

1 Prediction of Core Body Temperature from Multiple Variables  
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7 **Prediction of Core Body Temperature from Multiple Variables**

8

9 **ABSTRACT**

10 This paper aims to improve the prediction of rectal temperature ( $T_{re}$ ) from insulated  
11 skin temperature ( $T_{is}$ ) and micro-climate temperature ( $T_{mc}$ ) previously reported (Richmond  
12 et al. 2013) using additional physiological and/or environmental variables, under several  
13 clothing and climatic conditions. Twelve male ( $25.8 \pm 5.1$  yr;  $73.6 \pm 11.5$  kg;  $178 \pm 6$  cm)  
14 and nine female ( $24.2 \pm 5.1$  yr;  $62.4 \pm 11.5$  kg;  $169 \pm 3$  cm) volunteers completed six trials,  
15 each consisting of two 40 minute periods of treadmill walking separated by a 20 minute  
16 rest, wearing permeable or impermeable clothing, under neutral ( $25$  °C, 50 %), moderate  
17 ( $35$  °C, 35 %) and hot ( $40$  °C, 25 %) conditions, with and without solar radiation ( $600$   
18  $W \cdot m^{-2}$ ). Participants were measured for heart rate (HR) (Polar, Finland), skin temperature  
19 ( $T_s$ ) at 11-sites,  $T_{is}$  (Grant, Cambridge, UK) and breathing rate ( $f$ ) (Hidalgo, Cambridge,  
20 UK).  $T_{mc}$  and relative humidity were measured within the clothing.  $T_{re}$  was monitored as  
21 the ‘gold standard’ measure of  $T_c$  for industrial or military applications using a 10 cm  
22 flexible probe (Grant, Cambridge, UK).

23 A stepwise multiple regression analysis was run to determine which of 30 variables  
24 ( $T_{is}$ ,  $T_s$  at 11 sites, HR,  $f$ ,  $T_{mc}$ , temperature and humidity inside the clothing front and back,  
25 body mass, age, body fat, sex, clothing,  $\dot{V}O_2$ , Thermal comfort, sensation and perception,  
26 and sweat rate) were the strongest on which to base the model. Using a bootstrap  
27 methodology to develop the equation, the best model in terms of practicality and validity  
28 included  $T_{is}$ ,  $T_{mc}$ , HR and ‘work’ (0 = rest; 1 = exercise), predicting  $T_{re}$  with an SEE of  
29  $0.27$  °C and adjusted  $R^2$  of 0.86. The sensitivity and specificity for predicting individuals  
30 who reached  $39$  °C was 97 % and 85 %, respectively.

31 Insulated skin temperature was the most important individual parameter for the  
32 prediction of  $T_{re}$ . This paper provides novel information about the viability of predicting  
33  $T_c$  under a wide range of conditions, using predictors which can practically be measured in  
34 a field environment.

35

## 36 INTRODUCTION

37 High core body temperature ( $T_c$ ) is the single most reliable predictor of exhaustion  
38 during exercise in the heat (Montain et al. 1994) and the ability to monitor thermal  
39 responses could help reduce the risk of heat exhaustion for individuals working or  
40 exercising in these hyperthermic conditions (Malchaire et al 2001). However, the invasive  
41 monitoring of  $T_c$  is not practical in most cases, and to avoid the necessity to perform  
42 individual monitoring, many heat strain indices have been developed to predict human  
43 responses under certain conditions. These indices can be broken down into two main  
44 types; ‘empirical indices’ derived using samples of human subjects who’s responses to a  
45 range of thermal environments are used to form an equation or nomogram; and ‘rational  
46 indices’ that utilise several measurements (e.g. environmental and clothing) and uses heat  
47 transfer calculations to predict human responses to thermal environments, usually by  
48 means of a computer programme.

49 Of the two indices types, rational indices are the most comprehensive as they are  
50 designed to integrate all environmental and behavioural variables, but as there is no  
51 practical way to measure all of these directly, they are often assumed or regarded as  
52 constants (Epstein and Moran 2006). Additionally, these indices do not account for any  
53 variation in the responses between individuals, which would either place more people at  
54 risk, or necessitate a conservative limit for withdrawal from exercise (Havenith, 1997,  
55 2001; Havenith and Fiala 2015). Physiological monitoring of individuals in thermally  
56 challenging environments to assess their heat strain could help mitigate these limitations.  
57 Moran et al (1998b) attempted to do this with the physiological strain index (PSI), to  
58 produce a simple model, valid across any conditions. The PSI is based on heart rate (HR)  
59 and rectal temperature ( $T_{re}$ ), and describes the combined cardiovascular and thermal strain  
60 on a scale of 0-10. Although there are several studies which support the validity of the PSI  
61 in its ability to distinguish between different levels of hydration and exercise intensity  
62 (Moran et al. 1998a), between genders (Moran et al. 1999) and different levels of  
63 physiological strain for firefighters in personal protective equipment (PPE) (Petruzzello et  
64 al. 2009), the inclusion of an invasive measure of  $T_c$  does not provide an acceptable heat  
65 strain index for use in the occupational setting. As an alternative, other surrogate, non-  
66 invasive measurements that estimate  $T_c$  can be used that are suitable for field deployment  
67 such as tympanic, aural, forehead or axilla temperature. These however tend to show less

68 reliable associations with  $T_{re}$  and oesophageal temperature (Ganio et al. 2009), and a viable  
69 alternative remains to be identified. A recent study showed that a prediction equation  
70 including insulated skin temperature ( $T_{is}$ ) and micro climate temperature ( $T_{mc}$ ) can predict  
71  $T_{re}$  with a standard error of the estimate (SEE) of 0.2 °C in emergency service (ES)  
72 personnel wearing chemical biological, radiological and nuclear (CBRN) protective  
73 clothing (Richmond et al. 2013). However, these findings were only valid under the  
74 specific conditions used in these exposures and the study did not include other variables  
75 which may further improve the prediction of  $T_{re}$ .

