixed at 2.0 mmol·L for all participants.

4.3 Experimental Protocols

Incremental running test

The initial visit entailed a graded incremental running test to volitional fatigue, performed on a treadmill (HP Cosmos Saturn, Traunstein, Germany) (laboratory conditions: ambient temperature 18.0°C, barometric pressure 677 mmHg, ambient relative humidity 62%). Participants wore a sealed face mask around the nose and mouth to collect and analyse expired air through the static Jaeger Oxycon Pro metabolic system (Carefusion Germany, 234, GmbH, Hochberg, Germany). The test commenced with the treadmill on a 1% incline at 8.0 km·h^{-1} for the first minute and increased by 1.0 km·h^{-1} for each minute thereafter. The speed increase was controlled by the researcher and paced by the treadmill. This continued until the participant could no longer keep running, upon maximal effort voluntary fatigue, and the test was concluded. The graded incremental exercise test provided an accurate estimation of $\dot{V}O_{2max}$ (Beltz, et al., 2016; LourenÇo, et al., 2011). Work performed above $\dot{V}O_{2max}$ has been thought to correspond with anaerobic energy pathways (Wasserman, 1984; Davis, et al., 1976) and work performed below $\dot{V}O_{2max}$ suggests the primary source of energy is from aerobic respiration (Bassett & Howley, 2000; Davis, et al., 1976). The $\dot{V}O_{2max}$ further indicates the physical fitness level of the participants.

Repeated shuttle test

The 20 m shuttle runs were performed on a 400 m circular running track (mean ± SD: temperature 17.64 ± 5.78 °C, relative humidity 78.96 ± 14.97 %, barometric pressure 684.55 ± 3.78 mmHg, altitude 987.00 ± 0.00 m), between two markers continuously for 6 min. The test was run at a constant submaximal speed of 12 $km \cdot h^{-1}$. The pace was set by a pre-recorded metronome that was set to play a tone every 6 s through a portable MP3 device (Apple iPod Mini, Cupertino, California, United States) and earphones. Throughout all field tests, participants wore a Jaeger Oxycon Mobile (Carefusion Germany 234 GmbH, Hoechberg, Germany) portable metabolic system, fastened to the upper-back which sampled gas data every 15 s and a 15-Hz GPS device (AMR Sport Motion Trax, Gold Coast, Qld, Australia), containing a skytraq venus module chipset, as used in other commercially available GPS receivers (personal communication, April 2021), mounted within a harness, placed between the shoulder blades. Following the 6 min exercise period, the participant immediately began a 6 min period of passive recovery whereby blood capillary samples were collected from the fingertip with a lancet and analysed on-site with a Lactate Pro device (Arkray, Japan).

Repeated sprint test

The repeated sprint test was performed over 40 m, identified by set markers on the track, and participants were required to perform a total of six repetitions separated by a 30 s rest interval. Participants were instructed to run as fast as possible (maximal effort) for each sprint repetition. On completion of all six repeated sprints, the test was ended, and blood samples were taken at the beginning of the passive recovery and immediately analysed.

Continuous running test

Six minutes of continuous running was performed around a 400 m athletics track at a constant speed of 12 $km \cdot h^{-1}$. The track had markers placed every 20 m, and the participant was informed they had to reach each marker on the tone played by the pre-set recording. A tone was played every 6 s to pace the participants. On completion of the 6 min of exercise the recording ended, and participants commenced 6 min of seated passive recovery, in which time blood capillary samples were collected.

Four-hundred metre sprint test

Participants were asked to perform a singular 400 m sprint in the quickest time possible. The 400 m bout was followed by 6 min of seated passive rest when the investigator collected blood capillary samples to analyse lactate concentration immediately.

Rationale for exercise test selection

The outlined exercise tests were selected to provide an insight how the models can be implemented within a variety of field-based team sports. Most athletes, in field-based team sports, will at some time have to perform, in competition or training, steady-state, aerobic work, which is represented by the continuous running test. Also, most team field sports are intermittent in nature with the predominant amount of work performed below maximal intent such as the shuttle running test. In many cases in attacking play, within field sports, athletes will be required to either perform an extended run at high intensity as simulated by the four-hundred metre test or be required to perform repeated high intensity sprints when a tactical advantage or disadvantage suddenly occurs within a game.

4.4 Data Analysis

Blood lactate

The B[La] was estimated from the net accumulation above rest, assumed to be 1 mM, using an energy equivalent of 3 ml $O_2 \cdot kg \cdot mM$ (di Prampero & Ferretti, 1999; di Prampero, 1981) to calculate EE. B[La] EE was then collated with that determined by indirect calorimetry gas analysis, hereon, the combined data will be referred to solely as gas analysis, to obtain overall total EE (see Figure 5).

Indirect calorimetry

Using respiratory gas collection, the sum of EE from the aerobic energy system was calculated using oxygen consumption, normalised by body mass $\dot{V}O_2 \cdot kg$ (ml·min·kg), and multiplying by the energy equivalent of 20.9 J·ml of oxygen (respiratory quotient = 0.96) as done by Buglione and di Prampero (2013), to calculate aerobic energy contribution (Aer). Anaerobic alactic (AnAl) EE was obtained from $\dot{V}O_2$ kinetics over the 6 min recovery phase. Net values of $\dot{V}O_2$ were taken from the final 2 min of the recovery phase and linearly interpolated. By back extrapolation of the obtained function from the recovery phase to zero, permitted the estimation of the fast component of the AnAl oxygen debt (Figure 5). A sum of the aerobic and anaerobic (AnAl and Bla) was used to calculate overall EE, expressed as:

$$\mathrm{Aer} + \mathrm{AnAl} + \mathrm{Bla} = \mathrm{Overall\ EE} \tag{42}$$

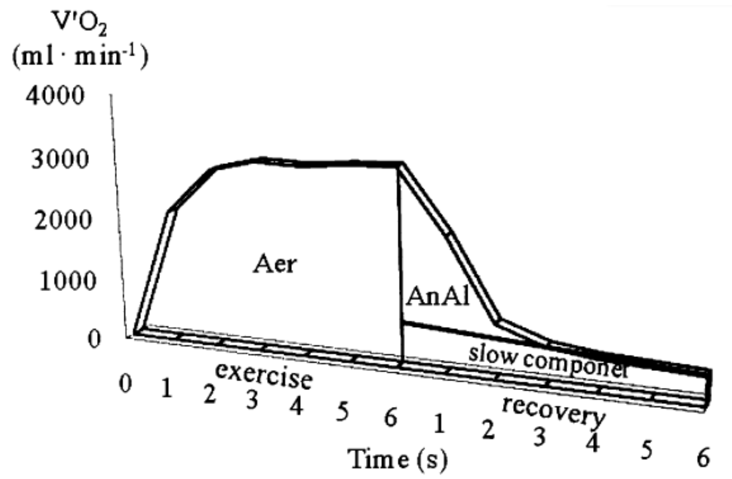

Figure 5 Typical example of the time course of $\dot{V}O_2$ above resting during 6 min of exercise and 6 min of recovery. The straight-line shows regression for obtaining the slow component of $\dot{V}O_2$ kinetics after exercise. The area below the $\dot{V}O_2$ curve during exercise is a measure of the aerobic energy yield. The area between straight line and actual $\dot{V}O_2$ kinetics in recovery is a measure of the anaerobic alactic energy yield (AnAl). Reproduced from Buglione and di Prampero (2013).

di Prampero Model

Velocity data were processed through the di Prampero metabolic power model outlined in section 2.1 to gain an estimate of EE. Once EE estimation is obtained, the results are compared with that of the indirect calorimetry and the Gray model.

Gray Model

The velocity data were input into the Gray model, through which mechanical and metabolic modelling (described in section 2.2) calculations produced an estimated value of metabolic power and EE. The results generated from the model were then compared with those from indirect calorimetry and the di Prampero model.

