No Needles Attached? Inferring Energy Metabolism Zones and Lactate Accumulation from Touchscreen Input

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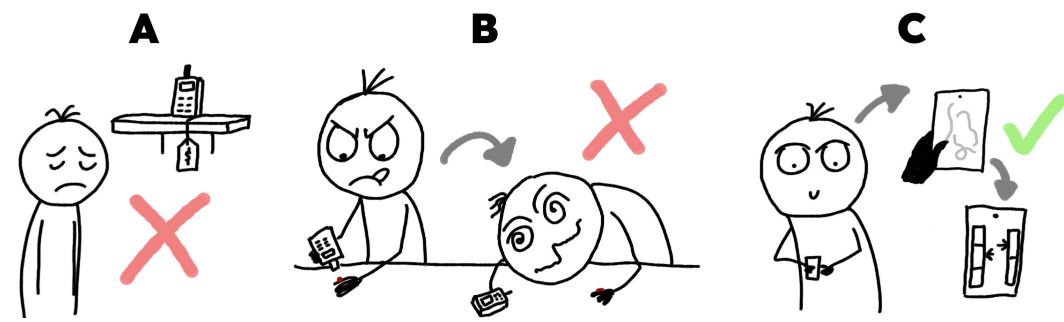

Figure 1: Devices to track biomarkers and physiological zones, e.g., for blood lactate, can be expensive (A) or might require invasive methods to conduct (B). Our approach investigates the use of built-in smartphone sensors to provide a non-invasive, quick assessment (C).

Abstract

Recreational athletes increasingly adopt quantified-self practices to track and advance their training, recovery, and fitness. Blood lactate is a key biomarker in this context, but testing remains invasive and costly, limiting its use to professional sports and clinics. For everyday exercisers, even a coarse distinction, such as whether they are training below or above key thresholds, already provides actionable insight. We investigate whether commodity smartphones can classify these thresholds non-invasively using swipe input and built-in sensors. In a data-collection study, participants completed touchscreen tracing tasks at varying physiological states during their workout, while collecting blood samples. We analyzed touch, pressure, motion, and task features to understand their role in classifying the Energy Metabolism and Lactate Accumulation Zones and trained a Support Vector Machine and a Recurrent Neural Network. Our results demonstrate the feasibility of estimating these zones from short smartphone interactions, suggesting a path toward accessible, non-invasive on-device training guidance.

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CCS Concepts

• **Human-centered computing** → HCI theory, concepts and models.

Keywords

Blood Lactate, Quantified Self, Mobile Assessment

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1 Introduction

Over the past decade, the quantified-self [26, 44, 72] movement has driven growing interest in technologies that help individuals better understand their bodies and performance. Smartphones and wearables have made tracking step counts, heart rate, and sleep patterns accessible for enthusiasts and recreational athletes [26, 72], turning personal informatics into an everyday practice. With the growing number of people participating in recreational and semi-professional sports, the interest in investigating training and recovery to progress more quickly and efficiently has also increased.

While tracking heart rate, body temperature, or blood pressure has become ubiquitous with modern wearables, one biomarker, the blood lactate level, remains inaccessible to most due to its high cost and invasive assessment. However, lactate is highly informative, as it reflects the body's response to physical exercise. Athletes gain insights into their energy metabolism [65], training progress [77], recovery [52], and risk of overtraining [10]. To gain such insights, athletes are not always dependent on exact lactate concentrations. In most cases, assessing whether key thresholds are crossed provides sufficient guidance. Two important thresholds are Lactate Threshold 1 (LT1) and Lactate Threshold 2 (LT2). LT1, also called the aerobic threshold, and LT2, also called the anaerobic threshold, mark the intensities where the body shifts fuel use and potential lactate accumulation. Knowing and assessing these thresholds helps athletes set training zones, pace races, and track fitness and recovery. One issue remains: accessing this information requires invasive blood sampling and costly equipment, making it inaccessible outside elite sports.

Recent research in HCI and ubiquitous computing has shown that everyday device interaction can reflect a user's physiology. By exploiting smartphone sensors, researchers have detected changes in fine-motor control [70], blood alcohol level [6, 46], and cognition [13, 28, 39, 58, 59]. These findings suggest that physiological states can affect how we interact with technology. Building on this line of work, we ask: How can we exploit built-in smartphone sensors to non-invasively classify their Energy Metabolism Zones, as well as their Lactate Accumulation?

As training intensity exceeds the lactate thresholds (LT1, LT2), lactate accumulation reduces neuromuscular performance [47, 48] and increases micro-tremor [50, 62]. As a result, trajectory accuracy may diminish with the onset of lactate. We hypothesize that these changes manifest in everyday phone interactions as longer reaction and travel times, larger trajectory offsets, altered touch-pressure dynamics, and higher short-time IMU variance during tracing tasks.

To test this hypothesis, we combine inertial measurement data with touch inputs collected on a smartphone during different physiological states. We train a Support Vector Machine (SVM) and Recurrent Neural Network (RNN) to classify key lactate markers, namely LT1, LT2, and the Onset of Blood Lactate Accumulation (OBLA). Our findings provide evidence that smartphone interactions can convey this information in short swipe and tracing tasks. While not intended to replace medical diagnostics, our method points toward new possibilities for accessible, low-cost training feedback. With our approach, sports enthusiasts gain insights into Energy Metabolism Zones and Lactate Accumulation using a smart phone. More broadly, our work is in line with previous work [55, 79] to contribute to the ongoing HCI research on how commodity devices can serve as biosensors and support personal informatics practices.

Augmenting humans relies on a closed loop in which systems sense the user, infer their state, and adapt feedback or interaction to enhance perception or performance. This requires accurate and unobtrusive tracking. While prior work has shown that smartphone interactions can reflect aspects of motor control [70] or cognition [13, 28, 39, 58, 59], it remains unclear how interactive systems can implicitly capture physiological exercise states in the background. By examining how subtle changes in touchscreen interaction relate to lactate-linked metabolic states, our work advances the sensing side of this closed loop. We show that smartphones can act as biosensors for exercise intensity, laying the groundwork for augmented human systems that adapt training guidance and feedback to users' metabolic state.

In summary, our work contributes (1) a paired dataset of swipe tracing task data with capillary blood lactate levels; (2) baseline models for lactate threshold classification (*Lactate Accumulation Zone* and *Energy Metabolism Zone* classification); (3) feasibility results for these classifications; and (4) implications for low-burden personal informatics. Dataset, models, and code can be found on github (https://github.com/Dominik-Schoen/NoNeedlesAttached) and TU-Datalib (https://tudatalib.ulb.tu-darmstadt.de/handle/tudatalib/5018).

2 Related Work

Our work builds on research in personal informatics, lactate sensing, and smartphone-based augmentation.

2.1 Quantified Self and Personal Informatics in Physical Exercise

With the rise of smart devices and the continuous decrease in sensor size and cost to obtain personal health data [26, 72], a community formed around tracking and analyzing everyday habits using these technologies [26]. The Quantified Self movement emerged from this trend [44]. People in this community not only collect and analyze their own data, but also use it to gain insights into individualized medical treatments, for example for chronic diseases [26].

Research shows a steady increase in work related to Quantified Self [22, 23] and Personal Informatics. Similar to Quantified Self, Personal Informatics research focuses on collecting personally relevant information for self-reflection and self-knowledge[43]. A recent review highlights challenges with compliance in active data collection, and inconsistency and authorization issues in passive data collection[74].

Studies have also explored how athletes use personal informatics and wearables [66]. Amateur athletes often start tracking out of curiosity, but continue once they notice improvements in performance. They tend to trust the objectivity of the data and use trackers to regulate workouts and quantify progress. For example, for them a lower heart rate when repeating the same workout directly signals performance gains.