76 Similarly, Buller et al. (2011), proposed a model to estimate core temperature, heat  
77 production and heat loss from the body using real-time physiological measurements of  
78 heart rate, accelerometer and skin heat flux using a dynamic Bayesian Network model and a  
79 Kalman filter to enable forward predictions, but results may not be reliable enough to  
80 protect individuals in high heat stress conditions. Yokota et al. (2008), presented a model  
81 for predicting core temperature based on measured heart rate and environmental  
82 conditions, observing SEE's up to 0.31°C for the various datasets, and finally in 2013,  
83 Buller et al. (2013) used a Kalman filter approach in the estimation of human body core  
84 temperature from sequential heart rate observations as a single parameter with 95% of  
85 predictions falling within  $\pm 0.63^\circ\text{C}$ . Though all these methods may be acceptable for  
86 prediction of group responses, for individual's protection the discrepancies were too large.  
87 Further, the datasets used had only a limited amount of data at very high core temperatures,  
88 and thus most of these statistics are based on the lower core temperature values, where the  
89 deviation is not relevant in any case (Havenith and Fiala, 2015).

90 As indicated by the studies mentioned above, there are known physiological  
91 responses that occur in association with exercise and climate induced hyperthermia which  
92 could be included in the model to help explain more of the variance in  $T_{re}$  than can be  
93 attributed to  $T_{is}$  and  $T_{mc}$  only. Heart rate increases during passive heat stress as a result of  
94 the changes in skin blood flow (SkBF). As  $T_c$  increases, cutaneous vasodilation occurs to  
95 allow increased volumes of blood to flow to the skin to aid dry heat loss. Elevated skin  
96 temperature ( $T_s$ ) is associated with reduced cardiac filling and stroke volume; therefore, the  
97 way to maintain cardiac output is by increasing HR. However, identifying the  
98 cardiovascular response to hyperthermia during exercise is complex because HR increases  
99 not only to assist cooling, but also to meet the additional oxygen requirement by the

100 working muscles. The inclusion of a variable in the model which changes only in response  
101 to the increase in metabolic rate due to ‘work’ may improve the predictive power of HR.  
102 One such possibility is to investigate changes in breathing frequency ( $f$ ) as another  
103 physiological response which may reflect an increase in  $T_c$ . Around 100 years ago it was  
104 first established by Haldane (1905) that hyperthermia increases ventilation ( $V_E$ ) (Tidal  
105 volume,  $[V_T] * f$ ) in humans. The study showed that HR increased by about  $36 \text{ b} \cdot \text{min}^{-1}$  for  
106 every  $1 \text{ }^\circ\text{C}$  rise in  $T_c$ , and that as  $T_c$  rises, the alveolar  $\text{CO}_2$  decreases (suggesting  
107 hyperpnea has occurred). While some papers suggest that the change in  $V_E$  during passive  
108 heat stress is due to an increase in  $f$  (Fan et al. 2008; Petersen and Vejby-Christensen  
109 1977), other show that the change in  $V_E$  is due to an increase in  $V_T$  (Cabanac and White  
110 1995; Gaudio and Abramson 1968). During exercise, identifying the thermal component  
111 of the increase in  $V_E$  is complicated due to the added impact of exercise on breathing;  
112 however the relationship between  $V_E$  and thermoregulation may result in  $f$  explaining some  
113 of the variance in  $T_{re}$ .

114         The aim of this study was to investigate the potential of using a combination of  
115 simple non-invasive measures associated with  $T_c$  to improve the prediction of  $T_{re}$  over  
116 several, substantially different heat stress scenarios. Variations in the environment were  
117 introduced (work/rest cycles; clothing; environmental conditions; solar radiation) to ensure  
118 a more general applicability and validation of any prediction model developed. In order to  
119 assess the accuracy of  $T_{re}$  prediction, a pre-defined ‘acceptable’ limit should be set;  
120 however, opinion in the literature is divided on this point. While some authors have agreed  
121 that the standard deviation (SD) of a measurement site should not be greater than  $0.1 \text{ }^\circ\text{C}$   
122 (Moran and Mendal 2002), other are less stringent, accepting an SEE of  $0.3 \text{ }^\circ\text{C}$  (Gant et al.  
123 2006) and  $\pm 0.5 \text{ }^\circ\text{C}$  (Gunga et al. 2009) between a ‘gold standard’ and a surrogate measure  
124 of  $T_c$ . However, accepting such large prediction errors would require work to stop at quite  
125 low predicted  $T_c$ ’s to avoid placing workers at the extremes of the  $T_c$  distribution at risk.  
126 Based on evidence from the literature, and the SEE achieved using non-invasive measures  
127 in previous work (Richmond et al. 2013), this study aimed to achieve an SEE of  $\leq 0.2 \text{ }^\circ\text{C}$ .

128

## 129 **1.1 METHODS**

130 Twenty one participants volunteered to take part in the trial. All participants were  
131 verbally briefed, issued with a participant information sheet and gave written informed  
132 consent. Ethics approval for the procedures was secured from the Loughborough  
133 University ethics committee. All participants completed a health screening questionnaire  
134 prior to taking part in the study.