4.5 Statistical Analysis

Checks for sphericity were conducted using Mauchly's test, sphericity was violated and the Greenhouse-Geisser correction was used. Repeated measures two-way analysis of variance (RM 2-way ANOVA) were conducted, for each exercise test, 400 m, continuous running, repeated shuttle running, and repeated sprint running, for gas analysis measures of overall aerobic EE, overall anaerobic EE, and total overall EE, compared to modelled data of EE below threshold power, EE above threshold power and total overall EE, respectively, across independent variables (three levels: the di Prampero model, the Gray model, and gas analysis). A second RM 2-way ANOVA was conducted across each exercise test to compare gas analysis measures of the aerobic contribution to EE during exercise, aerobic contribution to EE during recovery, and total overall EE from aerobic contribution to modelled values of overall EE during exercise, overall EE during recovery, and total overall modelled EE. Bonferroni *post hoc* tests were used to examine specific differences between the three methods. Statistical significance was set at $P < 0.05$. Two continuous running, one 400 m, two repeated shuttle, and three repeated sprint trials were excluded from statistical analysis due to incomplete GPS or metabolic cart data sets.

Chapter 5.0 Results

5.1 400 m total energy expenditure

There was an effect of the method used to derive overall EE during 400 m running ($F_{(1.028,10.277)} = 253.585$, $P < 0.001$, $\eta_p^2 = 0.962$). Pairwise comparisons showed the Gray model to produce greater EE values than the di Prampero model ($P < 0.001$), the gas analysis produced greater EE values than the di Prampero model ($P < 0.001$), and gas analysis yielded larger EE values than the Gray model ($P < 0.001$). During 400 m running, there was an interaction effect between method to calculate EE x exercise intensity ($F_{(1.287,12.867)} = 37.258$, $P < 0.001$, $\eta_p^2 = 0.788$). In 400 m running, the Gray model estimated larger EE above threshold power, than the di Prampero model ($P < 0.001$), the di Prampero model estimated significantly lower values than that determined by gas analysis for EE above threshold power ($P < 0.001$), and the Gray model produced lower values than gas analysis for EE above threshold power ($P = 0.003$) (Figure 6A). In 400 m running, when measuring EE below threshold power, the EE measured by gas analysis produced greater values than di Prampero model ($P < 0.001$) and the Gray model ($P < 0.001$), but the di Prampero and the Gray model produced similar estimations ($P = 0.951$) of EE (Figure 6B). Measured overall EE, during 400 m running, the gas analysis produced significantly greater values than that estimated by both the di Prampero model ($P < 0.001$) and the Gray model ($P < 0.001$). There was a difference between the two models, where the Gray model estimated a larger overall EE compared to the di Prampero model ($P < 0.001$) (Figure 6C).

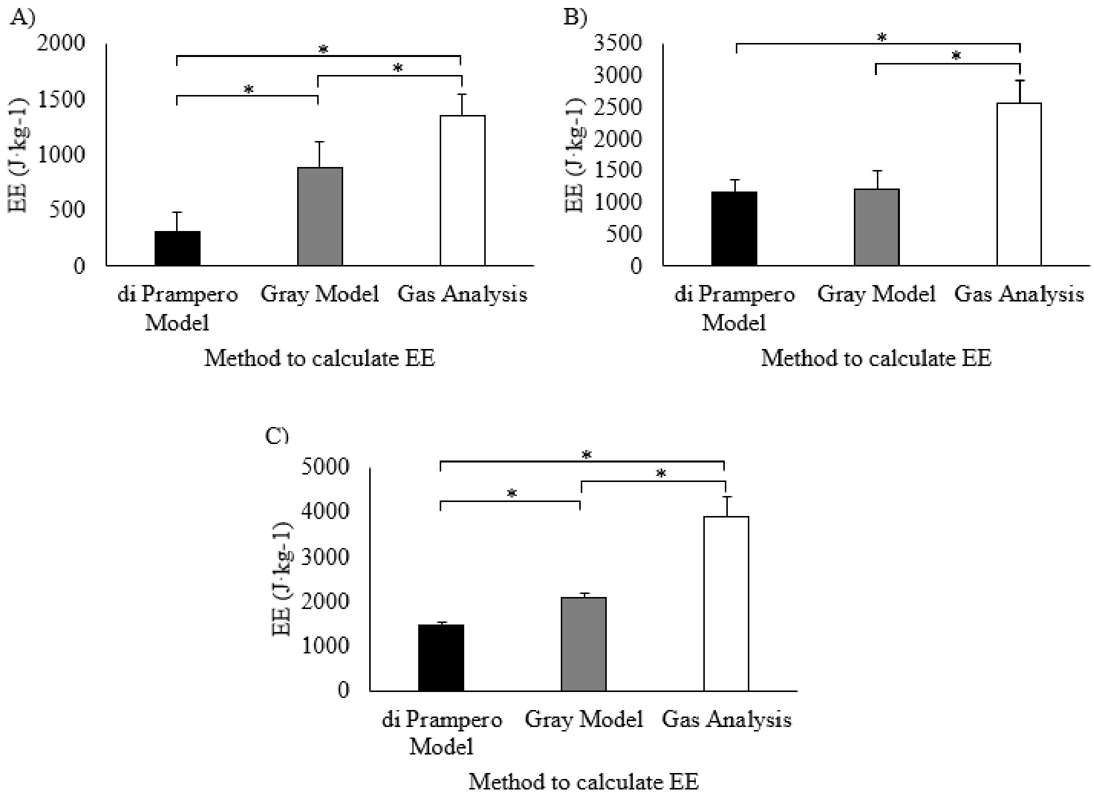

Figure 6 Means and standard deviations for 400 m A) energy expenditure above threshold power, B) energy expenditure below threshold power, C) overall energy expenditure (* = indicates significant difference between methods).

5.2 Continuous running total energy expenditure

There was an effect of the method used to obtain overall EE was identified in continuous running ($F_{(1.027,9.244)} = 135.045$, $P < 0.001$, $\eta_p^2 = 0.938$). Pairwise comparisons revealed the Gray model produced higher EE values than the di Prampero model ($P < 0.001$), gas analysis determined larger EE values than the di Prampero model ($P < 0.001$), and gas analysis produced higher values of EE than the Gray model ($P < 0.001$). There was an interaction effect for method to calculate EE x exercise intensity ($F_{(1.097,9.875)} = 9.641$, $P < 0.010$, $\eta_p^2 = 0.517$). The Gray model estimated similar EE values above threshold power with the di Prampero model ($P = 0.544$) and the EE from gas analysis ($P = 0.472$), and the di Prampero model estimated similar values of EE to that determined from gas analysis (*P* = 0.114) (Figure 7A). When measuring EE below threshold power, gas analysis measured significantly higher values of EE than produced by the di Prampero model (*P* < 0.001) and the Gray model (*P* = 0.007), and the Gray model produced larger estimations of EE below threshold power than the di Prampero model (*P* < 0.001) (Figure 7B). During continuous running, overall EE measured by gas analysis determined significantly greater values than that estimated by both the di Prampero model (*P* < 0.001) and the Gray model (*P* < 0.001). Similarly, there were meaningful differences by those produced by the models, whereby the Gray model produced larger estimations of overall EE than the di Prampero model (*P* < 0.001) (Figure 7C).