In this context, our work contributes to Personal Informatics by offering an approach for active and potentially passive data collection for blood lactate estimations, supporting amateur athletes with insights into their lactate levels.

2.2 Blood Lactate and Training

Blood lactate is a byproduct of glucose metabolism [65]. When muscles need more energy than aerobic metabolism can supply, glucose is broken down anaerobically, producing lactate. Small amounts are always present in the blood, but levels rise during intense exercise when energy demand exceeds oxygen availability. Measuring this rise provides insights into how the body responds to physical load, how quickly fatigue develops, and how well recovery takes place.

As such, blood lactate is widely used in both sports and clinical settings as a marker of exercise intensity and performance [27, 76].

Specific concentration ranges correspond to meaningful physiological states. At low levels at around $1 - 2$ $mmol/l$ [34, 37], physical effort can be sustained with little strain. At moderate levels at about $2 - 5$ $mmol/l$ [34, 37, 73, 76], lactate rises gradually, indicating increasing effort while still balancing production and clearance. At high levels above ~ 5 $mmol/l$, lactate accumulates faster than it can be cleared, leading to exhaustion and fatigue.

Several metrics formalize these points. The first Lactate Threshold (LT1) marks the first rise above baseline, often around 2 $mmol/l$. The second Lactate Threshold (LT2) marks rapid accumulation, typically around 5 $mmol/l$ [34, 37]. Related concepts include the anaerobic threshold, reflecting the balance between production and clearance [31, 76]; the maximal lactate steady state (MLSS), where this balance can still be maintained [24, 38]; and the onset of blood lactate accumulation (OBLA) [73, 76]. While these thresholds are widely used, they vary between individuals [63, 75]. Still, they highlight why certain lactate levels are of particular interest.

Recent studies also link blood lactate levels with physiological tremor [50, 62], showing that rising lactate induces measurable tremor. Similar to previous work, we use the smartphone's IMU to capture such tremors [64].

Based on these concepts, we define two classification tasks. First, a binary classification of the *Lactate Accumulation Zone*, distinguishing lactate levels below and above 5 $mmol/l$. Crossing this threshold indicates that lactate accumulates faster than it can be cleared, leading to eventual fatigue. Second, we define three *Energy Metabolism Zones*, splitting the sub-5 $mmol/l$ range at 2 $mmol/l$. This yields three zones: < 2 $mmol/l$, $2-5$ $mmol/l$, and > 5 $mmol/l$, which correspond to predominant fat, mixed, and sugar metabolism [76]. In summary, thresholds vary across individuals, but most metrics converge on three states: a low baseline, a moderate steady state, and a strong accumulation state. These are highly relevant for training design, avoiding overexertion, and tracking adaptation.

2.3 Augmenting Smartphone Sensing Capabilities

Previous work has shown how smartphone sensing can be extended beyond its original purpose. Researchers explored alternative inputs such as the palm [41], knuckle [71], or tangibles [69]. Richer fingertip interactions have been studied, including finger orientation [30, 49], finger identification [35, 42], and full-hand pose tracking [4, 15, 35]. Beyond touch, accelerometers have been used to distinguish human versus computer input [1], detect modes of transportation [7], and, with sensor fusion, even enable full-body pose estimation [3].

On a higher level, smartphones have also been used to detect inter- and intrapersonal differences, for example through swipe patterns [20], gait [21], or general movement patterns [57]. For intrapersonal differences, smartphones have been exploited as makeshift biosensors. Tracing tasks have been used to detect changes in fine-motor control [70], or blood alcohol levels through motor-control assessment [6, 46], gait analysis [5], or driving behavior [19]. Other work has related smartphone use to brain health, mood, and cognition [13, 28, 39, 58, 59], enabling longitudinal observation of neuropsychological functioning. Finally, some research has combined the built-in camera with custom hardware to create low-cost mobile lab equipment [11, 29, 68, 80].

In summary, prior work has used smartphones for a wide range of biosensing applications, from mimicking laboratory tests to exploiting sensor data from everyday interactions. Our research adds to this body of work by focusing on how swipe-based interaction can reveal underlying physical state. Our work builds on previous and related work of personal informatics, blood lactate build-up and response, as well as the augmentation of smartphones' sensing capabilities.

3 Data Collection Study

In this study, we collected detailed time-series data from touch, pressure, and motion sensors together with path tracing performance metrics under different physiological states.

3.1 Study Design and Task

In this study, we collected labeled datasets linking blood lactate levels with smartphone interaction. Participants performed tracing tasks on a smartphone at three stages of their regular training sessions: pre-exercise, during exercise, and post-exercise after cooldown, while we measured their blood lactate levels. For our user study, the exact training-type, -times or lactate values were less important. We were mainly interested in capturing interaction data at different exertion and lactate levels. Observing participants in varying training scenarios allowed us to record smartphone interaction data at different physiological states, supported by corresponding lactate measurements.

The study was conducted over three weeks and integrated into the regular training routines of participants at a local gym. People could join the study if they met the requirements set by the ethics board, see subsection 3.7. During this period, each time participants trained, they could freely decide whether to join the study that day or continue their workout without participation. The study protocol required participants to complete three sessions consisting of tracing tasks and a blood lactate measurement: pre-exercise (rested lactate level), during exercise (elevated lactate), and post-exercise after cooldown (medium-to-low lactate) [75]. In this way, we captured a wide physiological range while keeping the study safe and beneficial for participants.

Each session consisted of a lactate measurement and 24 tracing tasks, see Figure 2. In each tracing trial, participants first pressed and held a button for a random duration between 0.2 and 1.2 seconds. After this delay, the start of the tracing path appeared as a blue circle, which participants had to tap and hold. This random delay allowed us to measure the Reaction Time between the appearance of the circle and the user's response, as well as the finger's travel time. The delay was kept short so that the entire session could be completed within two minutes. A longer session would allow lactate levels to drop, weakening the link between physiological state and interaction data. Once the blue circle was reached, a red path starting from the circle appeared, see Figure 2. Participants were asked to trace this path and hold the smartphone using just one hand.

The paths were designed to resemble swipes across the smartphone screen. To cover the entire display, we divided the screen into

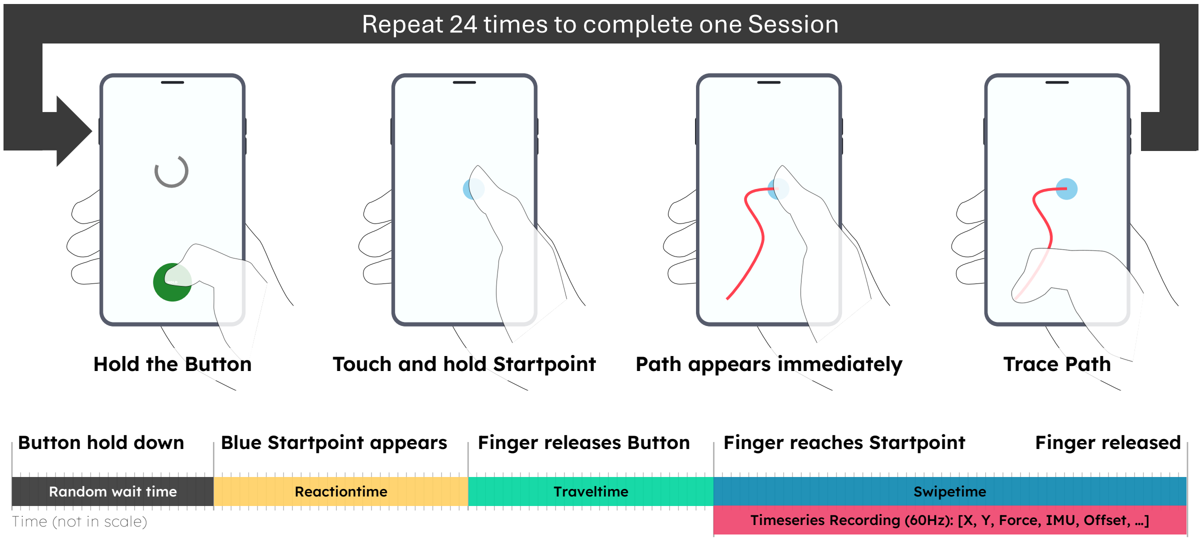

Figure 2: The top figure shows one tracing session. The bottom figure shows how the different timings and time series were assessed throughout the task.

four quadrants. For each quadrant, we created two tracing tasks leading to each of the three other quadrants, see Appendix A. This resulted in a total of 24 tasks ($4 StartQuadrants \times 3 EndQuadrants \times 2\ Paths = 24$, see Appendix A). To introduce curvature, we generated Bézier splines with four control points, creating non-linear, rounded paths. The set of 24 tracing tasks kept the session duration under two minutes. This ensured that lactate levels did not drop significantly during task completion.