### 135 **1.1.1 Experimental protocol**

136 The study took place in the environmental chamber at Loughborough University.  
137 Prior to the trial, all participants carried out a sub maximal and maximal intensity fitness  
138 test on a treadmill to determine maximum HR and maximum oxygen uptake ( $\dot{V}O_{2\max}$ ).  
139 Participants were measured for height and body mass, as well as estimated body fat (%)  
140 (Durnin and Womersley 1974). All participants completed between 2-6 trials under  
141 different environmental and clothing conditions (Table 1). Though temperatures were very  
142 different in conditions C1 to C5, vapour pressures/concentrations were kept almost  
143 identical, and moisture load was instead induced by wearing PPE with different  
144 permeability. The experimental protocol involved sitting in the chamber for ten minutes,  
145 followed by 2 x 40 minutes walking on a treadmill at a set speed and gradient (depending  
146 on the fitness and capability of the participant). The exercise intensity was  $\sim 40\% \dot{V}O_{2\max}$ ,  
147 which was set using the corresponding HR identified from the fitness test. This was  
148 regarded as a reasonable work rate that could be sustained over the duration of a work  
149 shift. The 40 minute periods of exercise were separated by seated rest outside the  
150 chamber. The rest was included because a heat strain monitor needs to be valid during rest  
151 as well as exercise, not only so that  $T_c$  can continue to be monitored once exercise has  
152 ceased, but because heat exhaustion can still occur at rest. The length of the rest was  
153 determined by the  $T_c$  of the individual, with participants returning to the chamber once  $T_c$   
154 had dropped by 0.4 °C. In C6 the work period was increased to 60 minutes in order to  
155 elicit a greater hyperthermic response.

156 Two different PPE ensembles were worn: one permeable (PERM) and one  
157 impermeable (IMP). The PERM ensemble was a cotton coverall (Arco Ltd, Hull, UK) and  
158 the IMP ensemble was a coated nylon coverall (FRS Countryware limited, Bridgnorth,  
159 UK). The same clothing was worn underneath the coveralls by all participants which

160 consisted of black Lycra shorts and a long-sleeved cotton t-shirt. The clothing ensembles  
 161 had the same total local thermal resistance ( $0.166 \text{ m}^2\text{K}\cdot\text{W}^{-1}$ ), but the total local evaporative  
 162 resistance was considerably higher for IMP ( $213 \text{ m}^2\text{P}_a\cdot\text{W}^{-1}$ ) than PERM ( $42.4 \text{ m}^2\text{P}_a\cdot\text{W}^{-1}$ )<sup>1</sup>.  
 163 In the two solar conditions, two 1000 watt metal halide Compact Source Iodide lamps (GE  
 164 Lighting) were used to simulate solar radiation; directed to the back of the participants.  
 165 The amount of direct radiation was measured with a Pyranometer (CM11, Kipp & Zonen,  
 166 Netherlands) and kept at a fixed level of  $\sim 530 \text{ W}\cdot\text{m}^{-2}$ .

167 There were five termination criteria:

- 168 •  $T_{re}$  of  $39.5 \text{ }^\circ\text{C}$
- 169 •  $T_s$  of  $45 \text{ }^\circ\text{C}$
- 170 • HR  $>95 \text{ \% max}$
- 171 • Voluntary withdrawal
- 172 • Withdrawal by experimenter

173 **Table 1-** Experimental conditions, including the ‘real-life’ conditions replicated

Condition	$T_{amb}$ , RH, $P_a$ and PPE	Real-life conditions
C1	$25 \text{ }^\circ\text{C}$ , $50 \text{ \%}$ , $11.5 \text{ g}\cdot\text{m}^3$ , IMP	Indoors, cool conditions, protective clothing
C2	$40 \text{ }^\circ\text{C}$ , $25 \text{ \%}$ , $10.2 \text{ g}\cdot\text{m}^3$ , PERM	Indoors, hot factory conditions, basic level PPE
C3	$40 \text{ }^\circ\text{C}$ , $25 \text{ \%}$ , $10.2 \text{ g}\cdot\text{m}^3$ , IMP	Indoors, hot factory, protective clothing
C4	$30 \text{ }^\circ\text{C}$ , $35 \text{ \%}$ , $10.7 \text{ g}\cdot\text{m}^3$ , PERM, solar	Outdoors, hot sunny day, basic level PPE
C5	$40 \text{ }^\circ\text{C}$ , $25 \text{ \%}$ , $10.2 \text{ g}\cdot\text{m}^3$ , PERM solar	Desert environment, basic level PPE
C6	$40 \text{ }^\circ\text{C}$ , $35 \text{ \%}$ , $17.9 \text{ g}\cdot\text{m}^3$ , PERM	Indoors, hot factory, basic level PPE

<sup>1</sup> The thermal and evaporative resistance of the clothing was measured using thermal manikin by EMPA, Switzerland

174  $T_{amb}$  = ambient temperature, RH = relative humidity,  $P_a$  = water vapour pressure, PPE = personal  
175 protective equipment, PERM = permeable and IMP = impermeable

