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Non-Invasive Prediction of Blood Lactate During Incremental Exercise via Heart Rate, Core Body Temperature, and Sweat-Derived Indices

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Abstract

Blood lactate concentration (BLa) is a key marker of metabolic stress, but invasive sampling limits real-time monitoring. We developed a non-invasive model to estimate BLa during incremental exercise using heart rate (HR), core body temperature (CBT), and sweat-derived indices. Thirty-one healthy adult males performed a graded treadmill test. HR and CBT were monitored continuously. Sweat was sampled from the forehead, chest, and back to quantify sweat lactate concentration ([La−]sw) and lactate excretion rate (LER = [La−]sw × sweat rate). Linear mixed-effects models (LMMs) were fitted with log-transformed BLa (Log[BLa]) and participant-level random effects. BLa increased with exercise intensity ($p < 0.001$), accompanied by increases in HR, CBT and LER (both $p < 0.001$). LMMs combining HR, CBT, and sweat indices showed strong performance for Log[BLa]. The best model (HR + CBT + forehead LER) achieved conditional R^2=0.939 and RMSE = 0.229 (log units), and forehead-based models outperformed chest and back. Combined cardiovascular, thermoregulatory, and sweat-derived measures enable accurate, non-invasive estimation of BLa during graded exercise, supporting wearable-based metabolic monitoring and individualized exercise prescription.

Introduction

Blood lactate concentration (BLa) increases with exercise intensity and serves as a key indicator of aerobic capacity and endurance performance; accordingly, it is widely used in sports science and clinical rehabilitation[1,2]. However, conventional BLa assessment during exercise requires invasive blood sampling, which limits continuous and real-time monitoring due to discomfort, procedural complexity, and potential infection risk[3].

Recent advances in wearable devices for sweat lactate measurement have enabled non-invasive approaches to estimating BLa[4-7]. Importantly, sweat lactate concentration ([La^-]w) does not reflect passive diffusion from blood. It can also be locally produced through glycolytic activity within sweat gland cells, and is influenced by multiple physiological and environmental factors, including sweat rate, skin blood flow, and thermal stress[8,9]. As sweat rate increases, dilution effects may attenuate the association between [La^-]w and BLa[9]. To partially account for dilution, lactate excretion rate (LER; [La^-]w × sweat rate) has been proposed as a more informative index[10]. Nevertheless, regional differences in sweat gland density and sweating responses, as well as variation in sensor attachment and skin–sensor contact, may limit the representativeness of a single local measurement[11]. This suggests that additional physiological variables may be necessary to improve the robustness of non-invasive BLa estimation.

Heart rate (HR) and core body temperature (CBT) are potential physiological signals that may reflect metabolic strain beyond cardiovascular or sweat-derived indices[12,13]. HR typically increases with exercise intensity and shows moderate-to-strong associations with BLa, supporting its use for lactate estimation[12]. However, inter-individual variability in cardiovascular responses, training status, and fatigue resistance can reduce predictive reliability[13]. CBT also rises progressively during exercise due

to metabolic heat accumulation, and elevations in body temperature have been linked to increased glycolytic activation and lactate accumulation[14,15]. Despite this physiological rationale, CBT has rarely been incorporated as a predictor of lactate dynamics, as prior work has primarily focused on thermoregulatory function or heat-related illness risk[16].

Accordingly, the aim of this study was to develop and validate multivariable models to predict BLa during incremental exercise using only non-invasive physiological signals. We constructed regression models incorporating HR, CBT, and sweat-derived lactate indices. Based on the optimal combination of explanatory variables identified using a linear mixed-effects model, we additionally applied a random forest algorithm using the same inputs to evaluate predictive performance.

Results

Stage-dependent Responses of Physiological Variables. As shown in Figure 1, blood lactate concentration (BLa) increased progressively with increasing exercise intensity, showing marked elevation from stage 4 and peaking at stage 7 ($p < 0.001$; Figure 1A). Heart rate (HR) and core body temperature (CBT) significantly increased with workload ($p < 0.001$; Figure 1B), with HR increasing steadily from ~100 bpm to ~180 bpm and plateauing near stage 7, and CBT rising sharply between stages 6 and 8 to ~39 °C. Lactate excretion rate (LER) at the forehead, chest, and back significantly increased with exercise intensity ($p < 0.001$; Figure 1D), with the forehead showing the largest rise before stabilizing at higher stages. In contrast, sweat lactate concentration ($[La^-]_w$) significantly decreased across stages ($p < 0.001$; Figure 1C), peaking at stage 0 and a progressive decline that stabilized from stage 5 onward.

Correlations Between BLa and Non-Invasive Physiological Variables. Figure 2 shows the correlations between BLa and non-invasive physiological variables. HR strongly correlated with BLa ($r = 0.814$, $p < 0.001$; Figure 2A), and CBT showed a moderate positive correlation ($r = 0.563$, $p < 0.001$; Figure 2B). $[La^-]_w$ exhibited weak negative correlations across measurement sites—forehead ($r = -0.242$, $p = 0.002$; Figure 2C) and back ($r = -0.250$, $p < 0.001$; Figure 2E). LER showed significant positive correlations with BLa—forehead ($r = 0.391$, $p < 0.001$; Figure 2F), chest ($r = 0.254$, $p < 0.001$; Figure 2G), and back ($r = 0.224$, $p < 0.001$; Figure 2H).

Regression Models for Predicting Blood Lactate Concentration. Table 1 summarizes the regression performance for predicting BLa using various physiological signal combinations. Conditional and marginal R^2 values and corresponding RMSE were used to evaluate each model's explanatory power and prediction accuracy. Models that included HR demonstrated the highest predictive capability, with conditional R^2 values consistently > 0.90. Among these, combining HR, CBT, and forehead LER yielded the best performance (conditional $R^2 = 0.939$, marginal $R^2 = 0.788$, conditional RMSE = 0.2288). Models using CBT alone showed moderate predictive accuracy (conditional $R^2 = 0.799$, marginal $R^2 = 0.481$). Predictive performance improved when CBT was combined with sweat-derived parameters such as LER or $[La^-]_w$. The CBT + forehead LER model achieved a conditional R^2 of 0.901 and a conditional RMSE of

0.3662. Overall, regression models integrating cardiovascular (HR) and thermoregulatory (CBT) variables with sweat-derived parameters (LER or [La⁻]□w) exhibited conditional R^2 values ranging from 0.921 to 0.939.