3.2 Measures

This design allowed us to capture a wide range of parameters. For each tracing task, we collected the following data:

Reaction Time The time passed between the appearance of the path's start circle and lifting of the thumb to reach for it. For each tracing task, we assess one reaction time.

Travel Time The time needed to travel the distance between the hold button and the path's start. Effectively, the time between lifting the thumb from the hold button and touching the path's start circle for the first time. For each tracing task, we assess one thumb travel time.

We expect changes in the Reaction and Travel time as psychomotor performance changes at different lactate levels [14]. Additionally, while tracing along the path, we record the following data as a timeseries 60 times a second:

Finger Coordinates The current X and Y coordinate of the finger on the touch screen. We log the absolute X and Y coordinates each time we receive an update from the touch sensor. For the models, we transformed the absolute X and Y coordinates into delta X and delta Y, which represent the thumb's movement in relation to the last frame recorded. This way, we capture the motion patterns independent of starting point, screen size, and resolution. Training on these delta values makes the model translation- and device-invariant, reducing overfitting and improving generalization

Pressure The pressure the user applies to the touch screen with the finger. This metric is recorded whenever the touch sensor updates. This way, the coordinate and pressure logging are synchronized.

Pathoffset The minimal Euclidean distance between the swipe and the tracing path. This distance estimates how close the user traces the defined path. Like the pressure, the offset is logged whenever the touch sensor provides an update reflecting the current tracing accuracy.

IMU The IMU data to assess the shakiness of the phone. The IMU provides data for the accelerometer as well as the gyroscope of the phone. For both sensors, we save a scalar for the X, Y, and Z axes on a touch sensor update. In total, we receive six values for each touch sensor update.

3.3 Lactate Classifications

Based on related work, see subsection 2.2, we define two blood lactate classifications that we are going to infer:

Lactate Accumulation Zone This is a two class classification. The threshold of the *Lactate Accumulation Zone* is defined by LT2 at 5 $mmol/l$. Reaching the *Lactate Accumulation Zone* will result in the buildup of lactate in the body, as it is not able to clear the lactate quickly enough anymore. Reaching this zone will result in exertion and fatigue at some future point. See Figure 3.

Energy Metabolism Zones For a more fine-grained classification, we further define three *Energy Metabolism Zones*. The additional classification refines the zone below LT2 at 5 $mmol/l$, by splitting it at the threshold of LT1 at 2 $mmol/l$. Our three *Energy Metabolism Zones* are therefore $< 2\ mmol/l$, $2 - 5\ mmol/l$, and

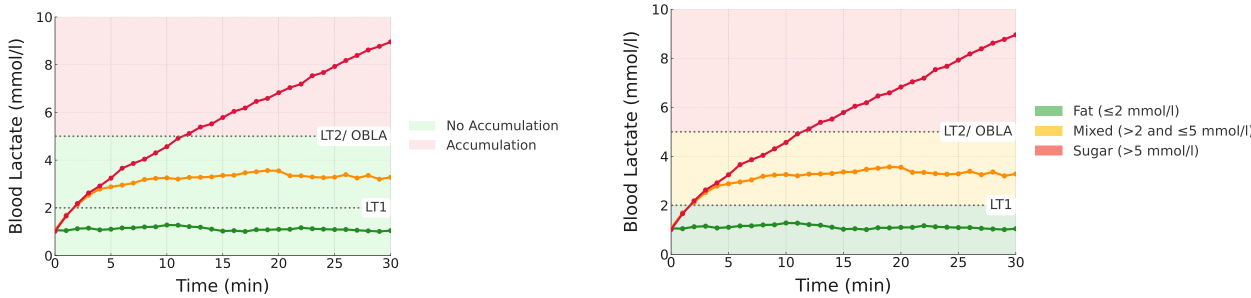

Figure 3: The left plot illustrates our two classes *Lactate Accumulation Zone* classification. The right plot shows the three classes of *Energy Metabolism Zones.*

> 5 *mmol*/*l*, which reflect the main source for energy production (fat, mixed, and sugar metabolism [76]), see Figure 3. Using these zones, athletes can balance their training intensity [45] and is often used by endurance athletes to directly target aerobic adaptation and metabolic efficiency [51].

3.4 Apparatus

To record the swipes, we used an Apple iPhone XS Max. This model is equipped with a pressure sensor. The sensor captures the pressure applied to the touchscreen surface. While newer phones estimate pressure from the size of the finger's contact area, this value is not always accessible to apps and is less precise. The built-in pressure sensor, therefore, provided more accurate pressure data.

We developed a custom app for the iPhone that guided participants through the study and recorded sensor data, including touch points, pressure, and IMU signals, at about 60 Hz. We opted against using external tracking systems such as OptiTrack, since our goal was to rely only on sensors available in commodity smartphones. Although 60 Hz is lower than research-grade motion tracking, it is sufficient to capture swipe dynamics at the temporal resolution of human–touchscreen interaction [64]. The source code is available on GitHub[1].

To measure blood lactate levels, we used the Lactate Scout Sport by EKF-diagnostic. After washing and disinfecting the participants' hands, we collected a capillary blood sample following the vendor's instructions. The device requires only a minimal amount of capillary blood. According to the vendor, measurement accuracy is ≤0.2 mmol/l for the range 0.5–6.7 mmol/l lactate, and ≤3% for 6.8–25.0 mmol/l[2].

3.5 Participants

According to our ethics board approval, subsection 3.7, we recruited semi-professional and amateur athletes from a local gym. To take part, participants had to exercise regularly, consent to capillary blood sampling, and agree to receive only their blood lactate levels as compensation. The ethics board approved this form of compensation and restricted recruitment to participants who could directly benefit from the lactate readings. Such measurements are relatively costly (between \$3–\$5 per sample, and around \$400 for the device) and are usually inaccessible for non-professional athletes and are therefore a valuable compensation for our recruited participants. Recruiting already active athletes was also important for safety and ethical reasons. It would not have been appropriate to expose non-athletes to intense exercise solely for the purposes of our study.

Over a period of three weeks, we joined participants during their training sessions and collected multiple measurements when they agreed. In total, we recruited 14 participants, 9 identified as male and 5 as female, with ages ranging from 29 to 43 ($M = 33, 86$, $SD = 4, 19$), and gathered over 1800 swipes of the tracing tasks.

3.6 Procedure

Participants were informed about the purpose, goals, and tasks of the study, including the tracing task on the smartphone and the blood sampling procedure. We further educated them about the potential risks of capillary blood sampling, such as temporary pain, small bleeding, or infection risk and explained the hygienic procedures we followed to minimize these risks. Additionally, we had medically trained personnel around when sampling. To familiarize themselves, they could practice the tracing task as deemed necessary in a training mode without logging. We answered all questions, and obtained written informed consent.