### 176 **1.1.2 Measurements**

177 On arrival, approximately one hour prior to the start of a trial commencing,  
178 participants were issued with, and inserted a rectal probe (Edale Instruments, Cambridge,  
179 UK) to a depth of 10 cm. Rectal temperature was chosen as the ‘gold standard’ measure of  
180  $T_c$  for the purposes of this study. Participants were then asked to change into their  
181 standardised t-shirt and Lycra shorts, and return to the prep room for nude weight and  
182 clothed weight to be recorded (Sartorius IS 150 I GG-H scale, Sartorius, Goettingen, DE).  
183 Skin temperature was measured (iButton DS1192L, Homechip, Milton Keynes, UK) at 11  
184 sites (forehead, chest, upper back, upper arm, lower arm, hand, lower back, abdomen,  
185 thigh, calf and foot), and secured using a soft cloth hypoallergenic tape (3M Medipore, 3M  
186 Healthcare, UK). Insulated skin temperature was measured at the lower part of the neck  
187 between C7 and T2 (spinous process) using skin probes (Grant Instruments, Cambridge,  
188 UK) connected to a Squirrel SQ800 data logger (Grant Instruments, Cambridge, UK)  
189 which recorded data every 20 s. The probe was covered by a 5 cm x 5 cm x 1 cm block of  
190 closed-cell cross linked polyethylene foam (Rubber Astic International, Birmingham, UK),  
191 which was secured around the probe head and onto the skin surface by use of a double-  
192 sided adhesive patch (3M Health Care, UK). A further layer of 11 cm x 11 cm single-  
193 sided adhesive patch (woven spun lace tape 1776, 3M Health Care, UK) was used to cover  
194 the polyethylene block and provide additional skin adhesion. Micro-climate temperature  
195 was measured on the outer side of the insulation foam, also using a Grant thermistor.  
196 Heart rate,  $f$  and ECG were measured using the Equivital monitor (Hidalgo, Cambridge,  
197 UK). Heart rate was also measured using a polar heart rate monitor and watch (RS 800,  
198 Polar, Finland). Rectal temperature and HR were monitored ‘live’ throughout the trials for  
199 safety, and recorded at five minute intervals so changes in the rate of rise could be  
200 observed. At the end of each trial, participants were re-weighed, both nude and with their  
201 clothing, to enable sweat rate and evaporative heat loss to be estimated. Participants were  
202 asked for their subjective rating of thermal comfort (TC), thermal sensation (TS) and  
203 thermal preference (TP) at the start and end of each exercise bout.

### 204 1.1.3 Statistical analysis

205 All values are presented as mean  $\pm$  SD and statistical significance was accepted at  
206 the  $p < 0.05$  level. Multiple linear regression and univariate ANOVA were used to develop  
207 the prediction equation for  $T_{re}$ . The data from each condition for every participant taken at  
208 10 minute intervals were entered into SPSS in order to run an exploratory linear multiple  
209 regression analysis. Thirty potentially relevant variables ( $T_{is}$ ,  $T_s$  at 11 sites, HR,  $f$ ,  $T_{mc}$ ,  
210 temperature and humidity inside the clothing front and back, body mass, age, body fat,  
211 height, sex, clothing,  $\dot{V}O_2$ ,  $T_C$ , TS and TP and sweat rate) were entered into the model and  
212 a stepwise regression was performed. Using the results of that analysis, variables were  
213 added one by one to the model using the 'enter' method. In cases where the relationship  
214 between  $T_{re}$  and the primary variable in the equation was better described as a curvilinear  
215 model, the covariates were centred to reduce colinearity (Bland 2000). Once the best  
216 equation was determined using this model, fixed factors were added to the model using  
217 univariate ANOVA. In determining the most significant and practical covariates to include  
218 in the model, the improvement in the SEE and adjusted (adj)  $r^2$  were examined as variables  
219 were added and removed.

220 Adherence to the assumptions of multiple regression was assessed (Havenith and  
221 Fiala, 2015). Independence of data points was determined using the Durbin-Watson  
222 statistic (1950) which tests a regression model for serial correlation. A value near 2  
223 indicates non-autocorrelation, a value near 0 indicates positive autocorrelation and a value  
224 near 4 indicates negative autocorrelation. Although there are some specific tables for  
225 determining upper and lower bounds of acceptability depending on the number of variables  
226 in the model and the number of data points, a value of between 1 and 3 is often regarded as  
227 'acceptable' and is a useful rule of thumb for assessing the autocorrelation in a model.  
228 Data were also checked for outliers and heteroscedasticity.

229 Once the model structure in terms of included variables had been determined, it  
230 was validated using the same data set, with a 'leave-one-out' bootstrapping approach.  
231 Twenty one different equations (same variables, different coefficients) were developed,  
232 using 20 participants for each equation, leaving one out each time. Rectal temperature was  
233 then predicted for each participant using the equation from which they were excluded. The  
234 mean of the twenty coefficients was then taken to produce a more 'robust' equation based  
235 on an independent sample.



236 The validity of the model was assessed by 1) the SEE and 2) by calculating the  
237 sensitivity (number of individuals over 39 °C correctly identified) and specificity (number  
238 of individuals under 39 °C correctly identified) of the model. Determining the sensitivity  
239 and specificity of the model was chosen as an additional assessment as it shows how many  
240 individuals are correctly or incorrectly identified as 'safe' or 'at risk' and therefore  
241 provides a tangible way of describing the validity of a measure.

