

Skin-Interfaced Microfluidic System with Machine Learning-Enabled Image Processing of Sweat Biomarkers in Remote Settings

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Dehydration has many deleterious effects on cognitive and physical performance as well as physiological function, in the context of sports, industrial work, clinical rehabilitation, and military applications. Because sweat loss and electrolyte loss vary across individuals, conventional sweat testing strategies using absorbent patch techniques are employed in laboratory settings to characterize sweat biomarkers; however, these techniques are not suitable for remote environments. Here, an updated wearable microfluidic sweat testing system targeted for recreational athletes is presented that includes a microfluidic patch accommodating a broad range of sweating rates, and a smartphone app incorporating digital image processing algorithms to enable real-time analysis under different lighting conditions and patch orientations. Expansive field trials ($n = 148$ subjects) show significant correlations between the microfluidic patch and standard absorbent patch in measuring sweating rate and sweat chloride concentration during recreational exercise. This validation study demonstrates the applicability of the microfluidic patch and software platform for field testing in recreational athletes.

1. Introduction

Appropriate hydration practices during physical activity are critical for avoiding fluid-electrolyte imbalances and maintaining performance.^[1] One of the key factors impacting fluid intake requirements is sweat production and it is well known that there is significant inter-individual variation in sweating rates^[2–5] and sweat electrolyte concentrations^[6] during exercise. Research suggests that sweat losses are difficult to subjectively self-estimate.^[5] For example, competitive athletes tend to underestimate their sweat losses and experience some level of voluntary dehydration,^[7–11] while recreational exercisers seem to be at a higher risk from overdrinking relative to sweat losses and developing hyponatremia during prolonged events.^[12,13] Still, there is interindividual

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variation in the ability to self-estimate sweat losses regardless of training status.^[5] Thus, individualized sweat testing is important to inform appropriate drinking strategies to avoid the potential health and performance consequences of both over- and under-hydration during exercise and daily living.^[1,14]

Sweat testing has long been available for elite athletes. This testing is typically conducted during moderate to high-intensity training and competition scenarios and requires trained staff and complex lab equipment for analysis. Sports practitioners are usually involved in interpreting the results and translating them into meaningful actions.^[6,15] For these reasons, sweat testing has not typically been widely available for everyday use outside of controlled laboratory settings. Because of the many public health benefits of physical activity, it is recommended that adults should engage in moderate to vigorous-intensity aerobic exercise and muscle-strengthening activities on a regular basis.^[16] In the United States, more than 200 million people participate in physical activity, mostly at a recreational level.^[17] Popular recreational activities include running/jogging, cycling (e.g., spin classes), and a mix of various aerobic and anaerobic activities involving both the upper and lower body (e.g., fitness class, circuit training), among others.^[18] Many recreational exercisers tend to workout at lower intensities and/or durations; consequently, their average sweat losses are generally lower than those of competitive athletes. However, this is not exclusive, and the combination of intensity, duration, and environmental conditions can still result in recreational exercisers losing significant quantities of body water and electrolytes. Sweat tests for everyday users need to operate under these conditions without the need for complex lab equipment, and to present results to users in an actionable and interpretable way.

Measurements of sweat electrolyte concentrations along with sweating rate via fully integrated wearable systems offer insights into personal fluid replacement needs during exercise.^[19–28] A recent study conducted by our group compared a wearable microfluidic sweat patch with colorimetric analysis to the standard absorbent patch technique and off-device, lab-based ion chromatography analysis. This study highlighted the utility of microfluidic patches with usability in athletic settings that exceed conventional techniques and established the validity of the microfluidic patch and image processing strategies in real-world environments.^[29] In that study, the patch design and image processing algorithms were developed primarily for testing in warm-hot environments (mean of 29–32 °C) during exercise mostly in competitive athletes (e.g., team and endurance sports) where sweat losses were in the moderate to heavy range.

Here we present a set of design advances and signal processing enhancements to this microfluidic system that allow wearers to monitor their sweat profiles after a workout, spanning a significantly broader range of wearer fitness levels, workout intensities and durations, and weather conditions. In addition to the wider range of test conditions, modifications include guided image capture to assist naive users in taking photos of the microfluidic patch, automated analysis of digital photos to measure properties of the microfluidic sweat patch, changes to the microfluidic patch collection areas to accommodate lower sweating rates, and updated reference color bars to improve chloride measurement accuracy over a wider range of ambient lighting conditions. With these developments, we show that researchers and/or wearers can use a smartphone and a microfluidic sweat patch to measure local sweating rate and sweat chloride concentration, which is significantly correlated with traditional absorbent patch methods. Moreover, we extend a model relating to local and whole-body sweating rates, enabling fluid intake recommendations for a large group of wearers over a wide range of environmental conditions.