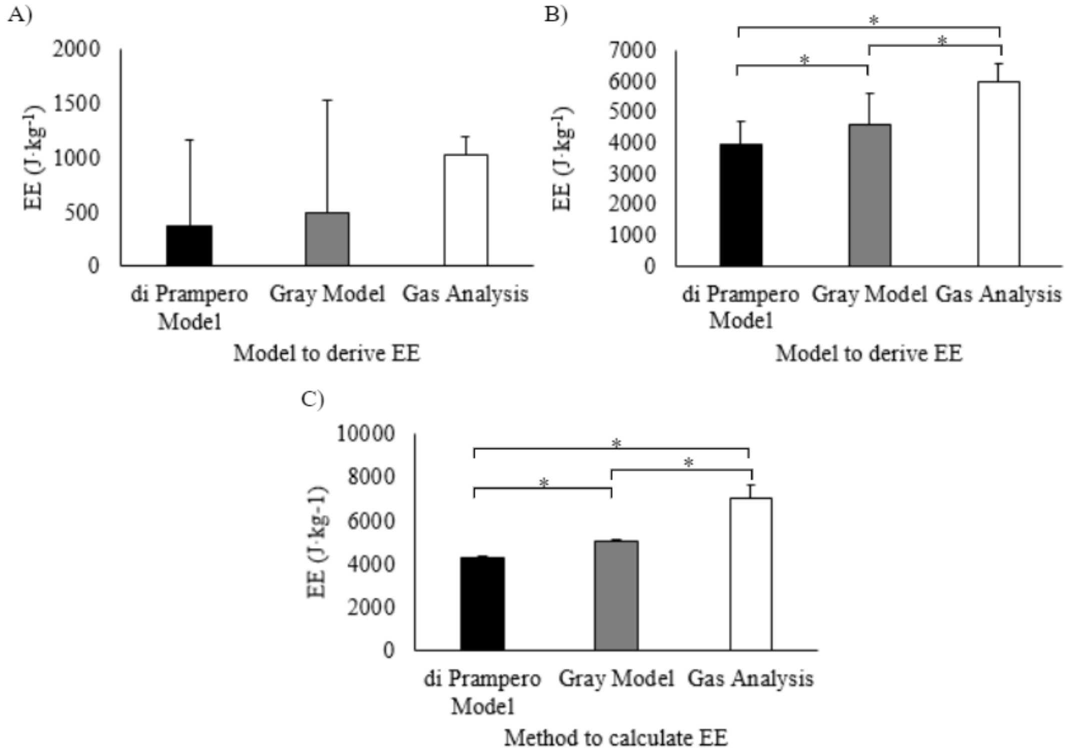

Figure 7 Means and standard deviations for continuous running A) energy expenditure above threshold power, B) energy expenditure below threshold power, C) overall energy expenditure (* = indicates significant difference between methods).

5.3 Repeated shuttle running total energy expenditure

There was an effect of the method used to acquire overall EE during repeated shuttle running ($F_{(1.021,9.193)}$ = 155.057, P < 0.001, η_p^2 = 0.945). Pairwise comparisons revealed the Gray model to produce higher EE values than the di Prampero model (P < 0.001), gas analysis generates larger EE values than the di Prampero model (P < 0.001), and gas analysis yield greater EE values than the Gray model (P < 0.001). There was an interaction effect, in the shuttle running protocol, for method to calculate EE x exercise intensity ($F_{(1.283,11.544)}$ = 240.998, P < 0.001, η_p^2 = 0.964). For EE above threshold power, in repeated shuttle running, the Gray model estimated greater values of EE than the di Prampero model (P < 0.001), the di Prampero model estimated significantly higher values of EE than that measured by gas analysis (P < 0.001), and the Gray model produced larger values than gas analysis for EE above threshold power (P < 0.001) (Figure 8A). When measuring EE below threshold power, in repeated shuttle running, the EE measured by gas analysis produced greater values than the di Prampero model (P < 0.001), also the gas analysis generated larger values of EE than the Gray model (P < 0.001), the di Prampero model and the Gray model produced similar estimations of EE below threshold power (P = 0.352) (Figure 8B). In repeat shuttle running, overall EE measured by gas analysis determined larger values than that estimated from the di Prampero model (P < 0.001) and the Gray model (P < 0.001). There was a difference identified between the two models, whereby the Gray model estimated a larger total EE overall compared with the di Prampero model (P < 0.001) (Figure 8C).

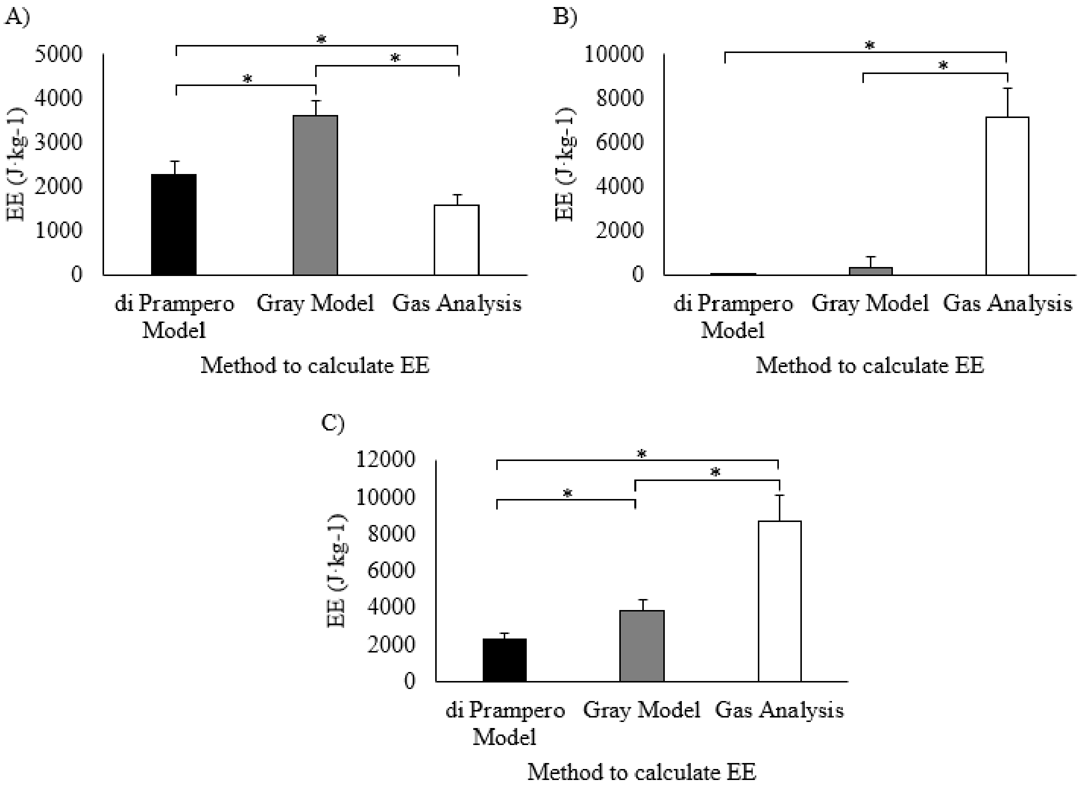

Figure 8 Means and standard deviations for repeated shuttle running A) energy expenditure above threshold power, B) energy expenditure below threshold power, C) overall energy expenditure (* = indicates significant difference between methods).

5.4 Repeated sprint running total energy expenditure

In the repeated sprint running an effect was identified of the method used to derive the overall EE ($F_{(1.019,8.149)}$ = 261.221, P = < 0.001, η_p^2 = 0.970). Pairwise comparisons showed the Gray model to estimate larger values of EE than the di Prampero model (P < 0.001), the gas analysis determined greater EE values than the di Prampero model (P < 0.001), and gas analysis produced larger EE values than the Gray model (P < 0.001). There was an interaction effect between the method to calculate EE x exercise intensity ($F_{(1.283,11.544)}$ = 240.998, P = < 0.001, η_p^2 = 0.964). During repeated sprint running, the Gray model estimated greater values of EE, above threshold power, than the di Prampero model ($P < 0.001$), the gas analysis generated greater EE values than that of the di Prampero model ($P < 0.001$), yet the Gray model produced similar values to that determined by gas analysis for EE above threshold power ($P = 1.000$) (Figure 9A). When measuring EE below threshold power, the di Prampero model estimated smaller values of EE than those generated by gas analysis ($P < 0.001$), also the gas analysis generated higher values of EE than the Gray model ($P < 0.001$), and the Gray model generated larger estimates than the di Prampero model of EE below threshold power ($P < 0.001$) (Figure 9B). The gas analysis method determined larger overall EE measured compared to the di Prampero model ($P < 0.001$) and the Gray model ($P < 0.001$). There was a statistical difference between modelled estimations of EE, whereby the Gray model estimated greater vales of total EE overall than the di Prampero model ($P < 0.001$) (Figure 9C).