Table 1. Regression Performance (R^2, RMSE) by physiological signal Combination

Factor	Conditional R^2	Marginal R^2	Conditional RMSE	Marginal RMSE
HR	0.908***	0.795***	0.2973	0.4678
HR+CBT	0.917***	0.807***	0.2818	0.4554
HR+Forehead[La-]sw	0.926***	0.807***	0.2648	0.4618
HR+Chest[La-]sw	0.918***	0.808***	0.2795	0.4510
HR+Back[La-]sw	0.916***	0.791***	0.2839	0.4681
HR+Forehead LER	0.921***	0.785***	0.2596	0.4561
HR+Chest LER	0.915***	0.797***	0.2779	0.4556
HR+Back LER	0.912***	0.789***	0.2829	0.4614
HR+CBT+Forehead[La-]sw	0.933***	0.818***	0.2429	0.4248
HR+CBT+Chest[La-]sw	0.921***	0.828***	0.2698	0.4231
HR+CBT+Back[La-]sw	0.926***	0.799***	0.2675	0.4634
HR+CBT+Forehead LER	0.939***	0.788***	0.2288	0.4572
HR+CBT+Chest LER	0.921***	0.806***	0.2684	0.4502
HR+CBT+Back LER	0.933***	0.792***	0.2668	0.4671
CBT	0.799***	0.481***	0.5549	0.9517
CBT+Forehead[La-]sw	0.871***	0.460***	0.4283	0.9407
CBT+Chest[La-]sw	0.854***	0.503***	0.4691	0.9873
CBT+Back[La-]sw	0.838***	0.522***	0.4816	0.9244
CBT+Forehead LER	0.901***	0.512***	0.3662	0.8807
CBT+Chest LER	0.854***	0.503***	0.4679	0.9804
CBT+Back LER	0.877***	0.505***	0.4507	1.0101

*** $p<0.001$, Note: RMSE values are reported on the log-transformed BLa scale (log units).

Agreement Between Predicted and Observed BLa. Figure 3 presents the agreement between predicted and observed log-transformed blood lactate concentration (Log[BLa]) values across different body

regions, based on conditional predictions from the linear mixed-effects model (LMM). Log-scale values can be back-transformed to the original scale using the exponential function (BLa = exp(Log[BLa])). Therefore, differences on the log scale correspond to multiplicative (ratio) differences in BLa. Predictive models incorporating HR, CBT, and sweat-derived variables showed strong consistency between predicted and measured values. Among [La^-]w-based models, combining forehead [La^-]w, HR, and CBT yielded the highest predictive accuracy (R^2 = 0.933, RMSE = 0.4204; Figure 3A), followed by chest [La^-]w (R^2 = 0.921, RMSE = 0.4109; Figure 3B) and back [La^-]w (R^2 = 0.926, RMSE = 0.4289; Figure 3C). When LER was used instead of concentration, similar predictive performance was observed. The forehead LER model showed the strongest agreement (R^2 = 0.938, RMSE = 0.4637; Figure 3D). The chest and back LER models also exhibited high predictive accuracy (R^2 = 0.921, RMSE = 0.4432; Figure 3E; R^2 = 0.923, RMSE = 0.4544; Figure 3F). The LMM models achieved high predictive accuracy for Log(BLa) across all body regions, indicating consistently strong relative agreement in (multiplicative) terms after back-transformation to the original BLa scale.

Discussion

This study demonstrated that blood lactate concentration during graded exercise can be reliably estimated by integrating non-invasive physiological signals. Specifically, HR and CBT exhibited strong and moderate positive correlations with BLa, whereas the lactate excretion rate (LER) showed a significant yet modest correlation. Regression analyses revealed that combined models incorporating HR, CBT, and sweat-derived parameters—particularly forehead LER—achieved the highest predictive accuracy, with conditional R^2 values > 0.93. Linear mixed-effects modeling enhanced interpretability and stability of predictions across participants. Collectively, these findings highlight the feasibility of integrated cardiovascular, thermoregulatory, and sweat-based indices for non-invasive monitoring of metabolic stress, with applications in exercise testing, performance optimization, and clinical rehabilitation.

In this study, all measured physiological variables exhibited characteristic response patterns across progressive exercise stages, reflecting coordinated cardiovascular, thermoregulatory, and metabolic system activation. BLa increased progressively with exercise intensity, consistent with established lactate accumulation patterns during incremental workloads[1]. HR increased in a near-linear pattern before plateauing at maximal exertion (117.3 ± 14.1 → 182.1 ± 16.0 bpm; Figure 1), aligning with previous reports showing that HR increases steadily with exercise intensity and levels off as sympathetic activation reaches maximum capacity[13,18]. CBT rose continuously throughout all stages, indicating cumulative heat storage as workload increased—a physiological response attributed to metabolic heat production-dissipation imbalance)[9,19]. In contrast, [La^-]w significantly decreased with increasing workload, whereas LER increased. This inverse relationship reflects dilutional effects associated with rising sweat rates at higher exercise intensities[8, 9]. Collectively, these results represented typical physiological adaptations to incremental exercise and confirmed that the variables measured appropriately characterize metabolic, cardiovascular, and thermoregulatory stress.