The study ran over three weeks, during which we accompanied participants in their regular gym sessions. Each time, they could freely decide whether to take part, without having to give a reason and without any negative consequences.

For each participation, we first collected a session, consisting of blood sampling and 24 tracing tasks, pre-exercise. Following the ethics board-approved procedure, participants washed and disinfected their hands, and we collected a capillary blood sample using a single-use lancet and the Lactate Scout Sport. In line with the vendor's instructions, we removed the first drop of blood and used the second for measurement. While the device analyzed the sample, the finger was cleaned and covered. Once done, the participants performed the 24 tracing tasks on the smartphone. Participants were standing while performing the tracing tasks, holding the phone in their dominant hand and performing the swipes using the thumb. The phone was locked in portrait mode, so that users could rotate the device without accidentally switching orientation. If unable to reach certain points on the screen to start or complete the trace, users were allowed to support the smartphone with their other

[1]https://github.com/Dominik-Schoen/NoNeedlesAttached or https://tudatalib.ulb.tu-darmstadt.de/handle/tudatalib/5018
[2]Last access: 25-11-2025: https://www.ekfdiagnostics.com/wp-content/uploads/2024/09/LSSport-Data-EN-EU-Rev-1.0-10-2023.pdf

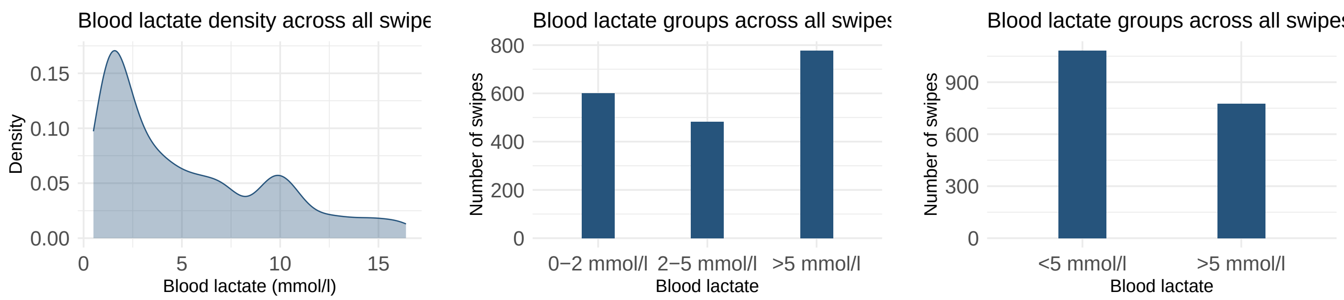

Figure 4: The distribution of our samples. The left plot shows our continuous distribution of samples. The center plot shows the sample count of our three *Energy Metabolism Zones*. The right plot shows the sample count of our two *Lactate Accumulation Zone*s.

hand. Performing all 24 tracing tasks completes one session. The order of the tasks was randomized for each session. After each session, the smartphone was disinfected, and the devices were prepared for the next participant. One full session of blood sampling and swiping took between two and four minutes.

After a final check about the participant's well-being, they continued their training on their own. We asked participants to join us two more times at self-chosen moments. We asked them to join us again during their physical exercise, where we expect elevated lactate levels, and a final time post-exercise to capture the drop in lactate. First, this flexibility in timing allowed them to align the measurement with their training goals, for instance, around their LT1/LT2 or to observe the drop-off after training, and second, provided us with assessments at different lactate levels.

3.7 Ethics Approval

The ethics board of our university approved the study design. To run the study safely, we adhered to the following advices and conditions by the board. Since the study involved physical exercise, participants had to be physically active, join the exercise voluntarily, and benefit from the lactate measurements. As such, our participants in our study should be experienced enough to use and interpret their individual lactate measurements to improve and reflect on their training or track biomarkers. We therefore recruited participants at a local gym who had been exercising regularly for several years, and who welcomed the additional feedback on their lactate levels. All participants confirmed that they felt comfortable with capillary blood sampling for lactate assessment. All participants provided written informed consent, and their personal and physiological data were stored and analyzed in accordance with data protection regulations.

4 Generalized Model

This section investigates a user-agnostic model to predict the *Energy Metabolism Zones* and *Lactate Accumulation Zone*.

4.1 Modeling

We infer the *Energy Metabolism Zones* and *Lactate Accumulation Zone* using machine learning. For interpretability, we first train a linear SVM [17] to gain insights into which features matter for classification. To address the limitations of linear models, we also train an RNN, trading interpretability for potential gains in accuracy.

4.1.1 Support Vector Machine. Using a linear kernel, we can see how each input feature influences the output. We trained two models: one for the two *Lactate Accumulation Zone*s and one for the three *Energy Metabolism Zones*.

Each model input represents one session of 12 swipes from the same participant and labeled with the same physiological class. Each swipe includes two scalar features (Reaction Time, Travel Time) and ten time series (two for the Finger Coordinates in the form of delta X and delta Y, one for Pressure, one for the Pathoffset, and six for the IMU in form of three axis time series for the accelerometer and the gyroscope), see subsection 3.2 for details. Because swipe durations vary, the time series have different lengths. To create fixed-size inputs for the SVM, we convert each time series into 10 features using Welch's method for Power Spectral Density estimation [40], summarizing the energy of a signal across frequencies and producing equal-width frequency bands. We then average the 12 swipes' frequency bands and scalar features to form one feature vector per session. All features are standardized on the training split, and the same preprocessing is applied to the evaluation split.

4.1.2 Recurrent Neural Network. Because time series are complex and not easily captured by scalar metrics, we also trained an LSTM [33]. LSTMs can handle variable-length sequences without resampling and show strong performance on temporal data [2, 20]. To combine time series and scalar features, we use a two-stage architecture.

Like the SVM, the RNN processes sessions of 12 swipes from the same participant and class. In the first stage, an LSTM encodes each swipe's time series into a fixed-size embedding. Different swipe lengths are handled through padding and masking. This produces 12 embeddings per session.

A learned attention mechanism scores each embedding with a linear layer and normalizes the weights with a softmax. The session vector is the weighted sum of these embeddings. The scalar features are pooled using the same attention weights and concatenated with the session representation. A lightweight Multi-Layer Perceptron

(Linear → ReLU → Linear) maps the final vector to the *Lactate Accumulation Zone* or *Energy Metabolism Zones*.

4.2 Evaluation

4.2.1 Support Vector Machine. Our model was evaluated using two cross-validation schemes, each using a ten-fold cross-validation. One cross-validation split the data by participant, while the second split the data by target class. Therefore, the first model evaluates on unseen participants, reassembling a user-agnostic approach, while the second model has prior knowledge of the participant. See Table 1 for the *Lactate Accumulation Zone*'s performance and Table 2 for the *Energy Metabolism Zones*' performance.

	Unseen Participant			Prior Participant knowledge		
Lactate Accumulation Zones	Precision	Recall	Accuracy	Precision	Recall	Accuracy
No accumulation (< 5 mmol/l)	0.691	0.530	0.565	0.710	0.756	0.676
Accumulation (> 5 mmol/l)	0.552	0.665	0.565	0.624	0.564	0.676

Table 1: Averaged SVM performance for *Lactate Accumulation Zone*

The results in Table 1 show that for *Lactate Accumulation Zone* classification, the SVM performs differently depending on whether participant-specific data is available during training. When evaluated on unseen participants, accuracy remains around 56%, with relatively low precision of 0.55 for the accumulation class but higher recall of 0.67. This means the model often detects accumulation when it occurs, but also produces more false positives. In contrast, with prior participant data, accuracy increases to 68%, and the trade-off shifts: precision improves for both classes, 0.71 and 0.62, while recall is more balanced. This suggests that the model benefits from individual calibration, reducing false positives and negatives. Overall, the classifier can separate accumulation and non-accumulation states, but robust generalization across participants remains challenging. This underlines the need for personalized or adaptive models when using interaction data to infer biomarkers.