2. Results

2.1. Soft Microfluidic Patch Design Strategies

The soft microfluidic patch consists of an enclosed multi-layered network of microchannels, bioassays, colored dye, and reservoirs that collect microliter amounts of sweat from the skin and route it for colorimetric analysis. Image processing algorithms implemented on a smartphone provide machine-learning-based detection and analysis with real-time sweat profile feedback to the wearer (**Figure 1a**). Upon completion of the workout, the user would take a photo of the patch with the smartphone. The application would process the results to determine the user's sweat profile (i.e., sweating rate, total sweat loss, and sweat electrolyte loss). Personalized fluid intake recommendations would be provided on the basis of the user's sweat profile. The user would then follow the recommendations to properly rehydrate immediately after the workout and/or properly hydrate during their next workout of similar intensity, duration, and environmental conditions. The sweat profile results and recommendations are provided as a range (prediction interval) to account for inherent day-to-day variation and error in the prediction models.

A patterned hypoallergenic skin adhesive integrated on the bottom surface of the microfluidic patch defines the sweat collection areas across two distinct microchannels. Microchannel 1 contains a sweat collection region with a surface area of 115 mm² and geometry designed to support rapid collection of sweat and analysis of sweat volume (μL) for recreational exercise, while enabling robust adhesion over long-term wear. It contains an embedded orange dye that mixes with excreted sweat near the inlet and flows down the channel pathway in a highly visible manner for real-time analysis of sweat volume. Microchannel 2 contains a smaller sweat collection area with a surface area of 32 mm², suitable for colorimetric analysis of chloride concentration in excreted sweat. Sweat entering microchannel 2 mixes with an integrated colorimetric chloride assay, which allows for in situ analysis based on the purple color intensity of the reaction. **Figure 1b,c** highlights the geometry,

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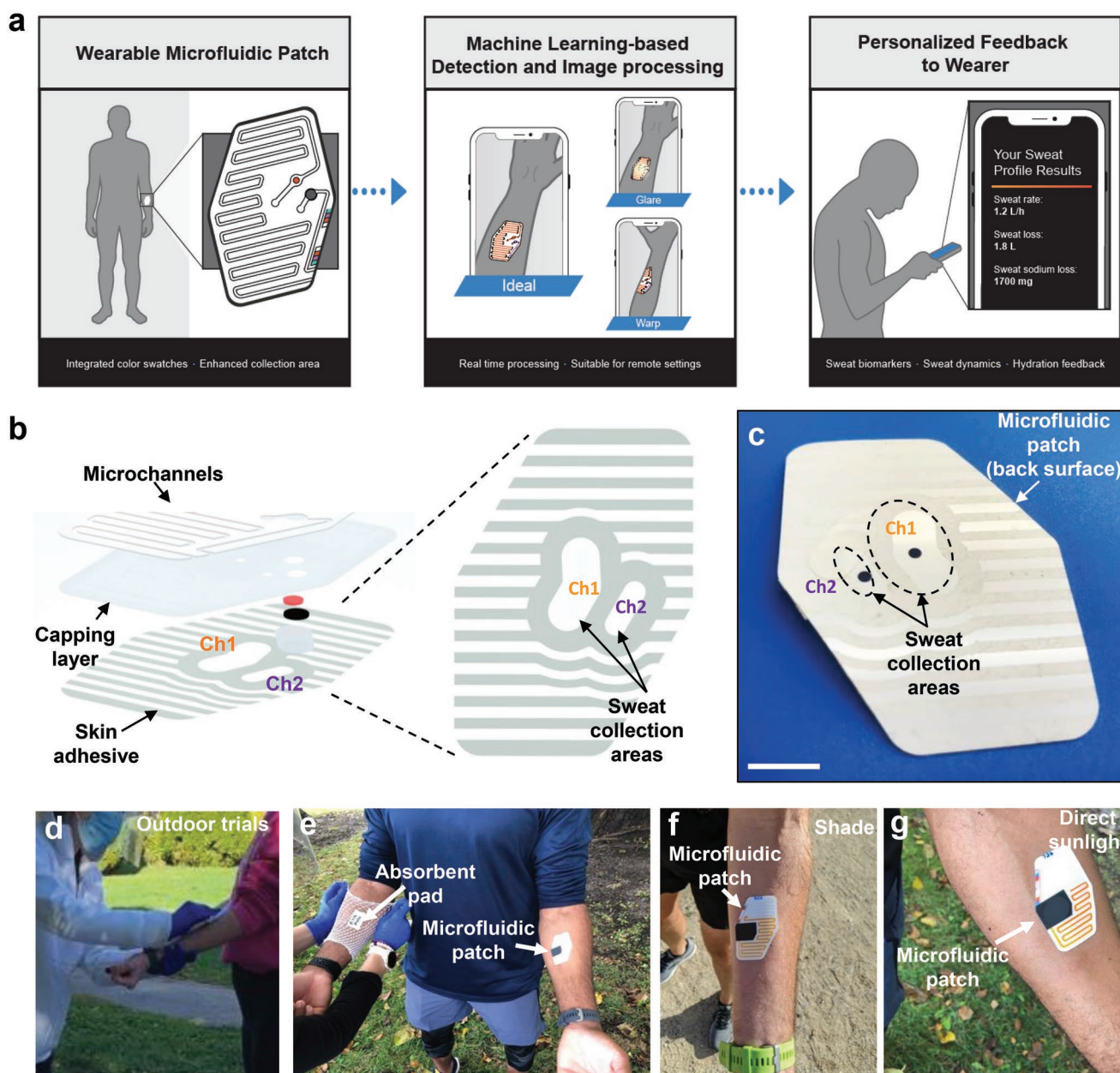