Correlation analyses were conducted to evaluate the physiological relationships among these variables during exercise. HR showed a strong positive correlation with BLa ($r = 0.814$, $P < 0.001$), consistent with prior evidence linking HR to metabolic intensity and lactate kinetics during graded exercise[12,20]. CBT demonstrated a moderate positive association with BLa ($r = 0.563$, $P < 0.001$), aligning with previous findings that elevated internal temperature parallels increased lactate accumulation owing to enhanced glycolytic flux under thermal load[10.14]. The weaker correlation of CBT relative to HR likely reflects the multifactorial nature of thermoregulation, which is influenced by metabolic heat production, heat dissipation mechanisms such as sweating, skin blood flow, and environmental conditions[21,22]. Prior studies have similarly reported progressive increases in CBT with workload; however, it shows greater variability due to environmental and individual thermoregulatory differences, weakening its direct association with lactate kinetics[19,23].

$[La^-]_w$ exhibited the weakest negative correlations with BLa ($-0.135 \leq r \leq -0.250$) among the measured variables in this study. This weak association reflects the strong influence of local factors on $[La^-]_w$ rather than systemic metabolic status. Specifically, sweat composition depends on sweat gland activity, skin blood flow, evaporation rate, and local dilution effects, which vary across body sites and individuals. With increasing exercise intensity, total lactate excretion increases; however, sweat concentration decreases owing to higher sweat volume and dilution, obscuring its direct relationship with blood lactate[8,9].Regional variability (forehead vs. chest vs. back) and temporal lag between sweat and blood lactate changes further reduce the predictive value of sweat lactate concentation[24].

Regression analyses further demonstrated that models combining HR, CBT, and sweat-derived parameters yielded the most accurate predictions of BLa (Table 1). Conditional and marginal R^2 values and RMSE showed that integrated models consistently outperformed single-variable approaches, consistent with recent findings emphasizing multi-signal integration for physiological modeling[5]. The model combining HR, CBT, and forehead LER achieved the best performance (conditional $R^2 = 0.939$; marginal $R^2 = 0.788$; RMSE = 0.2288). This suggested that forehead-derived signals may offer practical advantages owing easier sensor attachment and enhanced signal stability in real-world monitoring. Similarly, models pairing CBT with sweat-derived variables improved prediction accuracy compared with CBT alone, consistent with prior studies reporting the additive predictive value of thermal and metabolic markers[10,25]. Integrating cardiovascular and thermoregulatory responses (HR and CBT) with peripheral sweat-based metrics enhances overall predictive capability.

Log transformation of lactate data and application of the linear mixed-effects model (LMM) improved model fit and interpretability, as recommended for physiological datasets exhibiting non-linear accumulation patterns[26]. The LMM incorporated both fixed (HR, CBT, and sweat-derived indices) and random effects (participant variability), enabling accurate estimation of within-subject trends. Although results are presented on the log scale, model effects can be interpreted on the original BLa scale via back-transformation; specifically, $\exp(\beta)$ denotes a multiplicative change (ratio) in BLa for a one-unit change in the predictor, and log-scale predicted values can be converted to BLa using $BLa = \exp(\text{Log}[BLa])$. Conditional R^2 values across all body regions ranged from 0.921 to 0.939, indicating

consistent predictive accuracy between predicted and observed log-transformed BLa values. This important methodological approach improves model stability and interpretability, particularly during high-intensity exercise stages.

Despite these promising findings, this study had several limitations. First, this study was conducted in a controlled laboratory setting with a relatively homogeneous group of healthy young adults. Future research should validate this model in more diverse populations, including athletes, clinical patients, and different environmental conditions. Second, manual and intermittent sweat sampling was performed may have limited temporal resolution. The use of wearable, real-time sweat biosensors could improve capture of dynamic lactate fluctuations with higher fidelity. Third, although HR, CBT, and sweat-derived parameters captured key physiological domains, integrating additional signals—such as skin temperature response—may further enhance prediction accuracy.

Collectively, these findings demonstrated that integrating non-invasive physiological signals—specifically HR, CBT, and sweat-derived lactate measures—provides a robust and physiologically interpretable framework for estimating BLa during graded exercise. The strong agreement between predicted and observed outcomes confirms the method's applicability for real-time, non-invasive metabolic monitoring, with potential implications for individualized exercise testing, performance optimization, and clinical rehabilitation.

Methods

Participants. Thirty-one healthy adult males aged 20–39 years were recruited. All participants engaged in ≥150 min of exercise per week for ≥3 months and maintained stable body weight (±10%) during the previous 6 months. Table 2 presents the physical characteristics of participants (n = 31). None used medication and all complied with a 12-hour fast before testing. Exclusion criteria included metabolic, cardiovascular, or neurological disorders; Type 1 or Type 2 diabetes; orthopedic limitations; history of surgery; or non-obesity related cancer. This study was approved by the Institutional Review Board of Korea University (KUIRB-2024-0280-01), and written informed consent was obtained from all participants. All methods were carried out in accordance with relevant guidelines and regulations and the Declaration of Helsinki.

Table 2. Descriptive characteristics of participants (n=31)

	Mean±SD	Minimum	Maximum
Age(yr)	26.2±5.82	18	37
Height(cm)	176±4.96	167	188
Weight(kg)	73.4±9.69	58	99.9
Body Fat(%)	14.7±4.5	6.5	23.3

Experimental procedure. Participants visited the laboratory on two occasions. The indoor environment was maintained at 29–31 °C and 50–70% relative humidity. At visit 1, written informed consent was obtained, followed by a preliminary assessment to confirm adequate sweating capacity. Body composition was assessed using a stadiometer and bioelectrical impedance analysis (InBody 270, Biospace, Seoul, Korea). While wearing a heart-rate monitor (Polar 810i, Polar Electro Oy, Finland), participants performed 30 min of treadmill exercise at 60% intensity based on previous protocols[7,10]. Using a gravimetric method[27], participants with a local sweat rate (LSR) ≤ 0.4 mg/cm2/min were excluded. For visit 2, participants were instructed to refrain from alcohol consumption, strenuous exercise, and smoking for at least 24 h before testing. They also fasted for ≥ 12 h, avoided caffeine-containing beverages, and maintained adequate hydration. These procedures were implemented to standardize physiological conditions and minimize potential confounding factors. Participants consumed the telemetric core-body temperature capsule with water approximately 2 h before testing. A licensed nurse collected venous blood samples immediately after each exercise stage. Thereafter, sweat samples were collected using double-film absorbent patches placed on the forehead, chest, and upper back.