	Unseen Participant				Prior Participant knowledge			
Energy Metabolism Zones	Precision	Recall	F1	Accuracy	Precision	Recall	F1	Accuracy
Fat (< 2 mmol/l)	0.224	0.226	0.225	0.413	0.422	0.560	0.481	0.499
Mixed (> 2 mmol/l and < 5 mmol/l)	0.475	0.352	0.404	0.413	0.454	0.350	0.395	0.499
Sugar (> 5 mmol/l)	0.639	0.627	0.628	0.413	0.653	0.545	0.594	0.499

Table 2: Averaged SVM performance for *Energy Metabolism Zones*

The three-class classification in Table 2 for *Energy Metabolism Zones* shows similar patterns to the binary *Lactate Accumulation Zone* classification. When tested on unseen participants, accuracy remains low at around 41%. The model detects the sugar zone with the highest precision and recall, with 0.64 and 0.63, but struggles with the fat zone, where precision and recall fall to about 0.22. The mixed zone lies in between, but with a weaker recall of 0.35, indicating frequent misclassification into the other zones. It is to be expected that correctly classifying between the fat zone and mixed zone is hard. The lactate margins, and therefore for the zones, are quite low. Also, in both of these zones, the human body is able to maintain the level of blood lactate, meaning that the body is at least as fast in deteriorating lactate as it builds up. The only difference is a slight increase in the overall base lactate level, which has different influences on the individual's body and therefore also on the reaction and phone interaction.

With prior participant data, overall accuracy improves to 50%, and class-wise performance becomes more balanced. Precision and recall for the fat zone rise considerably, to 0.42 and 0.56, and the sugar zone remains the most reliably detected with a precision of 0.65 and a recall of 0.55. However, the mixed zone still remains difficult to classify consistently, with both precision and recall near 0.35–0.45.

These results suggest that participant-specific calibration improves performance, but distinguishing the intermediate mixed zone remains challenging, as interaction patterns in this zone overlap with both low and high states.

4.2.2 Recurrent Neural Network. Like the SVM, the RNN was evaluated using two ten-fold cross-validations. See Table 3 for the *Lactate Accumulation Zone*'s performance and Table 4 for the *Energy Metabolism Zones*' performance.

	Unseen Participant			Prior Participant knowledge		
Lactate Accumulation Zones	Precision	Recall	Accuracy	Precision	Recall	Accuracy
No accumulation (< 5 mmol/l)	0.687	0.689	0.592	0.724	0.744	0.663
Accumulation (> 5 mmol/l)	0.660	0.498	0.592	0.602	0.550	0.663

Table 3: Averaged RNN performance for *Lactate Accumulation Zone*

The RNN in Table 3 just slightly outperforms the SVM in the binary *Lactate Accumulation Zone* classification. With unseen participants, overall accuracy rises to about 59%, and performance across classes is more balanced. For the no *Lactate Accumulation Zone*, both precision and recall are comparable at 0.69, while for the *Lactate Accumulation Zone*, precision is reasonable at 0.66 but recall drops to 0.50, suggesting that the model tends to miss some true accumulation.

When prior participant data is available, accuracy again increases to 66%. The no-*Lactate Accumulation Zone* remains robust with a precision of 0.72 and a recall of 0.74, and the *Lactate Accumulation Zone* shows a moderate drop in precision to 0.60 and a slight recall increase to 0.55. Compared to the SVM, the RNN better generalizes across participants, but still benefits from individual calibration.

Compared to the SVM, the RNN reduces the imbalance between classes, achieving more symmetric precision across the accumulation and non-*Lactate Accumulation Zone*s. However, recall for the *Lactate Accumulation Zone* remains weaker, showing that while performance is more balanced overall, detecting accumulation reliably is still challenging.

	Unseen Participant				Prior Participant knowledge			
Energy Metabolism Zones	Precision	Recall	F1	Accuracy	Precision	Recall	F1	Accuracy
Fat (< 2 mmol/l)	0.150	0.140	0.145	0.349	0.473	0.400	0.433	0.436
Mixed (> 2 mmol/l and < 5 mmol/l)	0.165	0.221	0.189	0.349	0.366	0.375	0.370	0.436
Sugar (> 5 mmol/l)	0.428	0.399	0.413	0.349	0.438	0.495	0.465	0.436

Table 4: Averaged RNN performance for *Energy Metabolism Zones*

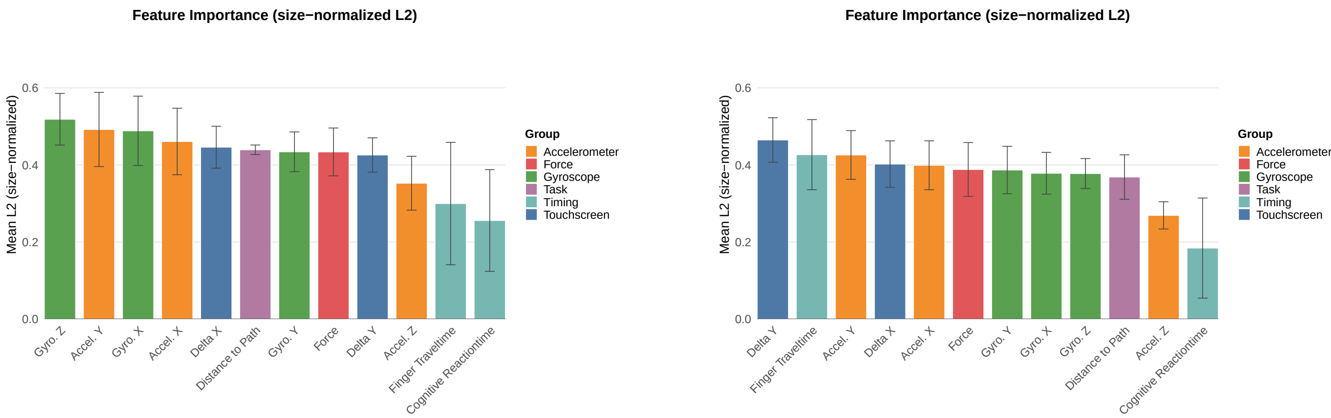

Figure 5: The mean L2 of all weights of *Lactate Accumulation Zone* models. On the left, the model with unseen participants on the evaluation split, on the right, the model with prior participant knowledge.

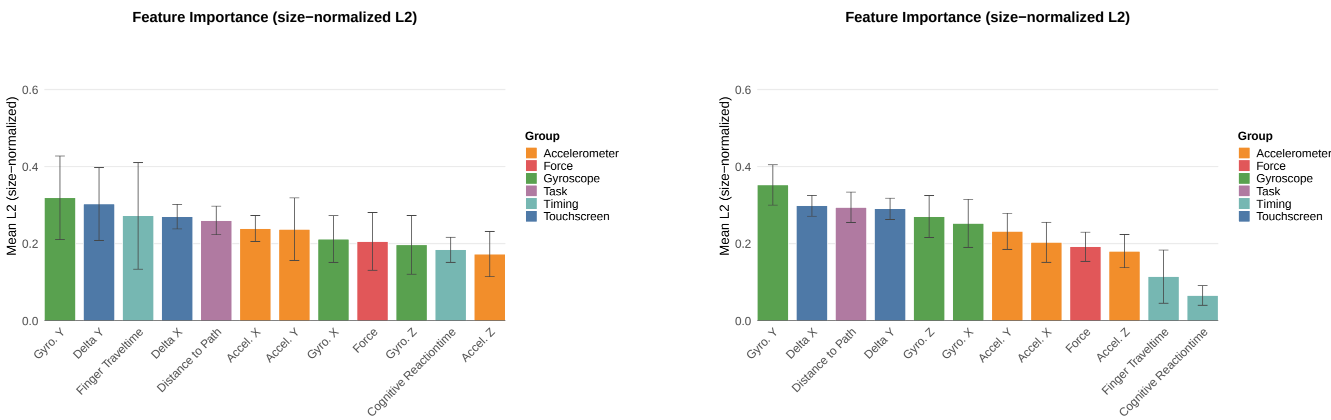

Figure 6: The mean L2 of all weights of *Energy Metabolism Zones* models. On the left, the model with unseen participants on the evaluation split, on the right, the model with prior participant knowledge.