Figure 1. Wearable microfluidic patch design and field studies. a) Flow diagram showing path of sweat data beginning with (left) sweat propagation and subsequent chemical reactions in the wearable microfluidic patch, (middle) scanning of the patch with a smartphone imager having integrated image processing algorithms in remote settings, and (right) real-time personalized hydration feedback to the wearer. b) Schematic drawing of patterned adhesive layer highlighting the enlarged collection area for microchannels 1 and 2 (Scale bar: 1 cm). c) Optical image of microfluidic patch showing the bottom surface and collection regions (Scale bar: 1 cm). d) Optical image of field study investigator and subject being instrumented with microfluidic patch and absorbent patch in outdoor environment. e) Optical image showing the microfluidic patch and absorbent patch on the ventral forearm of subject in an outdoor environment prior to exercise. f,g) Close-up images of microfluidic patch captured after exercise in the shade and direct sunlight, respectively.

extended surface area, and relative positions of the two collection areas tuned for rapid and optimal sweat capture.

Optimizing the collection areas requires careful consideration of the expected range of sweat rates, exercise intensities, and exercise durations for recreational users. From our previous work,^[1,14] we estimated rates of $0.5\text{--}2\ \mu\text{L cm}^{-2}\ \text{min}^{-1}$ for shorter (30–45 min) high-intensity workouts and $0.2\text{--}1\ \mu\text{L cm}^{-2}\ \text{min}^{-1}$ for longer (60–90 min) low- to moderate-intensity workouts. Microchannel 1 requires $10\ \mu\text{L}$ of sweat to produce a visible result; at

the lowest rates and durations, this requires a collection area of at least $83\ \text{mm}^2$. To avoid completely filling the channel ($112\ \mu\text{L}$) which would preclude a rate measurement, these rates and durations limit the maximum collection area to $\leq 124\ \text{mm}^2$. A collection area of $115\ \text{mm}^2$ was chosen to provide visual results quickly without risking saturation of the patch volume. For microchannel 2, the minimum collection area was determined in a similar fashion, including the fluid volume required to wet the hydrogel. The maximum collection area for this channel is