## 242 1.2 RESULTS

243 The physical characteristics of the 21 participants are shown in Table 2.

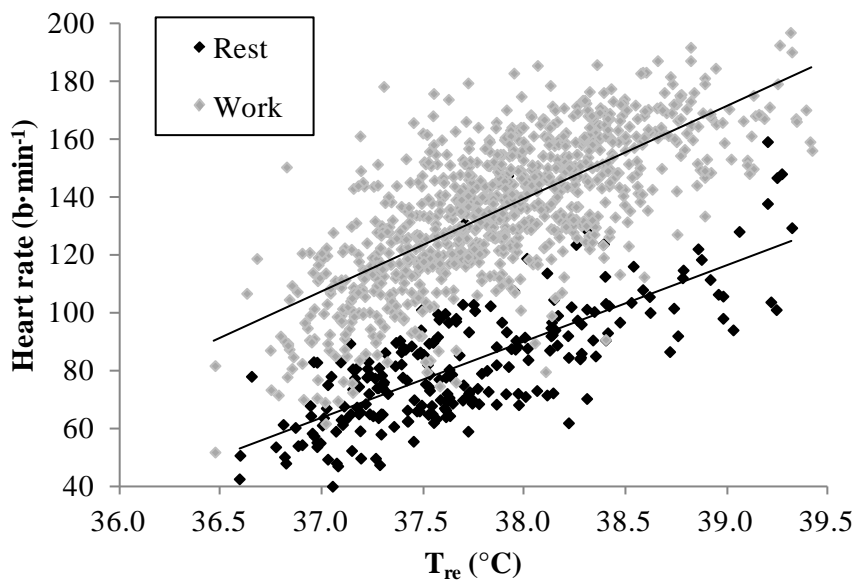
244 **Table 2-** Descriptive characteristics of the participants (mean  $\pm$  SD) (range)

	Male (n=12)	Female (n=9)
Age (years)	25.8 $\pm$ 5.1 (19 – 36)	24.2 $\pm$ 5.7 (19 – 36)
Body mass (kg)	73.6 $\pm$ 11.5	62.4 $\pm$ 6.1
Height (cm)	177.9 $\pm$ 5.6	168.7 $\pm$ 3.4
$\dot{V}O_{2\max}$ (ml·kg·min <sup>-1</sup> )	52.3 $\pm$ 11.4	52.5 $\pm$ 11.6
Body fat (%)	13.3 $\pm$ 4.6	19.3 $\pm$ 8.1

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246

### 1.2.1 Prediction of $T_{re}$



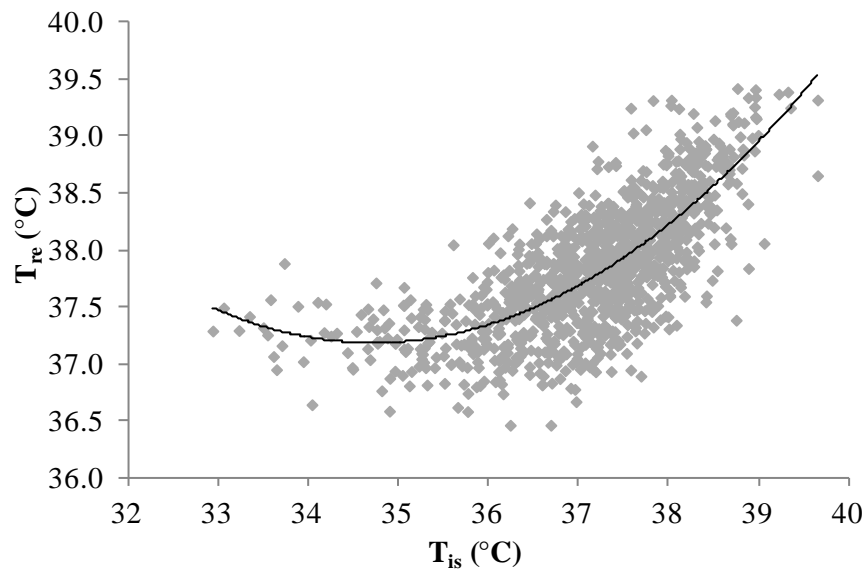
**Figure 1** Rectal temperature ( $T_{re}$ ) and heart rate during work and rest for all conditions

Figure 1 shows  $T_{re}$  and HR for all conditions, with data points coded by work or rest. The HR associated with a given  $T_{re}$  is lower during rest.

The exploratory stepwise regression analysis produced an equation that explained 82 % of the variance with an SEE of 0.25 °C, and included 13 variables (with most significant first;  $T_{mc}$ ,  $T_{is}$ , HR,  $\dot{V}O_2$ , chest temperature, lower arm temperature, upper arm temperature, age, sweat rate, hand temperature, mean  $T_s$  and TC). The next step was to determine the most appropriate model using all the data. Due to the outcome of the stepwise prediction,  $T_{is}$  and  $T_{mc}$  were chosen as the first physiological measure on which to base the prediction model. The  $T_{re}$  and  $T_{is}$  at 10 minute intervals from all participants ( $n=1091$ ) is shown in Figure 2. This figure shows that the relationship between  $T_{is}$  and  $T_{re}$  is better described as a curvilinear model ( $r^2=0.54$ ) than a linear model ( $r^2=0.46$ ), therefore a curvilinear model was applied. All input variables were centred in order to reduce the problem of multicollinearity, which can occur when a single variable is used twice in a model ( $x$  and  $x^2$ ) (Bland 2000).