The *Energy Metabolism Zones* RNN classification remains difficult, especially for unseen participants, as seen in Table 4. Overall accuracy is 35%, and performance is skewed toward the sugar zone, which reaches the highest precision of 0.43 and recall of 0.40. The fat and mixed zones are poorly detected, with precision and recall around 0.15–0.22, showing frequent misclassification.

When prior participant data is included, accuracy rises to 44%, and all classes improve. The fat zone, in particular, benefits. Precision rises to 0.47 and recall to 0.40, while the sugar zone remains somewhat the most reliable with a precision of 0.44 and a recall of 0.50. The mixed zone, however, continues to be challenging, with precision and recall remaining below 0.40.

Compared to the SVM, the RNN again reduces class imbalance, producing more consistent performance across *Energy Metabolism Zones*. Still, the intermediate lactate range remains the hardest to distinguish, as its interaction patterns overlap with both low and high states.

4.3 Weight interpretation

Using a linear SVM, we inspected feature importance through the learned weights [12, 56]. Each time series was represented by 10 frequency-band features, so we aggregated their weights into a single importance score using a size-normalized L2 norm. Because the SVM inputs were standardized, weight magnitudes are comparable across features. We averaged the resulting importance scores across folds and visualized them in Figure 5 and Figure 6.

Overall, all smartphone sensors (touch, IMU, and pressure) contributed similarly to classification. Their frequency-based representations appear to capture physiological tremor, in line with prior work [50, 62]. The comparable SVM weights indicate that subtle tremor changes during interaction are detectable across the different sensors. Our frequency features also carried most of the predictive power for *Lactate Accumulation Zone* and *Energy Metabolism Zones*. Using an LSTM on raw time series did not improve performance, suggesting limited additional value from longer temporal dependencies or relations not linked to the jerkiness of the physiological tremor.

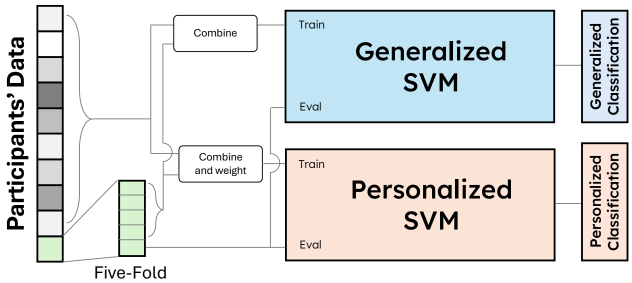

Figure 7: Participant-level data split and model training procedure for generalized and personalized SVMs.

In contrast, cognitive Reaction Time appears to contribute less. Reaction time is highly individual [14, 67], which aligns with the higher weight variance we observed. Prior work links reaction time changes to biomarkers other than lactate [14]. This suggests that Reaction Time might not be a reliable predictor of lactate-related states in our setting.

5 Case Study: Personalized Models

While modest, the above-chance to predict the correct zone indicates that the generalized models are learning. Aligning with previous work [63, 75], we expect that the model needs personalization, as with most biomarkers, blood lactate has different influences on the individual's body. Therefore, the reaction to the changes in lactate requires calibration. For that, we investigated further into fine-tuning a model to fit an individual's assessment.

5.1 Modeling

Since the SVM and RNN performed similarly in our previous tests, we used an SVM to create the personalized models. The core architecture of the personalized SVM is the same as the generalized model. The model receives sessions containing 12 swipes from the same class and participant each time. It applies the same preprocessing by converting the time series to 10 equal-width frequency bands using Welch's PSD. Frequency bands and scalars get averaged and standardized before being used in an SVM with a linear kernel. In order to personalize an SVM for a user, we introduce higher sample weights for sessions of the specific user. This way, the model has a chance to include the underlying concepts of the different *Energy Metabolism Zones* and *Lactate Accumulation Zone* while paying more attention to the changes the individual introduces.

5.2 Evaluation

We trained two SVMs: a generalized model and a personalized model. For the personalized model, we removed one participant's data from the training set. The remaining participants' data were used to train the generalized SVM, while the held-out participant's data were used to finetune the personalized SVM and evaluate, see Figure 7.

Personalization was achieved by weighting the individual's samples more strongly. We assigned a weight of 1.2 to the individual's training samples and 0.3 to all others. The individual's data were split using five-fold cross-validation, and each fold's held-out split served as the evaluation set. The personalized SVM was trained on the individual's weighted training samples plus the down-weighted data from other participants. Both models were evaluated on unseen held-out data to ensure comparability.

Since this approach requires plenty of data from an individual in order to perform the five-fold cross-validation, we conceptually use this technique on three of our participants with enough data to create a split. See Table 5 for the *Lactate Accumulation Zone*'s performance and Table 6 for the *Energy Metabolism Zones*' performance.

Looking at Participant 1, the benefit of personalization becomes clear. The generalized SVM reaches an overall accuracy of 66%, but shows a strong imbalance. While the no *Lactate Accumulation Zone* is detected with a high precision of 0.77 and a recall of 0.75, the accumulation state is much weaker. Precision and recall are only 0.37. After personalization, accuracy rises sharply to 89%, with both classes performing well. Precision and recall rise drastically, especially for the *Lactate Accumulation Zone*. This illustrates how weighting participant-specific data helps the model adapt to individual interaction patterns based on individual body responses.

Participants 2 and 3 show the same trend. For Participant 2, accuracy increases from 52% to 75%, while for Participant 3, the personalized model even reaches perfect accuracy. However, both cases are based on a small evaluation set, and the results should therefore be interpreted with caution.

For Participant 1, the generalized SVM reaches an overall accuracy of 54%. The model detects the fat and sugar zones reasonably well with F1 scores around 0.61 and 0.60, but struggles with the mixed zone, where recall drops to 0.27. After personalization, accuracy again improves to 61%, with a more balanced performance throughout the zones. The fat zone improves to an F1 of 0.76, and the mixed zone also gains slightly to 0.42. However, performance on the sugar zone becomes weaker with an F1 of 0.45, showing that personalization does not uniformly benefit all classes but helps to reduce the strong skew toward only high or low states.

Participants 2 and 3 show a similar trend. For Participant 2, accuracy rises from 38% to 48%, with particularly strong improvements for the sugar zone with an F1 of 0.69. For Participant 3, accuracy increases from 65% to 73%, though class performance remains uneven, with perfect precision and recall for the fat zone, but failure to detect the mixed zone. While again suggesting personalization improves performance, these cases are based on a few evaluation sessions, and therefore, the results should be interpreted with caution.

6 Discussion

In this work, we collected touchscreen swipe data from a tracing task with the respective blood lactate level under different physiological states. Using this data, we trained multiple machine learning models infering lactate zones. In this section, we discuss our findings from this work.