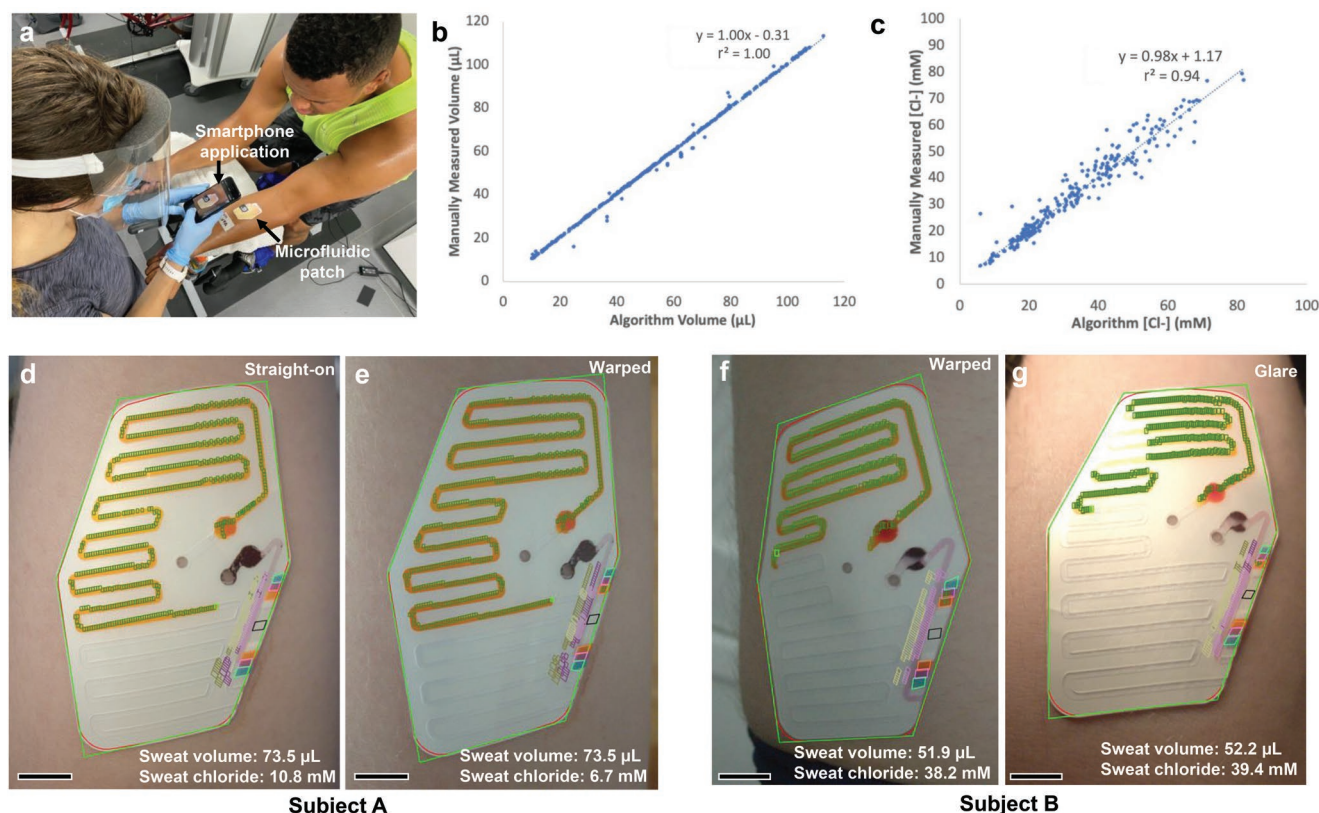


Figure 2. Optical analysis of microfluidic patch sweat metrics under different ambient conditions. a) Indoor study investigator taking a photograph of microfluidic patch on subject's ventral forearm during cycling exercise. b,c) Automated algorithm performance in field environments compared to manual analysis measured in CIELAB space by a trained data scientist. d–g) Robust detection of the microfluidic patch boundaries and aforementioned sweat volume and chloride data were demonstrated under various real-world scenarios, including representative examples of straight-on (d), skewed (e) optical images for subject A, and skewed (f) and glare (g) optical images for subject B (Scale bars: 1 cm). Sweat volume and sweat chloride concentration measurements are included as insets in each image.

limited by the quantity of assay available for consumption, the range of expected chloride concentrations, and the maximum flow rate at which the reaction is driven to completion. Taken together, the microchannel's cross-sectional dimensions (1 mm $\times$ 0.225 mm), total volume capacity, and collection area were optimized to meet the sweat testing needs of recreational exercise. Additional design updates include increasing the assay quantity embedded in microchannel 2 and optimizing the reference colors on the patch surface to improve color measurement accuracy.

To test the viability of this new microfluidic patch in non-competitive, recreational settings, patches were applied to subjects during low- to moderate-intensity exercise routines (Figure 1d). Figure 1e shows a subject instrumented with a microfluidic patch (left ventral forearm) and an absorbent patch (right ventral forearm) for comparative analysis. Photographs of the filled microfluidic patches were taken under different lighting conditions (e.g., shade, direct sunlight, indoors), highlighting the extent of sweat capture and utility of the microfluidic patch during “real world” use (Figure 1f,g).