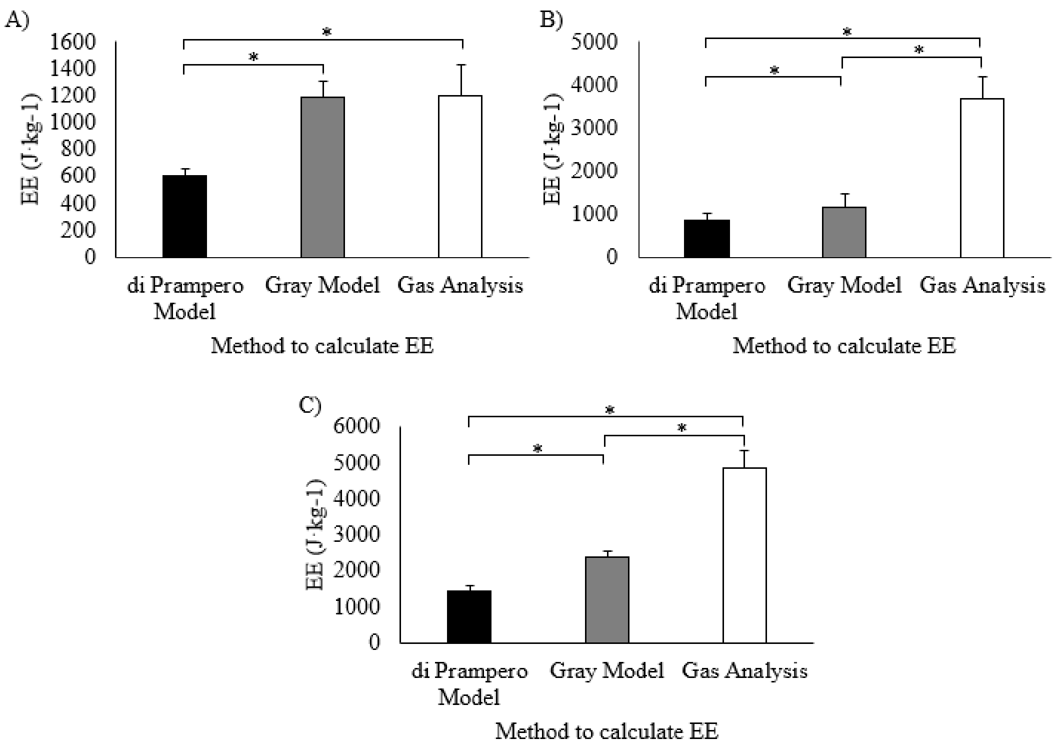

Figure 9 Means and standard deviations for repeated shuttle running A) energy expenditure above threshold power, B) energy expenditure below threshold power, C) overall energy expenditure (* = indicates significant difference between methods).

5.5 Total modelled energy expenditure compared to aerobic energy expenditure in 400 m running

There was an effect seen between methods to attain modelled EE and EE from indirect calorimetry in the 400 m running protocol ($F_{(1.042,10.416)}$ = 68.668, P < 0.001, η_p^2 = 0.873). Pairwise comparisons revealed the di Prampero model to significantly produce smaller overall estimations of EE than the Gray model (P < 0.001) and indirect calorimetry (P < 0.001), the Gray model obtained similar values to that from indirect calorimetry (P = 0.007). Interaction effect between model type x test phase condition was identified ($F_{(1.085,10.846)}$ = 537.269, P < 0.001, η_p^2 = 0.982). During the exercise phase, indirect calorimetry determined significantly lower values of EE than the di Prampero model (P < 0.001) and the Gray model (P < 0.001), whereas the di Prampero model and the Gray model estimated similar EE values (P = 0.307) (Figure 10A). During the recovery period, the Gray model estimated greater values of EE than the di Prampero model (P < 0.001), and aerobic EE from indirect calorimetry determined significantly greater values than the di Prampero model (P < 0.001) and the Gray model (P < 0.001) (Figure 10B). Overall EE expenditure from the di Prampero model underestimated that of the aerobic energy system from gas analysis (P < 0.001), also the di Prampero model estimated lower EE values than the Gray model (P < 0.001), the Gray model estimated similar values to that determined by gas analysis (P = 0.007) (Figure 10C).

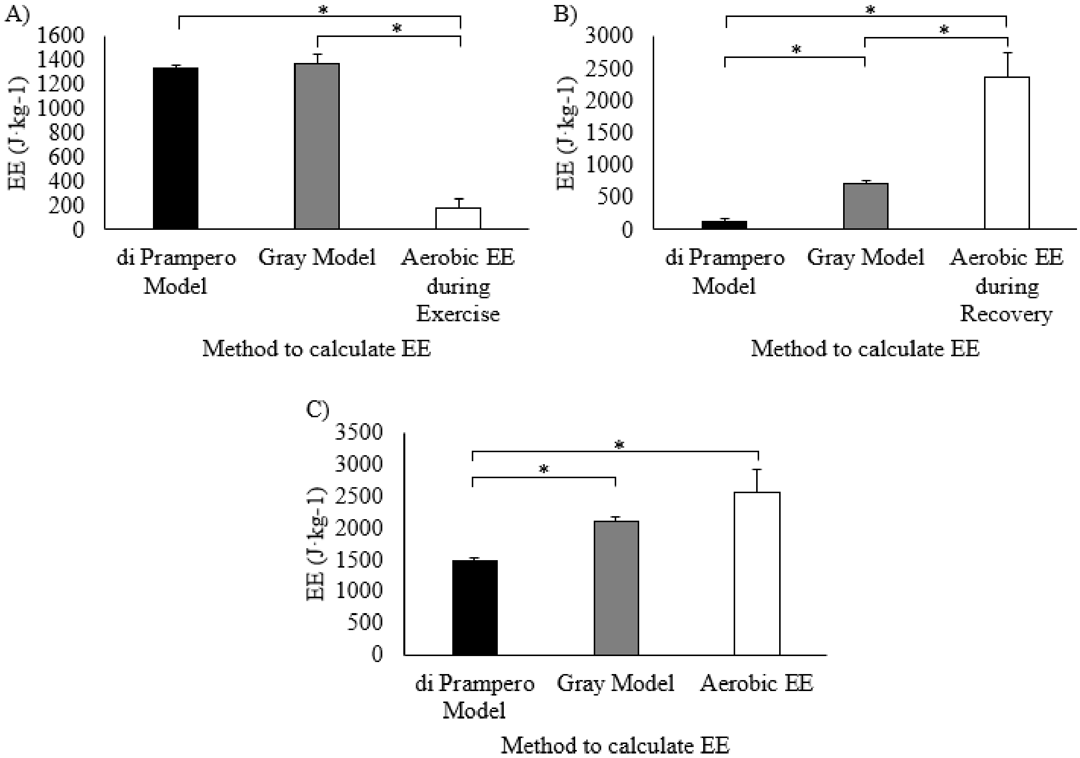

Figure 10 Means and standard deviations for 400 m modelled and aerobic energy expenditure A) during exercise, B) during recovery, C) overall aerobic energy expenditure (* = indicates significant difference between methods).

5.6 Total modelled energy expenditure compared to aerobic energy expenditure in continuous running

An effect was identified between models to obtain modelled EE and EE from indirect calorimetry during the continuous running ($F_{(1.040,9.359)} = 64.095$, $P < 0.001$, $\eta_p^2 = 0.877$). Pairwise comparisons revealed the di Prampero model to produce smaller overall EE values than the Gray model ($P < 0.001$) and indirect calorimetry ($P < 0.001$), the Gray model obtained smaller EE values to aerobic EE from indirect calorimetry ($P < 0.001$). Interaction effect between model type x test phase condition was identified ($F_{(1.719,15.467)} = 75.452$, $P < 0.001$, $\eta_p^2 = 0.893$). During the exercise period, the di Prampero model estimated smaller values of EE than the Gray model ($P < 0.001$), and the di Prampero model estimated similar results to that determined by gas analysis ($P = 1.000$), and the Gray model estimated similar values to that from gas analysis (P = 1.000) (Figure 11A). During the recovery phase, the Gray model produced greater estimations of EE than the di Prampero model (P < 0.001), EE determined from gas analysis produced significantly larger EE values than that estimated by the di Prampero model (P < 0.001) and the Gray model (P < 0.001) (Figure 11B). The overall aerobic EE by gas analysis was significantly larger than that estimated by the di Prampero model (P < 0.001) and the Gray model (P < 0.001), the Gray model generated larger estimated vales of EE that the di Prampero model (P < 0.001) (Figure 11C).