Exercise Protocol. The exercise test was performed on a motorized treadmill (Drex NR20 NR20X, Drex, Korea) according to a modified Bruce protocol (Figure 4). The test began with a 10-minute warm-up phase at 4.6 km/h and 0% incline, followed by a 2-minute rest period. The modified Bruce protocol was adopted to secure sufficient sweat volume over progressive workloads, enabling reliable sampling across both pre- and post-lactate threshold stages. This gradual intensity progression ensured stable thermoregulatory activation, facilitating continuous sweat excretion while delaying abrupt lactate accumulation. The protocol was suitable for this study because sustained sweat availability was essential for analyzing sweat-derived lactate biomarkers throughout dynamic metabolic transitions. The incremental treadmill subsequently commenced, consisting of seven mandatory 5-minute stages, with a 2-minute rests between stages. Speed increased by 0.5 km/h and incline by 1% per stage, as detailed in Figure 4. The test continued until volitional exhaustion, defined inability to maintain the required pace despite verbal encouragement.

Blood Sampling and Analysis. A 22 G catheter (Kovax-Cath, Korea) was inserted into the antecubital vein of the non-dominant arm before exercise. Venous blood samples (~3 mL) were collected immediately after each exercise stage. Samples were stored at 4 °C and analyzed colorimetrically for blood lactate concentration at a certified clinical laboratory (Seegene Medical Foundation, Seoul, Korea).

Measurements

Heart Rate (HR). HR was continuously monitored using a chest-worn heart rate sensor. Resting HR was recorded during a seated rest period before exercise. HR values were recorded 10 s before each stage ended.

Sweat Sampling and Analysis. Sweat collection patches were applied after the warm-up phase, after skin cleansing with 70% isopropyl alcohol and deionized water to remove debris and oils. Sweat samples

were collected continuously using double-film patches placed on three the forehead (midline, 1 cm above the eyebrows), chest (lateral side, near the pectoral muscle), and upper back (most medial side of the scapula), based on an anatomical mapping method[15]. Each patch consisted of an absorbent cotton layer, a parafilm barrier ((Disposable consumable laboratory film, CNWTC, Chongqing, China), and a transparent waterproof dressing (Tegaderm Film, 3M, St. Paul, MN, USA). Cotton sizes were 16.8, 33.6, and 33.6 cm² for the forehead, chest, and back, respectively, with corresponding parafilm sizes of 19.2, 38.2, and 38.4 cm. Patches were secured during each 5-minute exercise stage and replaced afterward. Only sweat patches producing ≥2 µL of sweat were analyzed to ensure adequate sample size. Collected sweat samples were immediately weighed using an analytical balance (Hansung HS-103, Hansung Instrument, South Korea; precision: 0.001 g) to determine sweat volume, and subsequently centrifuged at 2,000 rpm for 5 min at 4 °C (LC-8S, JoanLab, China) to separate the supernatant for further analysis. Samples were stored at 4 °C prior to analysis. $[La^-]$sw was quantified amperometrically at 0.1 V with a calibrated lactate sensor (Dongwoo Fine-chem Inc.) connected to a CHI-630 electrochemical workstation (CH Instruments, Inc.). The sensor was calibrated daily with standard lactate solutions (0–20 mM) to ensure measurement accuracy within ±5%.

Core Body Temperature (CBT). CBT was continuously monitored using an ingestible telemetric capsule transmitting data wirelessly to an external receiver (e-Viewer® Performance). Data were recorded throughout the test and recovery period to assess thermoregulatory and metabolic responses.

Statistical Analyses. Statistical analyses were performed using Jamovi version 2.3 for Mac (The Jamovi Project, Sydney, Australia). Statistical significance was set at $\alpha = 0.05$, data are presented as the mean ± standard deviation (SD) unless otherwise stated. Linear mixed-effects models (LMMs) were assessed associations between blood lactate concentration (BLa) and non-invasive physiological variables (HR, CBT, $[La^-]$sw, and LER). BLa data were log-transformed to improve normality, and participant-level random effects accounted for repeated measures across exercise stages. Pearson's correlation analyses additionally assessed linear relationships between BLa and each non-invasive variable. To confirm the robustness of the LMM findings, a supplementary random forest regression was applied using the same input variables (HR, CBT, and sweat-derived lactate variables) to explore the predictive relationships under a non-parametric framework. This analysis served as a secondary reference, suggesting that the variable combination retained predictive relevance beyond linear assumptions.

Perspective

Increasing interest in wearable biosensors has renewed the need for valid, non-invasive indicators of metabolic strain during exercise. Our findings show that integrating HR and CBT with sweat-derived lactate indices, particularly forehead LER, enables accurate estimation of log-transformed blood lactate during incremental running. This supports the view that multi-signal monitoring can outperform single-marker approaches when lactate dynamics are influenced by cardiovascular, thermoregulatory, and sweat-gland factors. Practically, these models may facilitate real-time intensity profiling and individualized training prescription without repeated blood sampling. Future studies should validate

performance across sex, fitness levels, environments (heat/humidity), and exercise modes, and test device-level implementation with prospective external validation and error thresholds that are meaningful for coaching and clinical decision-making.

Declarations

Funding

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Conflicts of Interest

This study was funded by Dongwoo Fine-Chem Co., Ltd. S. H. Chon and Y. K. Lee is an employees of Dongwoo Fine-Chem Co., Ltd. The authors declare no other conflicts of interest (The sponsor had no role in the study design, data analysis, or interpretation).