2.2. Real-Time Image Processing and Analytics under Different Uncontrolled Conditions

Real-time image analysis of sweat loss and chloride concentrations provides quantitative readout, feedback, and

recommendations to users with a personal smartphone. Having a well-framed, uniformly lit, and focused image of the patch is critical for obtaining accurate results, but taking such a photo requires skills and training that a typical user may not have. To enable users to capture images of sufficient quality and then quantify features of these images, custom software was developed using a combination of machine-learning and traditional computer vision algorithms. An on-screen overlay of a patch outline guides the user to properly frame the photo, while a real-time, machine-learning-based algorithm detects the sweat patch in the field of view and automatically captures a photo (Figure 2a, Figure S1, Supporting Information). Post-capture, a fully automated traditional computer vision algorithm enables precise measurement of small features of the patch. The algorithm detects the boundaries of the microfluidic patch, determines the extent of sweat fill in microchannel 1, and measures the chloride concentration from the color intensity in microchannel 2 after correcting for lighting conditions using the reference color spots. The resulting measurements and raw image data are retained. To test the robustness and performance of the image processing algorithms, we tested multiple smartphone models, including the iPhone X and the Google Pixel 2 and compared the sweat analysis results to the iPhone 8 (reference smartphone used in the study) (Figure S2, Supporting Information). These