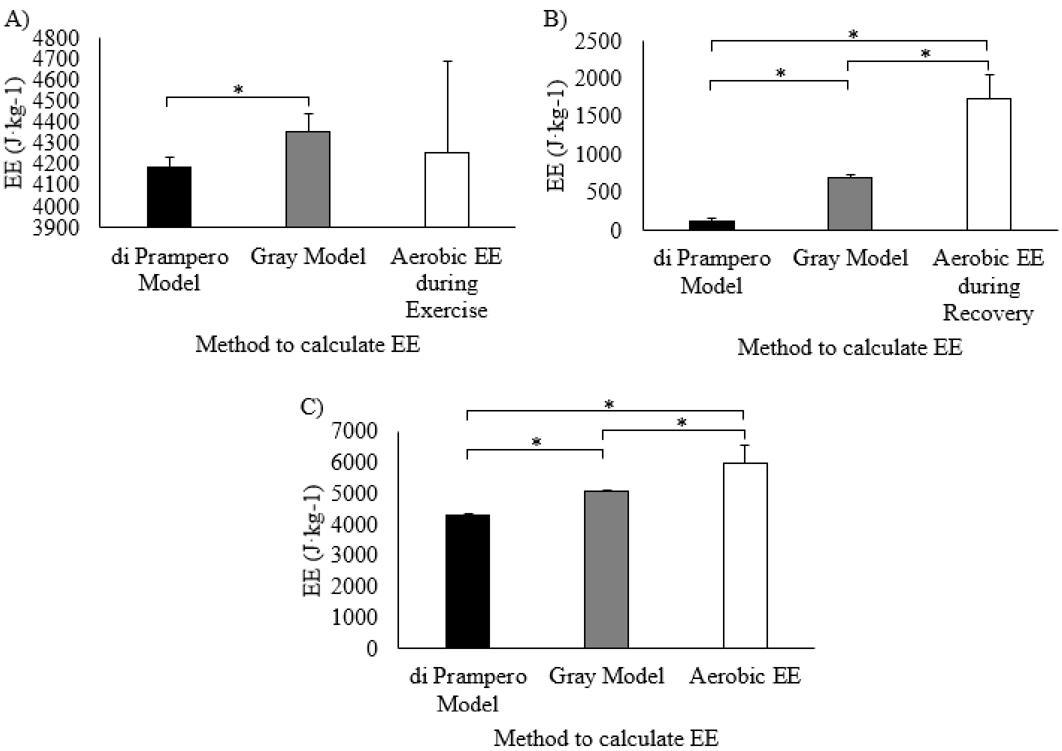

Figure 11 Means and standard deviations for continuous running modelled and aerobic energy expenditure A) during exercise, B) during recovery, C) overall aerobic energy expenditure (* = indicates significant difference between methods).

5.7 Total modelled energy expenditure compared to aerobic energy expenditure in repeat shuttle running

There was an effect of the model to produce EE during repeated shuttle running ($F_{(1.022,9.202)}$ = 92.003, $P < 0.001$, $\eta_p^2 = 0.911$). Pairwise comparisons revealed the Gray model to produce higher values than the di Prampero ($P < 0.001$), gas analysis to produce greater values than the di Prampero model ($P < 0.001$), and the gas analysis to determine larger values than the Gray model ($P < 0.001$). There was an interaction effect for model type x test phase condition was identified ($F_{(1.341,12.071)}$ = 56.065, $P < 0.001$, $\eta_p^2 = 0.862$). The Gray model estimated larger values of EE during the exercise phase than the di Prampero model ($P < 0.001$), the di Prampero model estimated significantly smaller values of EE than measured by gas analysis ($P < 0.001$), and the Gray model produced smaller values than gas analysis during the exercise period ($P < 0.001$) (Figure 12A). In the recovery period, the Gray model estimated greater values of EE than the di Prampero model ($P < 0.001$), the EE from the aerobic system measured by gas analysis determined significantly larger values than that estimated by the di Prampero model ($P < 0.001$) and the Gray model ($P < 0.001$) (Figure 12B). The overall EE from the aerobic gas analysis ascertained significantly greater values of EE than the di Prampero model ($P < 0.001$) and the Gray model ($P < 0.001$), and the Gray model generated larger EE values than that produced by the di Prampero model ($P < 0.001$) (Figure 12C).

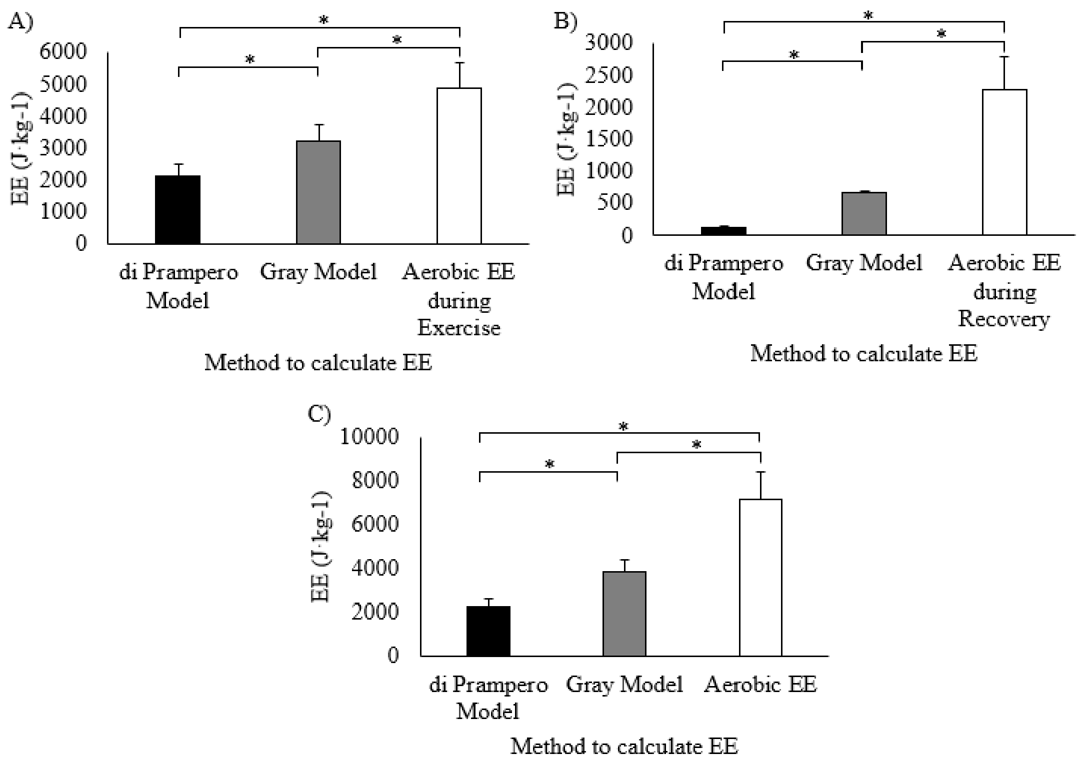

Figure 12 Means and standard deviations for repeated shuttle running modelled and aerobic energy expenditure A) during exercise, B) during recovery, C) overall aerobic energy expenditure (* = indicates significant difference between methods).