6.1 Some Needles Attached

Our results show a clear performance difference between the two classifications. The *Lactate Accumulation Zone*, defined by a single threshold LT2, can be predicted with above-chance accuracy. The binary split provides a clear physiological signal. Once the body

Model	*Lactate Accumulation Zones*	Participant 1			Participant 2			Participant 3		
		Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy
Gen.	No accumulation (< 5 mmol/l)	0.771	0.753	0.658	0.600	0.333	0.517	0.733	0.733	0.650
	Accumulation (> 5 mmol/l)	0.367	0.367	0.658	0.312	0.800	0.517	0.500	0.533	0.650
Pers.	No accumulation (< 5 mmol/l)	0.943	0.906	0.886	0.800	0.667	0.750	1.00	1.00	1.00
	Accumulation (> 5 mmol/l)	0.750	0.833	0.886	0.567	0.800	0.750	1.00	1.00	1.00

Table 5: Averaged performance for *Lactate Accumulation Zone* across the cross-validation for generalized and personalized models.

Model	*Energy Metabolism Zones*	Participant 1				Participant 2				Participant 3			
		Precision	Recall	F1	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1	Accuracy
Gen.	Fat (< 2 mmol/l)	0.583	0.640	0.610	0.542	0.300	0.300	0.300	0.383	0.700	0.500	0.583	0.650
	Mixed (> 2 mmol/l and < 5 mmol/l)	0.467	0.273	0.345	0.542	0.000	0.000	0.000	0.383	0.000	0.000	0.000	0.650
	Sugar (> 5 mmol/l)	0.500	0.733	0.595	0.542	0.400	0.800	0.533	0.383	0.733	1.000	0.846	0.650
Pers.	Fat (< 2 mmol/l)	0.793	0.720	0.755	0.611	0.200	0.200	0.200	0.483	0.683	1.000	0.812	0.733
	Mixed (> 2 mmol/l and < 5 mmol/l)	0.433	0.413	0.423	0.611	0.300	0.333	0.316	0.483	1.000	0.000	0.000	0.733
	Sugar (> 5 mmol/l)	0.433	0.467	0.449	0.611	0.600	0.800	0.686	0.483	0.800	0.800	0.800	0.733

Table 6: Averaged performance for *Energy Metabolism Zones* across the cross-validation for generalized and personalized models.

passes LT2, lactate accumulates faster than it can be cleared, leading to measurable changes in the smartphone interaction. These changes are strong enough to be captured by the smartphones' sensors.

By contrast, the three *Energy Metabolism Zones* are more challenging. The distinction between the fat zone below LT1 and the mixed zone between LT1 and LT2 is inherently subtle. Both zones represent steady states in which lactate production and clearance are balanced, and no accumulation occurs. The only difference is that the mixed zone stabilizes at a slightly higher plateau level. Given that the resting baseline is typically around 1 $mmol/l$, this leaves only a margin of about 1 $mmol/l$ before LT1 is crossed. Whether such a slight shift in lactate is reflected in tremor and interaction dynamics depends strongly on the individual's physiology, training state, and recovery. For some participants, the changes may be too subtle for the system to notice, while for others they may be pronounced enough to detect [32, 60]. As such, the interaction patterns in these ranges seem to overlap, too, and our models often confuse the fat and mixed zones. The sugar zone is again easier to detect, since it corresponds to lactate accumulation and thus has more apparent interaction effects. In subsection 6.2, we further discuss these findings and why detecting LT2 is important for training.

While our generalized models performed above chance, they are not yet accurate enough for practical use. The binary accumulation classification reached around 56–59% accuracy on unseen participants, showing that the models learned relevant patterns but were not robust across individuals. These SVMs weighted individual data more strongly and showed clear improvements in case studies. Personalized models achieved accuracies above 75–80%. This indicates that a calibration phase with user-specific data is required for reliable biomarker inference from smartphone interaction. In other words, our model still has some needles attached. From our current insights, we need calibration samples to be able to adapt the model to the individual. Once calibrated, the model can take over in assessing non-invasively. It is worth mentioning that body composition and physical shape changes might need recalibration. While we do not have evidence, this can be hypothesized based on related work [63, 75].

In summary, our models capture the onset of lactate accumulation in the *Lactate Accumulation Zone*, but fine-grained differentiation of *Energy Metabolism Zones* remains an open challenge. This suggests that coarse-grained feedback, such as detecting when a user crosses into the accumulation state, may already be realistic to achieve with commodity devices, whereas precise metabolic profiling will require more data, personalization, or new interaction paradigms. Something that needs to be mentioned here is that the recruitment for participants in order to align with the ethics committee resulted in a rather unbalanced and small population. However, we are confident that our study provides a basis for further research.

6.2 Area of Application

Our results suggest that while exact blood lactate concentrations remain difficult to infer, detecting coarse lactate states is feasible, especially when distinguishing below and above LT2. Even such a binary classification already provides actionable insights. LT2 marks the highest sustainable exercise intensity, above which lactate accumulates and fatigue follows [37, 76]. Knowing whether training stays below or exceeds this threshold helps athletes regulate intensity, pace endurance events, and avoid overtraining [10].

As such, previous work has shown that LT2 assessment can be used for monitoring training schedules and for determining performance training [25, 54]. Further endurance athletes, for instance, have a great benefit when training around the LT2 to improve their capabilities [36, 54]. As shown by multiple studies, this threshold has a strong correlation to the endurance and is therefore often used in adapting and managing an athlete's training [8, 18, 53, 78]. Knowing when you have reached or surpassed this threshold in a very short assessment time is key to balancing an athlete's ongoing training. With our approach, assessment takes only a few swipes on a smartphone. In this sense, our system does not replace laboratory diagnostics but lowers the barrier for everyday access to this key training information.

Short tracing swipes on smartphones could be integrated into exercise, cooldowns, or breaks, giving athletes quick feedback without costly devices or invasive testing. Repeated use can reveal longitudinal trends, such as shifts in LT1 or LT2 due to training adaptations. This creates new opportunities for personal informatics practices, extending metrics like heart rate, step count, or skin temperature to guide exercisers in their training.

6.3 Risks and Opportunities of Unnoticed Biomarker Tracking

While our work demonstrates the potential of smartphones as non-invasive biosensors, it also highlights risks. Unlike heart rate, ECG recordings, or step count, our data is accessible to any app without special permissions. This means that, in principle, an app could infer sensitive biomarkers without users being aware. For example, with our approach, an ordinary app could assess training intensity states without explicit consent, revealing personal routine and health.

Such capabilities could be exploited. A fitness app might silently estimate *Lactate Accumulation Zone*s and use this to push targeted ads for recovery products or training programs. More concerning are scenarios where biomarker inference is used for profiling beyond sports. An employer could estimate fatigue or recovery from everyday phone use to assess productivity. Insurance providers might be tempted to track physical stress and recovery to adjust premiums.

This concern resonates with broader HCI debates on inference without consent, such as emotion recognition from text input [39], stress detection from mobile sensors through binge-drinking [6], or digital phenotyping of mental health and mood [28, 39]. As with these domains, transparency, informed consent, and privacy-preserving designs are essential. Without safeguards, such an unrecognizable biomarker inference enables apps and their providers to gain very personal insights and could undermine trust in personal informatics technologies.

At the same time, the ability to infer biomarkers from everyday interactions also offers opportunities if designed responsibly. Non-invasive sensing could empower amateur athletes and casual exercisers to understand their bodies without costly equipment better. Further, patients could monitor recovery or chronic conditions without repeated clinical visits. This reveals design spaces around transparency, user agency, and meaningful feedback. Instead of hidden inference, systems should make physiological insights visible to the user, allow them to control when and how data is captured, weighing up advantages and disadvantages of active and passive data collection [74], and integrate such feedback into personal informatics tools. Exploring how to balance utility with privacy aligns with long-standing HCI interests in self-tracking, informed consent, and value-sensitive design.

7 Limitations and Future Work

Our results advance efforts to augment smart devices with implicit tracking and support lactate-based physiological state sensing. Below, we outline the main limitations of our work and directions for future research.