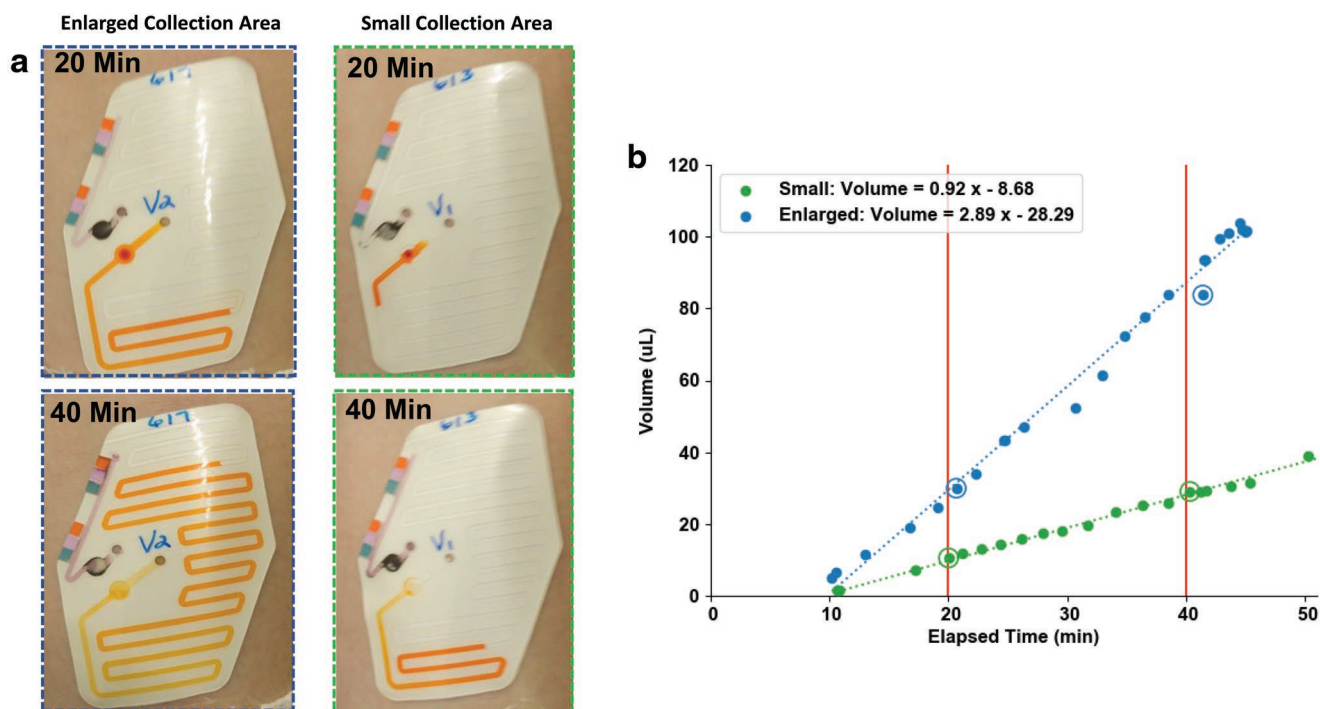


Figure 3. Comparative analysis of sweat capture using enlarged patch versus small patch for a subject across 20 and 40 min snapshots in time. a) Representative example of enlarged patch (blue dashed image, top left) filled approximately 29.6 μL at 20 min compared to 10.2 μL at 20 min for the small patch (green dashed image, top right) for the same subject (Scale bars: 1 cm). At 40 min, the enlarged patch reached 83.3 μL (blue dashed image, bottom left), compared to 28.7 μL for the small patch (green dashed image, bottom right). b) Sweat volume capture for the enlarged patch (blue) is significantly greater than sweat capture for the small patch (green) over time. This difference in overall sweat volume capture over time maintains a similar surface-area normalized regional sweating rate across both microfluidic patches. Circled points correspond to the photos in (a).

machine learning-based and image analysis algorithms enable deployment of the sweat microfluidics patch and software application across a variety of smartphones and camera models, which is necessary for use in uncontrolled remote settings.

To test the validity of the automated algorithms in remote environments, a set of photos was analyzed after being collected as part of an effort to train a machine-learning algorithm (Figure S1, Supporting Information). The sweat volume and chloride measured by the automated algorithms were compared to sweat fill extent (Figure 2b) and color intensity (Figure 2c) as post-processed manually by a trained data scientist. Previous studies conducted using manual assessment of sweat volume and chloride levels were validated in extensive field trials and compared to control measurements using gravimetric volume analysis and high-performance liquid chromatography for chloride analysis.^[29]

Taken together, these results demonstrate the robust performance of the automated algorithms under various conditions across the entire physiological range for sweat rates ($0.2\text{--}3 \mu\text{L cm}^{-2} \text{ min}^{-1}$) and chloride concentrations ($5\text{--}90 \text{ mmol L}^{-1}$). To enable detection of the microfluidic patch under various real-world scenarios, the patch detection algorithm was developed and tested in different image capture conditions, including straight-on, skewed, and glare. In these scenarios, the patch detection algorithm and sweat measurements were consistent across multiple subjects and trials, as shown in Figure 2d–g.

2.3. Quantitative Assessment of Enlarged Collection Area for Real-Time Sweat Capture

A key design consideration in this study was to enable rapid and robust capture and analysis of sweat across normal activities using an enlarged collection area and geometry. Our previous study^[29] showed the utility of the microfluidic patch in physically demanding exercise with a smaller sweat collection area and patterned adhesive configuration. To characterize the utility of the updated microfluidic patch design for recreational exercise, we directly compared sweat volume capture for the new enlarged collection area versus the existing microfluidic patch across multiple subjects ($n = 15$). For this comparison, subjects completed two identical exercise trials 3–16 days apart, under standardized environmental conditions (32°C , 50% relative humidity) and exercise intensity (85% maximum heart rate), in which they wore the microfluidic patch with either the enlarged or small collection area in random order. The two versions of the microfluidic patch were worn during separate exercise trials so the placement could be standardized to the left ventral mid-forearm. **Figure 3a** highlights a comparative assessment of sweat capture for a representative subject across 20 and 40 min snapshots in time. The enlarged collection area microfluidic patch (“enlarged patch”) filled approximately 29.6 μL at 20 min, compared to 10.2 μL for the small collection area microfluidic patch (“small patch”). At 40 min, the enlarged patch reached 83.3 μL , compared to 28.7 μL for the small patch. The increase in sweat capture for the enlarged patch (shown

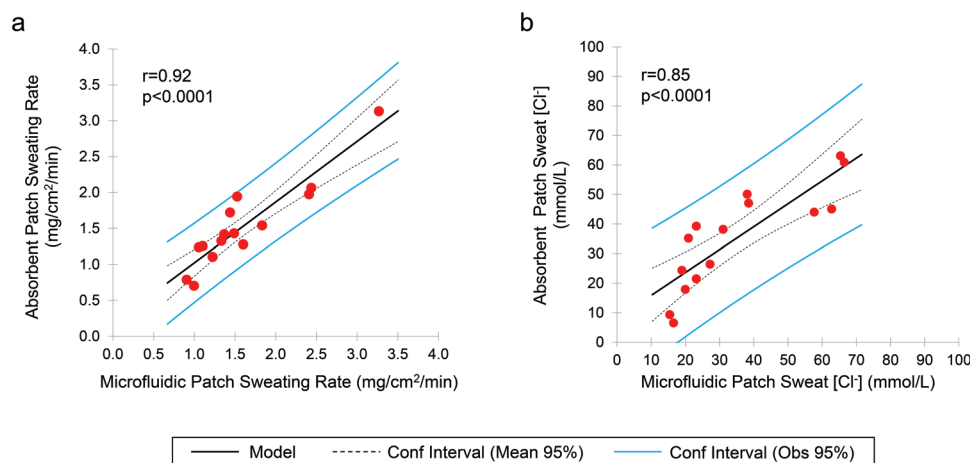


Figure 4. Scatterplots of the microfluidic versus absorbent patch data under controlled laboratory conditions. a) Regional sweating rate and b) regional sweat chloride concentration measured during cycle ergometry and treadmill running ($n = 15$ subjects).