The first model included centred  $T_{is}$  ( $cT_{is}$ ) and  $cT_{is}^2$  and both variables were significant ( $p<0.05$ ,  $adjr^2=0.54$ ,  $SEE=0.38$  °C). The addition of centred  $T_{mc}$  ( $cT_{mc}$ )

improved  $\text{adj}r^2$  to 0.76 and the SEE to 0.28 °C ( $p < 0.05$ ). In an attempt to improve this prediction, factors which might help distinguish between periods of work and rest were added to the model separately. Breathing rate and  $\dot{V}O_2$  were significant, but only marginally reduced the error ( $p < 0.05$ ,  $\text{adj}r^2 = 0.76$ ,  $\text{SEE} = 0.27$  °C). Heart rate provided the greatest increase in  $\text{adj}r^2$  (0.80) and decrease in the SEE (0.25 °C)<sup>2</sup>.



**Figure 2-** Measured rectal temperature ( $T_{re}$ ) against measured insulated skin temperature ( $T_{is}$ ) (°C) for all conditions

When ‘participants’ was added into the model as a fixed factor, there was an interaction effect between participant and  $T_{is}$ , which resulted in an increase in  $\text{adj}r^2$  to 0.83 and a decrease in the SEE to 0.23 °C. This shows that the model provides a closer prediction of  $T_{re}$  when each participant has a different equation, but as this is impractical, this option was not followed-up. Finally, PPE, sex, work and training status (individuals were classed as ‘trained’ or ‘untrained’ based on their  $\dot{V}O_{2\max}$ ) were added to the model as fixed factors. Only sex and work had an interaction effect with  $T_{is}$  ( $\text{adj}r^2 = 0.80$ ,  $\text{SEE} = 0.25$  °C and  $\text{adj}r^2 = 0.81$ ,  $\text{SEE} = 0.24$  °C respectively,  $p < 0.01$ ).

Using all the data, and taking into consideration practicality (limiting the number of predictors and considering the ease of obtaining them) and accuracy of the prediction, the following equation provides the optimal prediction of  $T_{re}$ :

<sup>2</sup> Using a linear model,  $T_{is}$ ,  $T_{mc}$  and HR produce an  $r^2$  of 0.70 and SEE of 0.30, supporting the use of a quadratic equation in this case.

$$T_{re} = 37.06 + (0.520 * [T_{is}-37.1]) - (0.061 * [T_{mc}-35.5]) + (0.089 * [T_{is}^2-1378]) + (0.007 * HR) - (0.294 * work) \quad (eq1)$$

rest = 0; work = 1

adjr<sup>2</sup>=0.82, SEE=0.24 °C

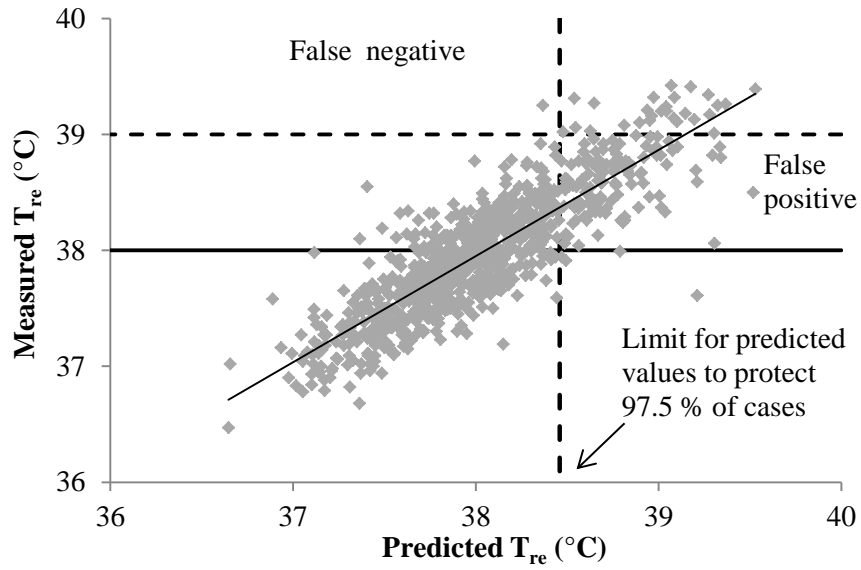
In an attempt to improve the SEE, the next stage of the analysis involved developing prediction equations for a sub-set of data (accurate prediction of low core temperatures was deemed irrelevant, and the focus was put on the higher values:  $T_{is} \geq 36.5$  °C, n=886). For this subset of data there was little difference in the relationship between  $T_{re}$  and  $T_{is}$  ( $\geq 36.5$  °C) when described as a linear ( $r^2=0.43$ , SEE=0.40 °C) or quadratic ( $r^2=0.44$ , SEE=0.39 °C) equation, so a linear equation was developed.

In order to remove the impact of any possible dependency between development and validation of the equation, twenty one regression equations were developed, leaving one participant out from each analysis and using that person to validate the equation (bootstrap method). Rectal temperature was then predicted for each participant using the equation they were left out of in the development process. Figure 3 shows the regression line for predicted against measured  $T_{re}$ . The equations were developed using only  $T_{is}$  data points above 36.5 °C, so with the exclusion of these data points the adjr<sup>2</sup> = 0.86 (p<0.05) and SEE = 0.27 °C. The following equation was developed by averaging the coefficients from the 21 equations:

$$T_{re} = 15.35 + (0.648 * T_{is}) - (0.064 * T_{mc}) + (0.008 * HR) - (0.381 * work) \quad (eq 2)$$

rest = 0; work = 1

Figure 3 also shows the sensitivity and specificity of predicted  $T_{re}$  with a theoretical upper threshold of 39 °C. The vertical dashed line takes into account the 0.27 °C error. To protect 97.5 % of individuals from exceeding a  $T_{re}$  of 39 °C, they need to stop at a predicted  $T_{re}$  of 38.46 °C ( $39 - (2 * SEE)$ ). The sensitivity is increased to 97 % (27 out of 28 data points correctly identified as >39 °C), but the specificity is reduced to 85 %. In protecting most individuals from possible heat illness, many individuals would be stopped at an actual  $T_c$  of below the designated  $T_{re}$  limit (bottom right quadrant of the graph). The solid horizontal line indicates the current safe recommendation by the World Health Organisation of 38 °C (WHO 1996).