5.5 Total modelled energy expenditure compared to aerobic energy expenditure in repeat sprint running

There was an effect of the model to produce EE was identified during repeated sprint running ($F_{(1.015,8.124)}$ = 85.928, P < 0.001, η_p^2 = 0.915). Pairwise comparisons showed the Gray model to produce higher values than the di Prampero (P < 0.001), gas analysis to produce greater values than the di Prampero model (P < 0.001), and the gas analysis to produce greater values than estimated by the Gray model (P < 0.001). There was an interaction effect for model type x test phase condition was identified ($F_{(1.791,14.332)}$ = 78.452, P < 0.001, η_p^2 = 0.907). During the exercise phase, the Gray model estimated greater values of EE than the di Prampero model (P < 0.001), the di Prampero model estimated similar values to that measured by gas analysis (P = 0.104), and the Gray model produced similar EE values to the gas analysis during the exercise period (P = 1.000) (Figure 9D). In the recovery, the di Prampero model estimated lower values of EE compared to the Gray model (P < 0.001) and the gas analysis(P < 0.001), the measured gas analysis determined higher values of EE than that produces by the Gray model (P < 0.001) (Figure 10D). The overall total aerobic contribution to EE determined significantly greater values than the di Prampero model (P < 0.001) and the Gray model (P < 0.001), and the Gray model estimated higher values of overall EE than the di Prampero model (P < 0.001) (Figure 11D).

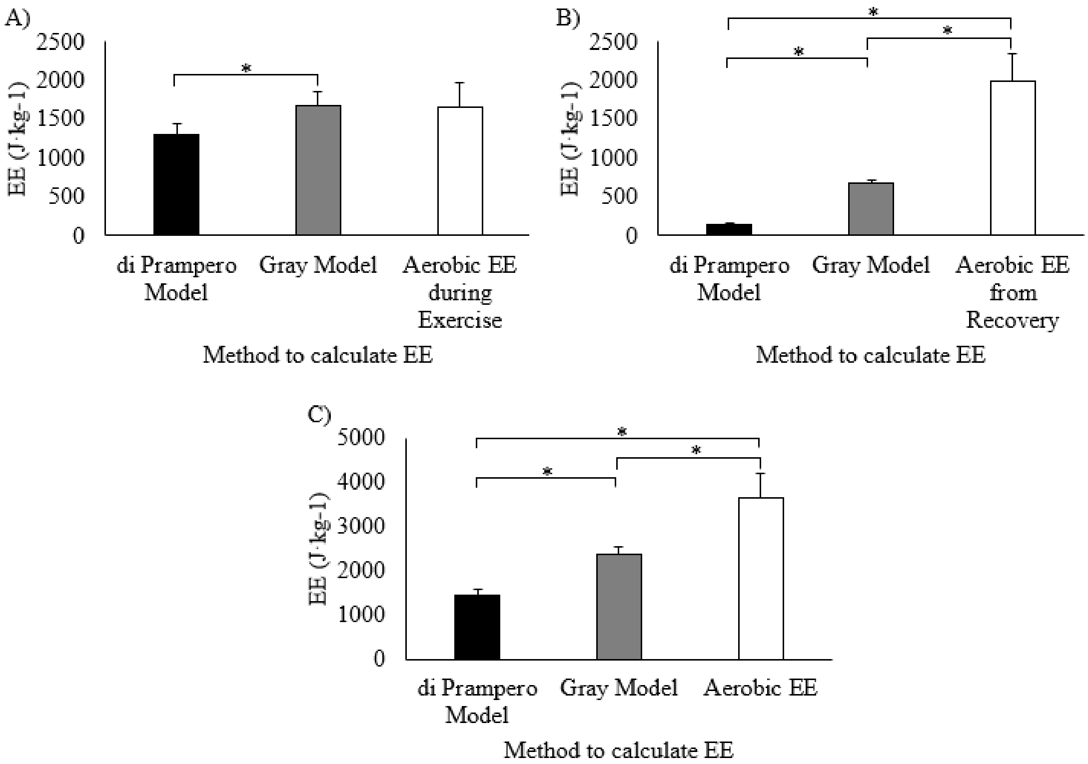

Figure 13 Means and standard deviations for repeated sprint running modelled and aerobic energy expenditure A) during exercise, B) during recovery, C) overall aerobic energy expenditure (* = indicates significant difference between methods).

Chapter 6.0 Discussion

The primary aim of this study was to understand whether modelling energetics, based on the demand of the exercise, is comparative to measuring energetics from the energetic supply, measured via gas analysis, to provide a global measure of internal load as EE. The findings of this study suggest that the modelled energetics may not be directly comparable with measured EE from indirect calorimetry and B[La] and so should be implemented with the understanding of the limitations of modelling by sports science practitioners.

In the present study, when comparing overall EE, across all exercise tests (400 m, continuous running, repeated shuttle running, and repeated sprint running) the EE measured from gas analysis was greater than the di Prampero and Gray models, supporting the initial hypothesis. This considerable underestimation of EE by the di Prampero (400 m ~62 %, continuous running ~39 %, repeat shuttle running ~74 %, and repeat sprint running ~70 %) and Gray (400 m ~28 %, continuous running ~28 %, repeat shuttle running ~55 %, and repeat sprint running ~52 %) models was associated with the greater contribution of EE from predominantly aerobic energy contribution. This is supported by the results of EE below threshold power, whereby both models underestimated values established by gas analysis. It is expected that both models' gross underestimation of EE below threshold power can be attributed to increased measured pulmonary VO_2 in the off-transient and -kinetics (recovery) associated with EPOC occurring in reciprocation to phosphocreatine depletion at the onset of exercise (Cleuziou, et al., 2004; Perrey, et al., 2002; Paterson & Whipp, 1991; Maehlum, et al., 1986). This idea is supported by limitations noted by the authors of the di Prampero and Gray models (Gray, et al., 2020; di Prampero, et al., 2005), given that the models require velocity data to estimate the EE demand, which is absent due to the passive recovery in the protocol, and so would not account for any EE accrued during EPOC. This was supported by detailed analysis between modelled data and the contribution of the aerobic system to EE, which demonstrated the di Prampero and Gray models to greatly underestimate EE during recovery compared to the measured EE from breath-by-breath analysis for all exercise tests (Figure 10). In addition, both models are limited to estimating energy cost from velocity data and do not account for work done to circulate blood and other functions within the body, which may describe some of the underestimations of EE compared to physiological measures from combined respiratory gas analysis and B[La].

Across the 400 m, continuous running, repeat shuttle running, and repeat sprint exercise tests, the di Prampero and Gray models estimated similar EE below threshold power, as was hypothesised. Although contrary to our hypothesis, the Gray model estimated significantly greater EE below threshold power compared to the di Prampero model ($P < 0.001$) in 400 m running (Figure 6B), and higher estimations of EE in all exercise tests in EE above threshold power and overall EE (Figure 6, 7, 8, & 9). These differences identified between the di Prampero and the Gray model could be attributed to the assumptions of the models and differing derivations EE. For example, the di Prampero model is based on the theory that sprint running, during acceleration, is similar to running at a steady state on an ES (di Prampero, et al., 2005). Prior understanding of the energy cost during ES running allowed for the metabolic modelling of constant speed running on a flat terrain, utilising instantaneous velocity data (Osgnach, et al. 2010; di Prampero, et al., 2005). Whereas, the Gray model estimates mechanical work of overground running (Gray, et al., 2020; Gray, et al., 2018). Here, the overall work performed is established from the sum of W_{hor}, W_{vert}, W_{limbs}, and W_{air} applied with the work-energy theorem (Gray, et al., 2020). These founding principles present the first limitation of the di Prampero model, where overall mass is assumed to be located at the COM and energy required to swing the limbs is neglected from the calculations (di Prampero, et al., 2005). Furthermore, di Prampero et al. (2005) assume the internal work is the same for uphill and sprint running, which is not accurate, as sprint running has a higher stride frequency than uphill running, and that the average applied force is the same during the duty factor. This is predicted to represent a minimum value of metabolic power and so likely underestimate energy cost. The Gray model states that work to swing the limbs is the main descriptor of internal work during locomotion (Gray, et al., 2020), which could be a contributing factor to higher estimations of EE determined by the Gray model. Although, the calculations in the Gray model to predict W_{limb} is based on work by Minetti (1998), which was formed upon numerous assumptions. One being a simplification that all limbs are straight segments with consistent inertial properties across all running velocities, which may provide an overestimation of work done (Gray, et al., 2020). The culmination of differing constructs, outlined above, between the di Prampero model and the Gray model could describe the different estimated outcomes. As such, the inclusion of W_{int} in the Gray model is likely to contribute to the higher estimation of EE than the di Prampero model, suggesting the mechanically derived model is more likely to closely represent the true exercise demand.