Author Contributions

Conceptualization: Jaesung Lee, Jihye Moon, Jonghoon Park. Investigation: Jaesung Lee, Jihye Moon, Seunghwan Chon, Youngkeun Lee. Formal analysis: Jaesung Lee, Jihye Moon, Youngim Kim, Hyeonmin Kim, Hyunseob Lee, Sungjin Yoon. Data curation: Jaesung Lee, Jihye Moon. Visualization: Jaesung Lee, Jihye Moon. Writing – original draft: Jaesung Lee, Jihye Moon. Writing – review & editing: Youngim Kim, Hyeonmin Kim, Eunbi Kim, Hyunseob Lee, Sungjin Yoon, Seunghwan Chon, Youngkeun Lee. Supervision: Jonghoon Park. Project administration: Jonghoon Park. Funding acquisition: Jonghoon Park. All authors have read and approved the final version of the manuscript.

Data Availability

The data supporting the findings of this study, including the raw and processed data underlying the figures and tables, are available from the corresponding author upon reasonable request.

Ethics Approval

The study protocol was approved by the Institutional Review Board of Korea University (KUIRB-2024-0280-01)

Patient consent

Written informed consent was obtained from all participants for study participation and the use of their data for research purposes.

Permission to reproduce

Not applicable.

Clinical trial registration

Not applicable.

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References

1. Beneke, R., Leithäuser, R. M. & Ochentel, O. Blood lactate diagnostics in exercise testing and training. *Int. J. Sports Physiol. Perform.* **6**, 8–24. https://doi.org/10.1123/ijspp.6.1.8 (2011).
2. Goodwin, M. L., Harris, J. E., Hernández, A. & Gladden, L. B. Blood lactate measurements and analysis during exercise: A guide for clinicians. *J. Diabetes Sci. Technol.* **1**, 558–569. https://doi.org/10.1177/193229680700100414 (2007).
3. Khabour, O. F., Ali, A., Mahallawi, W. H. & K. H. & Occupational infection and needle stick injury among clinical laboratory workers in Al-Madinah city, Saudi Arabia. *J. Occup. Med. Toxicol.* **13**, 15. https://doi.org/10.1186/s12995-018-0198-5 (2018).
4. Gao, W. et al. Fully integrated wearable sensor arrays for multiplexed in situ perspiration analysis. *Nature* **529**, 509–514. https://doi.org/10.1038/nature16521 (2016).
5. Yang, G., Ryu, S., Kim, K. & Kim, J. Wearable device for continuous sweat lactate monitoring in sports. *Front. Physiol.* **15**, 1376801. https://doi.org/10.3389/fphys.2024.1376801 (2024).
6. Karpova, E. V., Laptev, A. I., Andreev, E. A., Karyakina, E. E. & Karyakin, A. A. Relationship between sweat and blood lactate levels during exhaustive physical exercise. *ChemElectroChem* 7, 191–194, (2020). https://doi.org/10.1002/celc.201901703
7. Okawara, H., Sawada, T., Nakashima, D., Fujitsuka, H. & Katsumata, Y. Lactate threshold evaluation in swimming using a sweat lactate sensor: A prospective study. *Eur. J. Sport Sci.* **24**, 1302–1312. https://doi.org/10.1002/ejsc.12179 (2024).
8. Takei, N. et al. Differential patterns of sweat and blood lactate concentration response during incremental exercise in varied ambient temperatures: A pilot study. *Temp. (Austin).* **11**, 247–253. https://doi.org/10.1080/23328940.2024.2375693 (2024).
9. Seki, Y. et al. A novel device for detecting anaerobic threshold using sweat lactate during exercise. *Sci. Rep.* **11**, 4929. https://doi.org/10.1038/s41598-021-84381-9 (2021).
10. Buono, M. J., Lee, N. V. L. & Miller, P. W. The relationship between exercise intensity and the sweat lactate excretion rate. *J. Physiol. Sci.* **60**, 103–107. https://doi.org/10.1007/s12576-009-0073-8 (2010).
11. Taylor, N. A. & Machado-Moreira, C. A. Regional variations in transepidermal water loss, eccrine sweat gland density, sweat secretion rates and electrolyte composition in resting and exercising humans. *Extrem. Physiol. Med.* **2**, 4. https://doi.org/10.1186/2046-7648-2-4 (2013).

12. Bentley, D. J., Newell, J. & Bishop, D. Incremental exercise test design and analysis: Implications for performance diagnostics in endurance athletes. *Sports Med.* **37**, 575–586. https://doi.org/10.2165/00007256-200737070-00002 (2007).
13. Achten, J. & Jeukendrup, A. E. Heart rate monitoring: Applications and limitations. *Sports Med.* **33**, 517–538. https://doi.org/10.2165/00007256-200333070-00004 (2003).
14. Febbraio, M. A. Alterations in energy metabolism during exercise and heat stress. *Sports Med.* **31**, 47–59. https://doi.org/10.2165/00007256-200131010-00004 (2001).
15. van Hall, G. Lactate kinetics in human tissues at rest and during exercise. *Acta Physiol.* **199**, 499–508. https://doi.org/10.1111/j.1748-1716.2010.02122.x (2010).
16. Armstrong, L. E. et al. American College of Sports Medicine position stand: Exertional heat illness during training and competition. *Med. Sci. Sports Exerc.* **39**, 556–572. https://doi.org/10.1249/MSS.0b013e31802fa199 (2007).
17. Gerrett, N. et al. Thermal sensitivity to warmth during rest and exercise: A sex comparison. *Eur. J. Appl. Physiol.* **114**, 1451–1462. https://doi.org/10.1007/s00421-014-2875-0 (2014).
18. Vieira, S. S. et al. Does stroke volume increase during an incremental exercise? A systematic review. *Open. Cardiovasc. Med. J.* **10**, 57–63. https://doi.org/10.2174/1874192401610010057 (2016).
19. Sawka, M. N. & Wenger, C. B. *Physiological responses to acute exercise-heat stress. In Human Performance Physiology and Environmental Medicine at Terrestrial Extremes (eds Pandolf, K. B., Sawka, M. N. & Gonzalez, R. R.)*. 97–151Benchmark Press,. (1988).
20. Shen, T. & Wen, X. Heart rate based prediction of velocity at lactate threshold in ordinary adults. *J. Exerc. Sci. Fit.* **17**, 108–112. https://doi.org/10.1016/j.jesf.2019.07.002 (2019).
21. Periard, J. D., Eijsvogels, T. M. H. & Daanen, H. A. M. Exercise under heat stres : Thermoregulation, hydration, performance implications, and mitigation strategies. *Physiol Rev* 101, 1873– (1979). https://doi.org/10.1152/physrev.00038.2020 (2021).
22. Lindinger, M. *Homeostasis and its disturbance during exercise. In Open Textbook of Exercise Physiology (Open Educational Alberta*,). (2023). https://pressbooks.openeducationalberta.ca/physiologyexercise/
23. Lim, J., Park, H., Lee, S. & Park, J. Changes in heart rate, muscle temperature, blood lactate concentration, blood pressure, and fatigue perception following jogging and running: An observational study. *Exerc. Sci.* **31**, 72–79. https://doi.org/10.15857/ksep.2022.00045 (2022).
24. Heikenfeld, J. et al. Accessing analytes in biofluids for peripheral biochemical monitoring. *Nat. Biotechnol.* **37**, 407–419. https://doi.org/10.1038/s41587-019-0040-3 (2019).
25. Rabost-Garcia, G. et al. Non-Invasive Multiparametric Approach To Determine Sweat-Blood Lactate Bioequivalence. *ACS Sens.* **8**, 1536–1541. https://doi.org/10.1021/acssensors.2c02614 (2023).
26. Bates, D., Mächler, M., Bolker, B. & Walker, S. Fitting Linear Mixed-Effects Models Using lme4. *J. Stat. Softw.* **67**, 1–48. https://doi.org/10.18637/jss.v067.i01 (2015).