**Figure 3** – Measured vs predicted rectal temperature ( $T_{re}$ ) ( $^{\circ}\text{C}$ ). The vertical dashed line show participants would need to be stopped at a  $T_{re}$  of  $38.46^{\circ}\text{C}$  to prevent 97.5 % of the population exceeding  $39^{\circ}\text{C}$ . The horizontal line shows the recommended safe limit for a group of workers, as set by th World Health Organisation.

### 1.3 DISCUSSION

This study aimed to determine whether or not  $T_{re}$  changes during exercise can be modelled using non-invasive physiological, physical and/or environmental measures. To avoid the criticisms on earlier studies, rather than focussing of a single condition, the experimental trials included as many conditions and measurements as was feasible, with an exercise protocol developed to elicit physiological responses indicating high strain levels. This project covered 4 different, low humidity external climates, and by using impermeable garments too also produced skin microclimates with very high humidity, whereby a very wide range of skin microclimate conditions were achieved.

Insulated skin temperature was the most important individual parameter for the prediction of  $T_{re}$ , followed by  $T_{mc}$ . During heat stress, blood flow to the skin increases to dissipate the heat generated in the muscle (Bernard and Kenney 1994). Through conduction, convection, radiation and mostly evaporation, the blood loses heat through the skin before it is returned to the working muscle. The purpose of the insulation material at the surface of the skin is to impede this heat loss, therefore causing the temperature of the skin to become close or equal to  $T_c$ . The origin of the concept for using  $T_{is}$  to predict  $T_{re}$  comes from the convergence of  $T_s$  and  $T_c$  in conditions of uncompensable heat stress. As the temperature gradient between the core and environment reduces, the capacity for heat dissipation from core to skin is removed. Therefore,  $T_s$  will converge with  $T_c$  and the temperature of the skin will eventually reflect changes in  $T_c$  (Pandolf and Goldman 1978). Covering the skin thermistor with an insulation material should mimic this condition and provide an estimate of  $T_c$ .

In addition to  $T_{is}$  and  $T_{mc}$ , several other potentially relevant physiological measures were added to the equation to see whether they could improve the prediction. When added to the equation in combination with 'work', HR explained a significant amount of the variance in  $T_{re}$ ; thus improving the predictive capacity of the equation. During passive heat stress, SkBF increases in response to rises in  $T_c$  and  $T_s$ . This elevation in SkBF occurs through an increase in cutaneous vascular conductance and cardiac output (Crandall et al. 1999). Rowell et al. (1969) showed an increase in HR of  $82 \text{ b} \cdot \text{min}^{-1}$  following 30 min of passive heating

from a  $T_{re}$  of 37.12 °C to 38.23 °C. Similarly, Crandall et al. (1999) reported an increase in HR of 23  $b \cdot min^{-1}$  when  $T_{es}$  increased from 36.5 °C to 37.2 °C during passive heating, showing a cardiovascular response to hyperthermia. During exercise, this relationship becomes more complex. The onset of exercise is accompanied by an initial increase in cutaneous vasoconstriction as blood is directed away from the skin and towards the working muscles (Hunold et al. 1992). Therefore, any increase in HR at the onset of exercise is due to the increased requirement of blood to the working muscles. As exercise continues and metabolic heat production causes internal temperature to rise, a threshold is reached at which thermoregulatory reflexes are evoked (Johnson and Park 1982). Above this threshold, cutaneous vasodilation occurs to allow an increase in  $SkBF$  which enables dry heat loss from the skin. This redistribution of fluids from the blood plasma to the skin tissue, as well as the increased demand for  $SkBF$ , causes a decrease in stroke volume, which results in an increase in HR to maintain cardiac output. This is known as cardiovascular drift and although it is influenced by an increase in body temperature, it is also affected by the increased oxygen cost of exercise. It was hypothesised that by identifying the proportion of the rise in HR during exercise which is due *only* to the thermoregulatory response, HR may provide an even stronger prediction of  $T_{re}$ . Figure 1 shows a comparison of the regression lines for HR against  $T_{re}$  during ‘work’ and ‘rest’. This shows two things; firstly the increase in HR that occurs with increasing  $T_{re}$  during rest; and secondly, the increase in HR between rest and work (for a given  $T_{re}$ ) that occurs due to exercise. By including ‘work’ in the equation, the different intercepts of the two regression lines are accounted for; going some way to distinguishing between the cardiovascular response due to ‘work’ and due to the thermoregulatory response.

Breathing rate was included as a measurement due to the relationship that exists between  $V_E$  and changes in  $T_c$  (Fujii et al. 2012; Haldane 1905). However, there were issues in this experiment with the measurement of  $f$ . Firstly, analysis of the data was difficult due to the many factors that affect  $f$  including talking, drinking or sporadic deep intakes of breath. Secondly, measurement of  $f$  using the Equivital monitor was deemed unreliable: the monitor detects  $f$  in two ways; one using impedance of the chest strap; and, one using the ECG signal. The values reported by these two methods were different, and it was not possible to determine which was more reliable. Despite these problems with the measurement of  $f$ , it was found to be significant in the model, albeit not powerful enough to warrant inclusion in the model. However, the effect of changes in  $T_c$  on  $V_E$  is well established, and this is a

measure worthy of further investigation if the problems associated with its measurement can be overcome.