7.1 Internal Validity

In our data collection study, we did not control when participants joined their during- and post-exercise assessment, what exercises they performed, or how often they took part during their training days. We also did not track external factors such as time of day, hydration, caffeine, pre-workout booster, stress, or diet-related issues like hypoglycemia. These factors can influence smartphone interaction, but we chose not to prescribe procedures or add strict controls to keep the study close to real-world use. Our aim was to capture participants in varied physiological states. Allowing participants to follow their own workout routines also met ethics requirements. We did record the timing between measurements and the type of exercise performed, and these are included in the dataset for future analyses.

Another concern regards the assessment itself. Although participants washed their hands before sampling, continuous sweating may affected touchscreen interaction. Also, sweat can distort lactate measurement, on top of device-related imprecision. Further, we sampled the IMU at 60 Hz to align it with the touchscreen sampling. The full IMU stream was recorded independently at about 100 Hz and is available for future work tto investigate the higher-resolution IMU data.

Finally, our PSD and ML model parameters were not systematically optimized and may not capture all tremor-related signals. We used linear SVMs for interpretability, which might limited performance. In future work we will refine the models and tune their hyperparameters.

7.2 External Validity

Our results are based on one specific iPhone model with a built-in pressure sensor. It remains unclear how well the approach generalizes to devices without such hardware, although related work provides reasonable alternatives [9]. Future work could investigate ablation models that do not use pressure data or different hardware.

Further, we recruited only a relatively small group of trained athletes as participants. For now, the ethics committee has requested that only trained people who benefit from the data collected in the study be recruited, resulting in low participant numbers. With the insights gained from this study, we will investigate a broader range of the population in the future, in accordance with the ethics committee, to include untrained and sedentary populations. For now, the applicability of our approach for untrained users is unknown. Our case studies suggest that personalization improves performance, but it is based on limited data and should be viewed as a preliminary investigation for future work.

Finally, we used a guided tracing task in our study. While removing the PathOffset feature could bring the first insights into the importance of predefined tracing paths, future work could observe everyday swiping to generalize further the approach for passive data collection [74].

7.3 Towards Non Invasiveness and Sensor Fusion

Advances in mobile sensing continuously reduce the burden of self-tracking. Heart rate, movement, and sleep can already be monitored passively, requiring little to no user effort. Our approach points in a similar direction by enabling background assessment of *Lactate Accumulation Zone* and *Energy Metabolism Zones*. Previous work has shown strong correlations between lactate thresholds and respiratory thresholds [25, 61]. While respiratory thresholds are difficult to capture in everyday contexts, recent research demonstrates their detection using wearable respiratory sensors [16].

Future work should investigate sensor fusion between smartphone interactions and wearable respiratory sensing to increase accuracy and robustness further. Such combinations could allow continuous and background assessment of training states, paving the way for more reliable and unobtrusive tracking of exercise intensity in everyday contexts. This guides future work: how can multimodal biomarkers be integrated into personal informatics systems without overwhelming users, and how can feedback be designed to remain transparent, actionable, and respectful of privacy?

8 Conclusion

This work explored how smartphone swipes can serve as a non-invasive biosensor for blood lactate-linked physiological states. By linking short tracing tasks to blood lactate levels, we showed that coarse distinctions can be achieved. At the same time, our results highlight the limits of generalization. While the models beat chance, robust performance requires more data or personalization. In that sense, our vision of "No Needles Attached" comes with "Some Needles Attached". Yet our findings open a path toward accessible training feedback and new opportunities for personal informatics and human augmentation. Our work suggests that simple phone interactions can reflect lactate-based physiological states.

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Aids and Tools

This work used OpenAI's GPT-5 and Grammarly for grammar checking, style editing, and accessibility descriptions. The content was reviewed and edited by the authors. The authors take full responsibility for the written text.

A Paths for the Data Collection Study

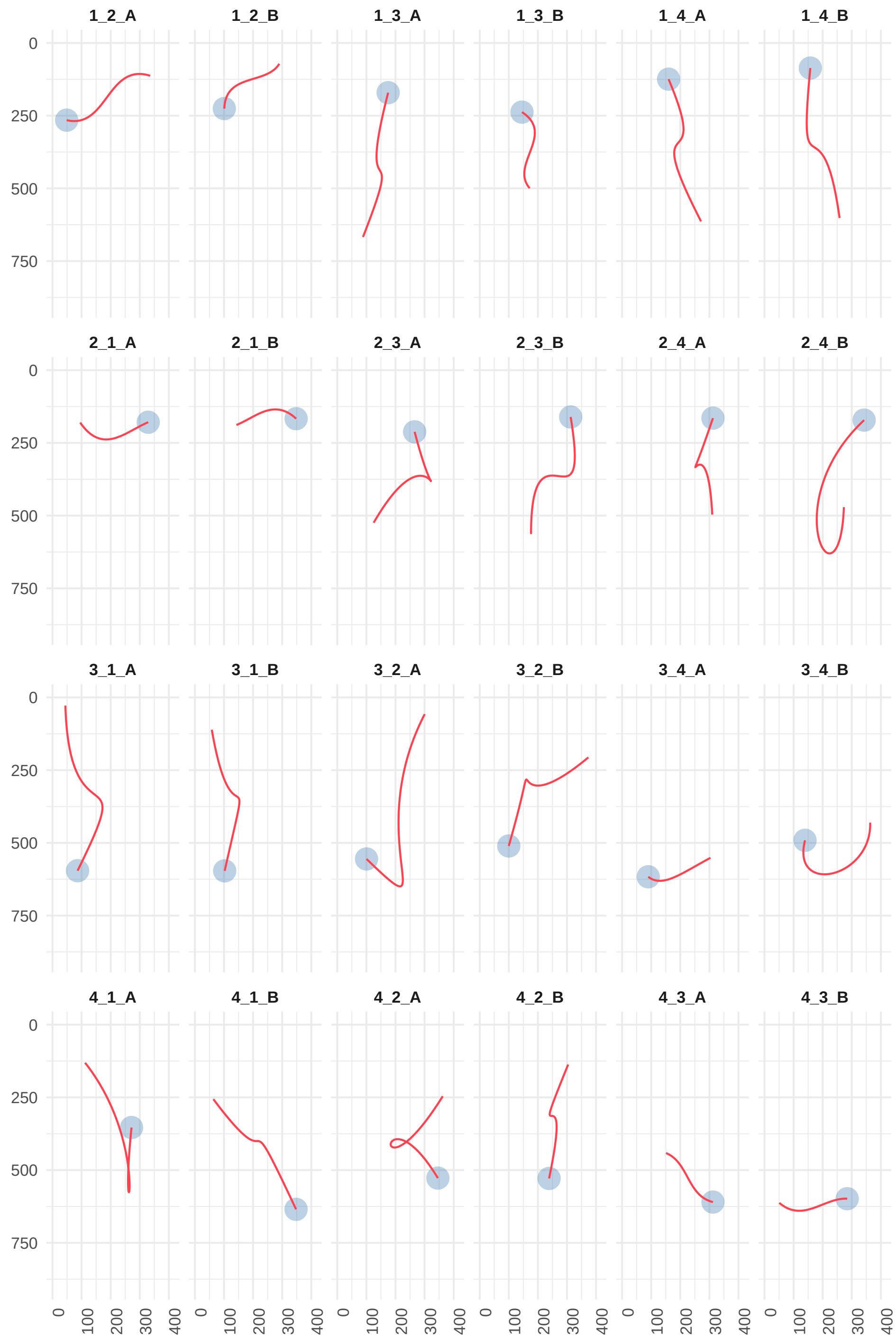

Figure 8: The Paths participants had to trace in the Data Collection Study. The Trial names on top of each plot follow this syntax: *{Start Quadrant}_{End Quadrant}_{A/B}*