27. Morris, N. B., Cramer, M. N., Hodder, S. G., Havenith, G. & Jay, O. A comparison between the technical absorbent and ventilated capsule methods for measuring local sweat rate. *J. Appl. Physiol. (1985)*. **114**, 816–823. https://doi.org/10.1152/japplphysiol.01088.2012 (2013).

Figures

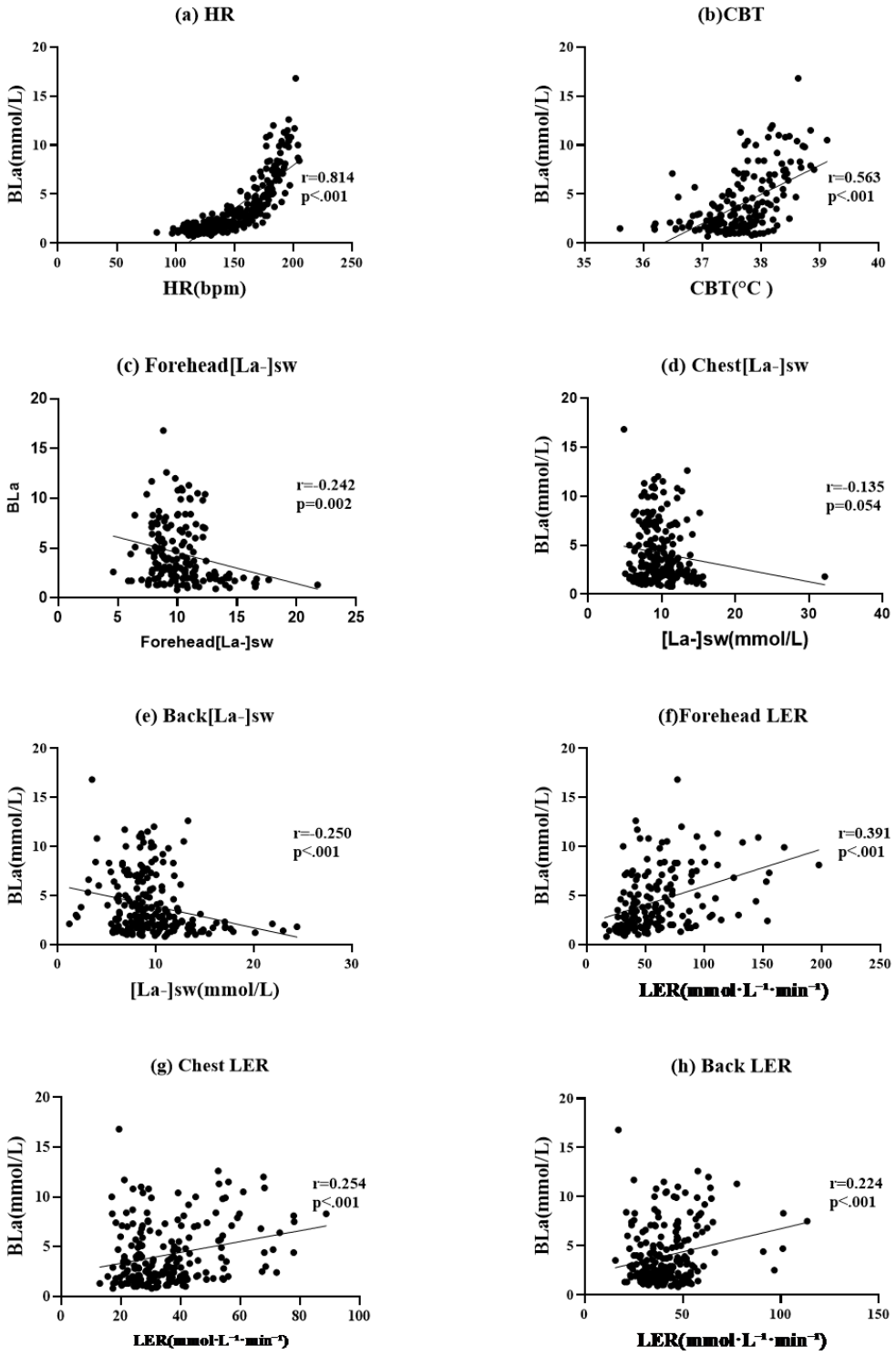


Figure 1

Changes in blood lactate (BLa), heart rate (HR), core body temperature (CBT), sweat lactate concentration ([La$^-$]sw), and lactate excretion rate (LER) during incremental exercise.