The prediction of  $T_{re}$  from  $T_{is}$ ,  $T_{mc}$ , HR and 'work' using the bootstrap method of validating the equation has a lower SEE (0.27 °C) and explained more of the variance in  $T_{re}$  (86 %) than previous work that has used similar non-invasive measures to monitor heat strain. Xu et al. (2013) reported that  $T_s$  and heat flux measured at the sternum explained ~75 % of the variance in observed  $T_c$  in hot environments for participants wearing army combat uniform and body armour. Niedermann et al. (2013) developed a model for participants exercising in hot (30 °C) and ambient (10 °C) conditions, and included three  $T_s$ , two skin heat fluxes and HR. The root mean square deviation ranged from 0.28 °C to 0.33 °C in the various conditions, and the variables in the model explained a maximum of 73 % of the variance in observed  $T_{re}$ . Taylor and Amos (1998) compared 4  $T_{is}$  sites with  $T_{es}$ , while cycling at different intensities under five thermal loads. Oesophageal temperature was regressed against  $T_{is}$  and the best prediction under all conditions was using  $T_{is}$  on the spine ( $r^2 = 0.86$ ). Although no values for error were given, the report states that temperatures were offset by as much as 2 °C during the temperate conditions, whereas they converged in the heat, particularly when  $T_{es}$  approached 39 °C. Bernard and Kenney (1994) reported lower errors in the prediction of  $T_{re}$  from non-invasive measures. Three thin copper disks each containing a thermocouple were placed on the skin with a thermal insulator between each disk. Under hot conditions in impermeable ( $T_{amb}$  55 °C) and cotton ( $T_{amb}$  45 °C) coveralls there was a high correlation of disk temperature with  $T_{re}$  (0.93) and an SEE of 0.2 °C.

Despite the positive findings from the current study in relation to much of the published literature, the model developed, using many more predictors, did not predict  $T_{re}$  with a lower SEE than the previous work by our group (Richmond et al. 2013) in which  $T_{is}$  and  $T_{mc}$  only were used to model  $T_{re}$  with an SEE of 0.2 °C and an  $adjr^2$  of 0.85 in ES personnel wearing CBRN protective clothing. One reason is the inclusion of several different climate and clothing conditions to develop a more universal equation. When the  $adjr^2$  and SEE were calculated for each individual condition, the equations for three of the six conditions gave an SEE of 0.21 °C; closer to the value deemed as 'acceptable' prior to the start of the study. However, when all the data were combined in order to develop a universal model, the additional variation added by the other conditions increased the error. Another possible reason is the different clothing that was used in this trial compared with previously. The PPE worn by ES personnel in our earlier study was fully encapsulated which reduces the



exchange of heat between the surface of the skin and the environment. The impermeable clothing worn in the current study did not cover the head and neck of the participant, leaving the sensor patch and surrounding skin exposed to the environment. While the insulating material over the skin thermistor should minimise evaporative heat loss from the skin, it is possible that cooling of surrounding tissue caused a reduction in  $T_{is}$  when exposed to open air conditions.

Although the SEE of 0.27 °C fell outside the pre-defined acceptable error of 0.20 °C, the impact of the error of the model developed on drop-out rate is still worthy of consideration. The sensitivity and specificity plot showed that to prevent 97.5 % of the population from exceeding 39 °C, they would need to be stopped at a predicted  $T_{re}$  of 38.4 °C. This would result in 50 % of the population being withdrawn from work at a true  $T_{re}$  of 38.65 °C; considerably lower than many people can tolerate in compensable conditions. This would have a negative impact on work productivity and efficiency. Despite the SEE being lower than hoped, it is clear from Figure 3 that using *eq 2* to predict  $T_{re}$  would improve considerably on the WHO standards (withdrawal at 38°C), with fewer individuals being stopped before reaching potentially critical temperatures, and therefore improving work productivity.

### 1.3.1 Conclusion

For the current study, which included six environmental conditions, two clothing ensembles, and a wide variety of physiological and environmental measurements, it was not possible to predict  $T_{re}$  within the SEE of 0.2 °C. However, the inclusion of ‘work’ and HR into the equation provided a better estimation of  $T_{re}$  than  $T_{is}$  and  $T_{mc}$  alone; with ‘work’ helping to distinguish between the different regression lines observed for HR at work and at rest. It was hoped that  $f$  might improve the prediction due to the relationship between  $V_E$  and increasing  $T_c$ , but this was not possible due to problems with the measurement of  $f$ . Nevertheless, the relationship between  $f$  and hyperthermia may be worth further investigation under other conditions (e.g. when the individuals are not drinking or talking), and using different monitoring equipment. The findings from this work could be used to implement a practical, valid prediction of body temperature under certain conditions in the workplace (i.e. for selected conditions), thereby improving health, safety and productivity. As these findings are specific only to the conditions trialled here, future work might also include repeating this study under additional conditions, and using fully-encapsulated PPE to establish whether the

addition of ‘work’ and HR improved further the errors reported previously (Richmond et al. 2013). However, given that in this study prediction models were investigated with the largest possible number of predictors, but in the end not achieving the required predictive power to work over the whole range of conditions tested here (which was extensive compared to other studies but not exhaustive), the idea that it is possible to create a universally usable non-invasive heat stress monitor may be unachievable.

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