The results from this study contradict those presented by Stevens et al. (2015), whereby estimations of EE using the di Prampero model were reported to overestimate energy cost values from measured gas analysis during continuous running (Stevens, et al., 2015). However, the study conducted by Stevens et al. (2015) only described EE during the exercise period and, therefore, would not account for $\dot{V}O_2$ during the recovery period, due to EPOC (Cleuziou, et al., 2004; Perrey, et al., 2002; Paterson & Whipp, 1991; Maehlum, et al., 1986), which would increase the measured overall EE from the gas analysis. The actual energy cost of repeated shuttle running was underestimated by the di Prampero model compared to gas analysis (Stevens, et al., 2015), which agreed with results reported in the current study. Unlike the current study, Stevens et al. (2015) obtained the measured supply of energy from only from the pulmonary VO_2 response, excluding B[La]. Despite the different methods of acquiring the supply of energy cost, both Stevens et al. (2015) and the current study produced comparable findings of the underestimation of EE from the di Prampero model in shuttle running. This, in turn, could be attributed to the speed of the exercise test being close to the participants speed at $\dot{V}O_{2max}$ and thus elicit a larger contribution of EE from the anaerobic energy systems (Figure 7).

Some results of the current study mirrored the findings of Buchheit et al. (2015), notwithstanding the uncertainties raised with the statistical analysis by only accounting for the exercise phase of the test (Osgnach, et al., 2016). This study used a GPS with a superior sampling frequency than that in the previous study to mitigate reliability and validity concerns (Buchheit, et al., 2015). The results of this study reveal that the di Prampero and Gray model significantly underestimate overall metabolic power compared with measured gas analysis, across all exercise tests (Figure 6, 7, 8, & 9). As was expected, and as demonstrated by Buchheit et al (2015), when solely comparing the measured $\dot{V}O_2$ to modelled EE during the recovery period, the $\dot{V}O_2$ measured significantly greater values than that estimated by the di Prampero and Gray model (Figure 10B, 11B, 12B, & 13B). However, in the current study, during continuous running and repeated sprint running, both the di Prampero model and the Gray model estimated similar values of EE compared with measured $\dot{V}O_2$ (Figure 11A & 13A). Conversely, during the 400 m sprint, the di Prampero and Gray models overestimated aerobic EE. This is to be expected due to the short duration of the exercise test and the intensity of the exercise bout is more closely associated with work above $\dot{V}O_{2max}$ and so a greater contribution of energy can be attributed to the anaerobic pathways (Figure 10A). As opposed to the results in the 400 m, continuous running, and repeated sprint test the di Prampero and Gray models underestimated EE compared to gas analysis during repeated shuttle running over 20 m, concurring with results reported by Stevens et al. (2015). These results contradict the findings of Buglione and di Prampero (2013), who found the energetic cost of shuttle running, over 20 m, to be similar to measured $\dot{V}O_2$. Notably, the participant pool used by Bulglione and di Prampero (2013) consisted of physically active adults, professional footballers, and high-level runners, whereas the current study used only physically active adults with a large SD of $\dot{V}O_{2max}$ (Table 1). As mentioned by Stevens et al. (2015), limitations of the di Prampero model could be drawn from the original work to derive the energy cost of running on an ES. Minetti et al. (2002) developed the principles of ES running with elite endurance athletes (elite mountain runners), who perform constant running tasks with greater efficiency, lower energy cost, than observed by field sport athletes (Sassi, et al., 2011). Additionally, the exclusion of the work performed by the limbs, in the di Prampero model, may contribute to the underestimated energy cost.

Limitations of modelling energetics

Whilst the mathematical modelling of an athletes energetics can provide practitioners with a global understanding of the physiological demands of exercise, mathematical modelling comes with inherent limitations. The first limitation to note is all model calculations are fundamentally built upon assumptions (Clarke & Skiba, 2013) and as such this characterises that there will be some deviation for true values.

The di Prampero model

The di Prampero model is built on the assumption that the total mass of an individual is located at their COM. This means the di Prampero model does not attribute any expenditure to come from the swing of moving limbs during locomotion which is inaccurate (di Prampero, et al., 2005). Another assumption of the di Prampero model is that limb joint angles are the same in uphill running and sprint running and so that internal work during sprint running at an ES on a flat terrain, is identical to running uphill. This is not the case as in sprint running over on a flat terrain has a higher stride frequency than that of uphill running and so will have a different energetic demand (di Prampero, et al., 2005). Also, this model assumes that the energy cost of per unit of distance run at a given slope is independent of speed, meaning the calculation for the energy cost of uphill running to sprint running can be done regardless of the speed of the individual (di Prampero, et al., 2005). Finally, the di

Prampero model determines the cost of energy from pervious literature on steady-state exercise (Minetti, et al., 2002), primarily supplied by aerobic pathways, which contrasts to that in sprint running which has greater contribution from anaerobic sources and so the energy cost of sprint running, when implementing the di Prampero model, should be used with caution (di Prampero, et al., 2005).

The Gray model

The Gray model first calculates the mechanical work performed before then converting it to energy expenditure as detailed in section x. In this section it is outlined that the calculations to predict internal work were taken from previous literature from Minetti et al. (2002). Minetti's model by extension is built upon assumptions such as that the limbs are all single straight limbs with constant inertial properties (2002). The Gray model being mechanical in nature does not account for the EE required for the body to perform involuntary actions such as ventilation, circulating blood through the body and organ function. Additionally, the model assumes that vertical work is solely done by the oscillation of the COM, rising and falling at a constant rate with each step during overground running. Furthermore, the Gray model assumes the displacement of the COM along with the stride frequency, and duty factor are estimated from forward horizontal velocity. Lastly the Gray model negates the effect of fatigue, running surface and running ability when calculating EE.

Conclusion

This study compared metabolic power obtained by measuring energy supply, via indict calorimetry combined with B[La], and exercise demand, modelled from GPS velocity data, across 400 m, continuous running, repeated shuttle running, and repeated sprint running tasks. In summary, the results of this study indicate the di Prampero and Gray models significantly underestimate the overall energy cost, the sum of exercise and recovery phases, compared with the measured sum of gas analysis and B[La]. Furthermore, the di Prampero and Gray models do not agree on the predominant source of energy i.e. aerobic or anaerobic system. This study revealed the di Prampero and Gray model to attribute significant energy cost to work performed above threshold power during the submaximal exercises test (repeated shuttle running) and so may be sensitive to velocities close to that achieved at an individuals VO_{2max} or the greater mechanical demand associated with deceleration and reacceleration in changing direction. When implementing modelled energetics, sports scientists must understand the constructs on which their chosen model is formed to appropriately interpret training data to plan suitable training strategies.

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Appendices

Appendix A: Ethical approval form

Ethics Office
Research Development & Integrity
Research Division
Armidale NSW 2351
Australia
Phone 02 6773 3449
Fax 02 6773 3543
jo-ann.sozou@une.edu.au
www.une.edu.au/research-services

HUMAN RESEARCH ETHICS COMMITTEE

MEMORANDUM TO: Mr Adrian Gray

School of Science & Technology

This is to advise you that the Human Research Ethics Committee has approved the following:

PROJECT TITLE:	Validity of energetic modelling from GPS derived running velocity
APPROVAL No.:	HE15-200
COMMENCEMENT DATE:	27 July, 2015
APPROVAL VALID TO:	27 July, 2016
COMMENTS:	Nil. Conditions met in full

The Human Research Ethics Committee may grant approval for up to a maximum of three years. For approval periods greater than 12 months, researchers are required to submit an application for renewal at each twelve-month period. All researchers are required to submit a Final Report at the completion of their project. The Progress/Final Report Form is available at the following web address: http://www.une.edu.au/research/research-services/rdi/ethics/hre/hrec-forms

The NHMRC National Statement on Ethical Conduct in Research Involving Humans requires that researchers must report immediately to the Human Research Ethics Committee anything that might affect ethical acceptance of the protocol. This includes adverse reactions of participants, proposed changes in the protocol, and any other unforeseen events that might affect the continued ethical acceptability of the project.