Abbreviations: BLa, Blood Lactate concentration; HR, Heart Rate; CBT, Core Body Temperature; [La$^-$]sw, sweat lactate concentration; LER, Lactate excretion rate

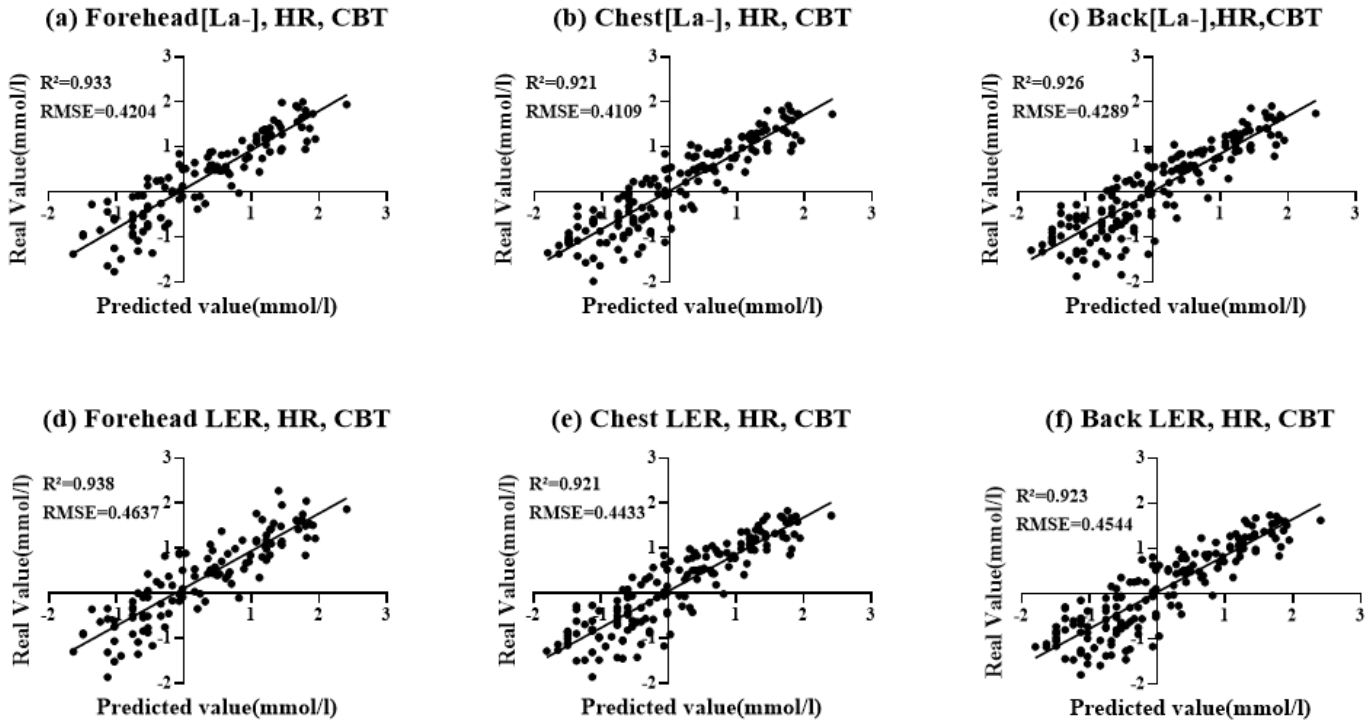


Figure 2

Correlation between blood lactate (BLa) and non-invasive physiological signals during incremental exercise.

Abbreviations: BLa, blood lactate concentration; HR, heart rate; CBT, core body temperature; [La$^-$]sw, sweat lactate concentration; LER, lactate excretion rate.