in Figure 3b) highlights how design optimization in the microfluidic patch supports real-time sweat capture across the entire physiological range of sweating rates. This difference in overall sweat volume capture over time is consistent with the scaling in surface area and maintains a similar surface-area normalized regional sweating rate across both microfluidic patches ($r = 0.70$, $p < 0.01$).

2.4. Microfluidic Patch versus Absorbent Patch and Day-to-Day Coefficient of Variation of Regional Sweating Rate and Sweat Chloride Concentration during Indoor Cycle Ergometry and Treadmill Running

Figure 4 shows scatterplots of the microfluidic versus absorbent patch data collected while 15 subjects completed moderate intensity cycling or treadmill running under controlled laboratory conditions ($32\text{ }^{\circ}\text{C}$). The microfluidic patch results were significantly correlated with the absorbent patch for both sweating rate (Figure 4a: $r = 0.92$, $p < 0.0001$) and

sweat chloride concentration (Figure 4b: $r = 0.85$, $p < 0.0001$). There was no difference in sweating rate per unit skin area ($1.60 \pm 0.65\text{ mg cm}^{-2}\text{ min}^{-1}$ vs $1.53 \pm 0.60\text{ mg cm}^{-2}\text{ min}^{-1}$, $p = 0.30$) or sweat chloride concentration ($35 \pm 19\text{ mmol L}^{-1}$ vs $35 \pm 17\text{ mmol L}^{-1}$, $p = 0.93$) between the microfluidic and absorbent patch. Note that we used a nominal sweat density of 1.0 g mL^{-1} to enable direct comparisons. Test-retest (day-to-day) reliability measured in 5 subjects was similar for the microfluidic patch and absorbent patches, with coefficients of variation (CV) of 9% and 13% respectively for sweating rate and 14% and 11% respectively for sweat chloride concentration.

2.5. Microfluidic Patch versus Absorbent Patch during Outdoor Running and Fitness Sessions

Scatterplots of the microfluidic versus absorbent patch data collected during outdoor running ($n = 25$ subjects) and outdoor fitness exercise sessions ($n = 9$ subjects) under varying environmental conditions ($8\text{--}32\text{ }^{\circ}\text{C}$) and ambient lighting

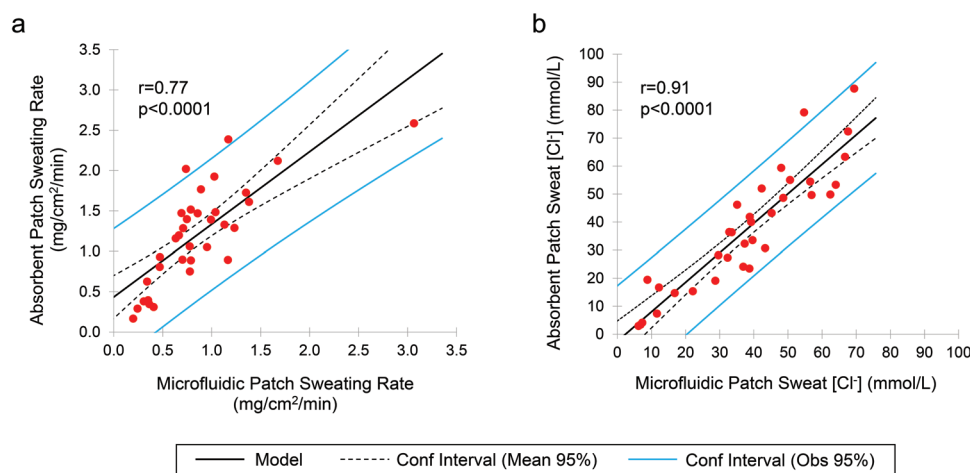


Figure 5. Scatterplots of the microfluidic versus absorbent patch data collected during outdoor running and fitness sessions. a) Regional sweating rate and b) regional sweat chloride concentration under varying environmental and ambient lighting conditions ($n = 34$ subjects).