In issuing this approval number, it is required that all data and consent forms are stored in a secure location for a minimum period of five years. These documents may be required for compliance audit processes during that time. If the location at which data and documentation are retained is changed within that five year period, the Research Ethics Officer should be advised of the new location.

[redacted]

Jo-Ann Sozou
Secretary/Research Ethics Officer

14/07/2015 A15/21

Appendix B: Participant information sheet

School of Science and Technology
University of New England
Armidale NSW 2351
Australia
Phone 02 6773 5022
Fax 02 6773 5011
admin-st@une.edu.au
www.une.edu.au/science-technology/

Information Sheet
for
Participants

Full Title: Validity of energetic modelling from GPS derived running velocity

Thank you for taking time to read this Information Sheet.

I wish to invite you to participate in my research project, described below. My name is Dr Adrian Gray and I am conducting this research to validate an energetic model that I have previously developed.

The purpose of this information sheet is to clearly explain the steps and procedures of this project. This information is to help you decide whether or not you would like to take part in this project. Please read the information carefully and ask any questions you may have. After reading this information sheet, if you wish to participate, please sign the attached consent form.

Aim of the research	This research aims to 1) determine the accuracy of velocity data from new commercially available GPS receiver; and 2) validate modelled energy expenditure derived from GPS data.
Participation Requirements	To participate in this study you must be between 18 and 40 years of age. You will be screened using the adult pre-exercise screening tool to determine your suitability to exercise. Only those identified as low-risk are eligible to participate. This study requires you to attend two 1-hour sessions at SportUNE, approximately 1 week apart. The first session will involve screening and a treadmill running test (see details below). The second session will involve two running tests outdoors (see details below). Your movements and physiological responses will be measured during the running tests.
Testing Protocols	Pre-Test Instructions: You will be asked to avoid heavy exertion/exercise the day prior to testing, abstain from stimulants/depressants 3 hours prior to testing, consume a high carbohydrate meal 1-4 hours prior to testing, and arrive for testing in a well hydrated state, dressed ready to exercise (running shoes, light clothing etc.). You will be familiarised with all testing equipment and protocols prior to participation.

Testing Protocols cont.

Testing Session 1:

- Body mass and height will be measured using standard techniques.
- A portable metabolic system will be fitted. This includes a small harness worn on the upper body and a face-mask that covers the nose and mouth to measure the air you breath out.
- Whilst wearing the metabolic system, you will run on a treadmill at 8 km/hr for 1 minute, then the treadmill speed will increase by 1 km/hr every minute thereafter. You are required to run for as long as possible i.e. maximal effort to voluntary fatigue.

Testing Session 2:

- A GPS receiver (size of a small mobile phone) will be fitted to your upper back in a neoprene harness and a portable metabolic system will be fitted as per Testing Session 1.
- Whilst wearing the GPS & metabolic system, you will perform repeated 20 m "shuttle runs" at a speed of 12 km/hr for 6 minutes, followed by 6 minutes of seated rest. A "radar gun" will be used to measure your running speed throughout this test. During the rest period, your finger will be cleaned and punctured using a sterile lancet. This site will be used to collect 6 drops of blood to be analysed.
- After a full recovery and whilst wearing the GPS & metabolic system, you will perform 6 x 40 m "maximal sprints" with a 30 second recovery between sprints, followed by 6 minutes of seated rest. A "radar gun" will be used to measure your running speed throughout this test. During the rest period, your finger will be cleaned and punctured using a sterile lancet. This site will be used to collect 6 drops of blood to be analysed.

Testing Session 3:

- Whilst wearing the GPS & metabolic system, you will perform 6 minutes of continuous running at a speed of 12 km/hr for 6 minutes, followed by 6 minutes of seated rest. During the rest period, your finger will be cleaned and punctured using a sterile lancet. This site will be used to collect 6 drops of blood to be analysed.
- After a full recovery and whilst wearing the GPS & metabolic system, you will perform a 400 m run in the shortest possible time i.e. a race, followed by 6 minutes of seated rest. During the rest period, your finger will be cleaned and punctured using a sterile lancet. This site will be used to collect 6 drops of blood to be analysed.

	All testing will be completed by a researcher with industry recognised qualifications in exercise testing and training. All test procedures will be performed in accordance with UNE OH&S guidelines and ESSA's code of professional conduct.
Risks/Side Effects	Due to the nature of exercise testing, there is a slight risk of a cardiovascular event or musculoskeletal injury occurring to the participant. However, screening protocols and study design aim to minimise these risks. The running bouts performed during participation may also cause some short-term discomfort e.g. tired/sore muscles, shortness of breath, sweating, elevated heart rate.
Benefit of Participation	Participants are not expected to benefit directly from this study. Should the participant wish, a copy of their test results will be provided to them. However, published results from the full study may benefit strength and conditioning &/or running coaches, helping them to monitor their athletes during training & competition.
Confidentiality	Any information or personal details gathered in the course of the study will remain confidential. No individual will be identified by name in any publication of the results. All names will be replaced by pseudonyms; this will ensure that you are not identifiable.
Participation is Voluntary	Please understand that your involvement in this study is voluntary and I respect your right to withdraw from the study at any time. You may discontinue the session at any time without consequence and you do not need to provide any explanation if you decide not to participate or withdraw at any time. For UNE students, participation or non-participation is entirely separate to UNE coursework, will not impact your assessment in any unit and will have nil effects on your academic progression.
Use of information	The information collected will be analysed and presented in journal articles and conference presentations before and after this date. At all times, I will safeguard your identity by presenting the information in way that will not allow you to be identified.
Upsetting issues	It is unlikely that this research will raise any personal or upsetting issues but if it does you may wish to contact Lifeline on 13 11 14.
Storage of information	I will keep hardcopy data in a locked cabinet at the researcher's office at the University of New England's School of Science and Technology.

	Any electronic data will be kept on a password protected computer in the same School. Only the researcher will have access to the data.
Disposal of information	All the data collected in this research will be kept for a minimum of five years after successful publication of the findings, after which it will be disposed of by deleting relevant computer files, and destroying or shredding hardcopy materials.
Ethical Approval	This project has been approved by the Human Research Ethics Committee of the University of New England (Approval No.........., Valid to ../../....).
Contact details	Feel free to contact me with any questions about this research by email at [redacted] or phone on [redacted].
Complaints	Should you have any complaints concerning the manner in which this research is conducted, please contact the Research Ethics Officer at: Research Services University of New England Armidale, NSW 2351 Tel: (02) 6773 3449 Fax: (02) 6773 3543 Email: ethics@une.edu.au

Thank you for considering this request and I look forward to further contact with you.

Regards,

[redacted]

Dr Adrian Gray
Lecturer in Exercise and Sports Science
School of Science and Technology
University of New England

Appendix C: Participant consent form

Consent Form for Participants

Research Project: Validity of energetic modelling from GPS derived running velocity

I, ………………………………………………………………………, have read the information contained in the Information Sheet for Participants and any questions I have asked have been answered to my satisfaction. Yes/No

I agree to participate in this activity, realising that I may withdraw at any time. Yes/No

I agree that research data gathered for the study may be published using a pseudonym Yes/No

I would like to receive a copy of my results from the session.

If yes please provide email: ……………………………………………… Yes/No

I am 18-40 years of age and have been stratified to Low Risk. Yes/No

……………………………… ………………………………
Participant Date

……………………………… ………………………………
Researcher Date