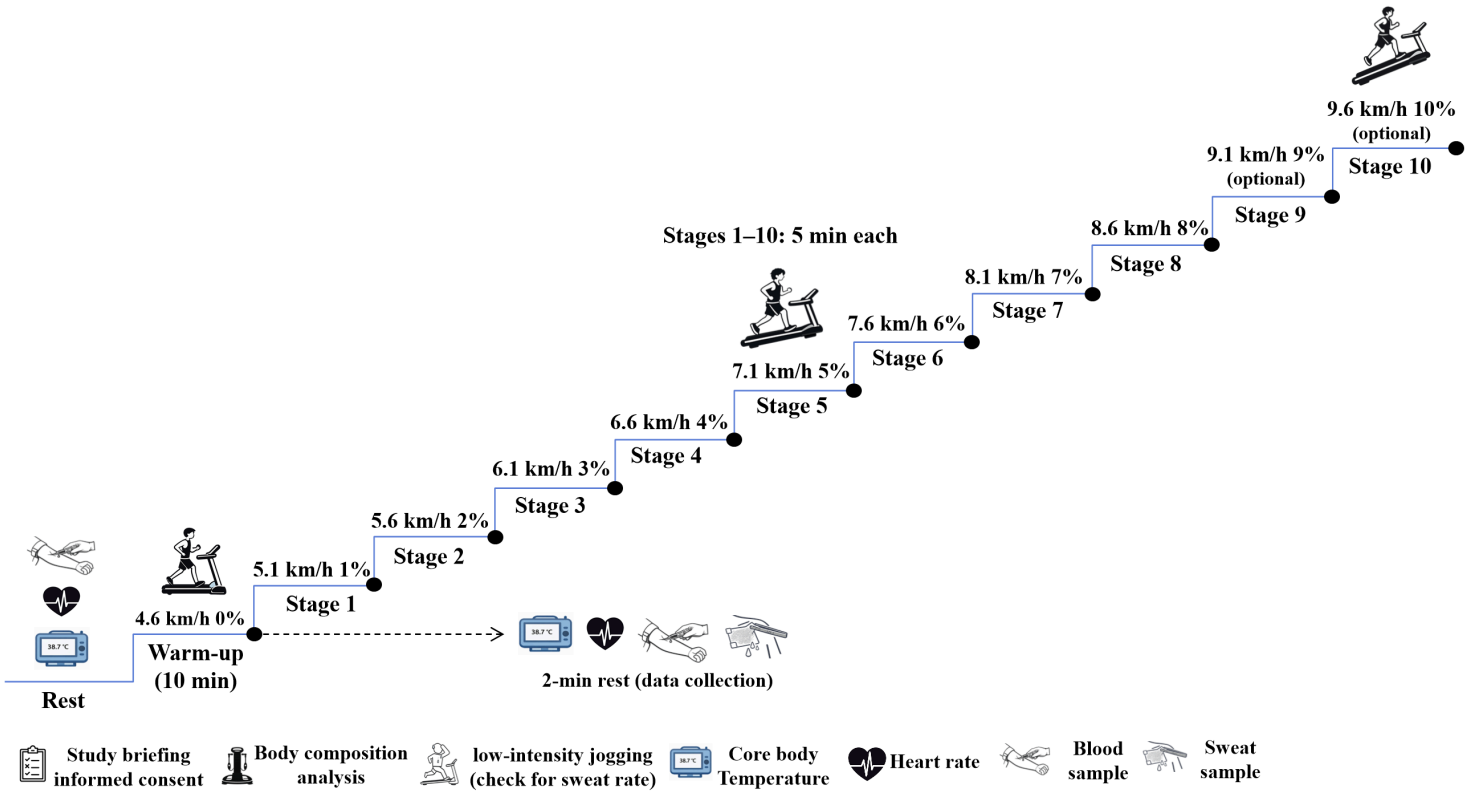


Figure 3

Agreement between predicted and observed log-transformed blood lactate concentration (log[BLa]) across body regions based on conditional predictions from the linear mixed-effects model (LMM).

Note: All input variables (HR, CBT, and [La^-]sw) were standardized (z-scores) to account for scale differences and multicollinearity. Abbreviations: BLa, blood lactate concentration; HR, heart rate; CBT, core body temperature; [La^-]sw, sweat lactate concentration; LMM, linear mixed-effects model.

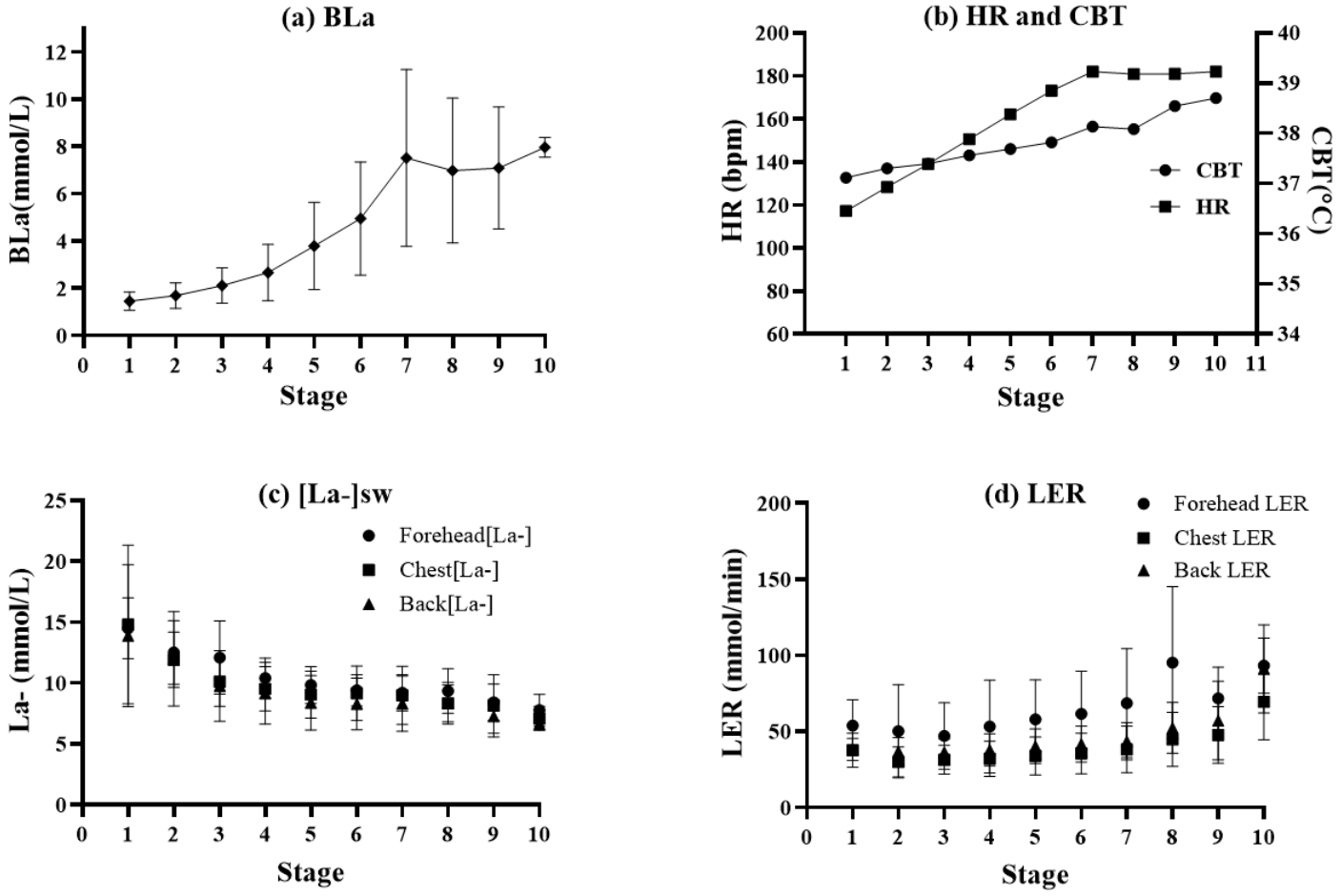


Figure 4

Overview of the experimental protocol: screening and main test procedures.