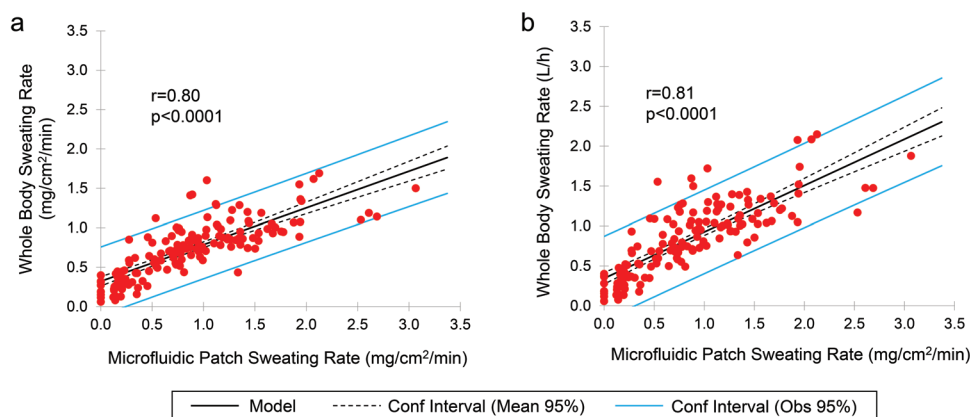


Figure 6. Scatterplots of microfluidic regional sweating rate versus whole body sweating rate ($n = 148$ subjects). a) Microfluidic regional sweating rate versus whole body sweating rate, expressed relative to body surface area ($\text{mg cm}^{-2} \text{min}^{-1}$). b) Microfluidic regional sweating rate versus whole body sweating rate, expressed in absolute terms (L h^{-1}).

conditions are shown in **Figure 5**. The microfluidic patch results were significantly correlated with the absorbent patch for both sweating rate (**Figure 5a**: $r = 0.77$, $p < 0.0001$) and sweat chloride concentration (**Figure 5b**: $r = 0.91$, $p < 0.0001$). Microfluidic patch normalized sweating rate per unit skin area was significantly lower than for the absorbent patch ($0.86 \pm 0.53 \text{ mg cm}^{-2} \text{min}^{-1}$ vs $1.20 \pm 0.61 \text{ mg cm}^{-2} \text{min}^{-1}$, $p < 0.0001$). There was no difference in mean sweat chloride concentration between the microfluidic and the absorbent patch ($38 \pm 19 \text{ mmol L}^{-1}$ vs $37 \pm 22 \text{ mmol L}^{-1}$, $p = 0.73$).

2.6. Development of a Whole-Body Sweating Rate Predictive Model Based On Regional Measurements

The whole body sweating rate prediction model analysis was conducted with $n = 148$ subjects tested in a broad range of environmental temperatures ($8\text{--}32^\circ\text{C}$): $n = 20$ from trial 1, $n = 34$

from trial 2, and an additional $n = 94$ from field tests of outdoor running ($n = 36$) and indoor ($n = 33$) and outdoor ($n = 25$) fitness sessions. There was a significant correlation between microfluidic regional sweating rate versus relative whole body sweating rate (**Figure 6a**: $\text{mg cm}^{-2} \text{min}^{-1}$, $r = 0.80$, $p < 0.0001$) and absolute whole body sweating rate (**Figure 6b**: L h^{-1} , $r = 0.81$, $p < 0.0001$). In this trial microfluidic sweating rate was $0.86 \pm 0.63 \text{ mg cm}^{-2} \text{min}^{-1}$ and whole body sweating rate was $0.72 \pm 0.36 \text{ mg cm}^{-2} \text{min}^{-1}$ or $0.84 \pm 0.45 \text{ L h}^{-1}$.

Figure 7a shows the multiple regression model for prediction of whole body sweating rate from microfluidic regional sweating rate and other factors in the present study ($r^2 = 0.75$, root mean squared error, $\text{RMSE} = 0.23 \text{ L h}^{-1}$, concordance correlation coefficient, $\text{CCC} = 0.86$, mean absolute error, $\text{MAE} = 0.16 \text{ L h}^{-1}$, and mean absolute percentage error, $\text{MAPE} = 23\%$). **Figure 7b** shows the multiple regression model for prediction of whole body sweating rate when data from the present study ($n = 148$) are combined with data from our previous study with the

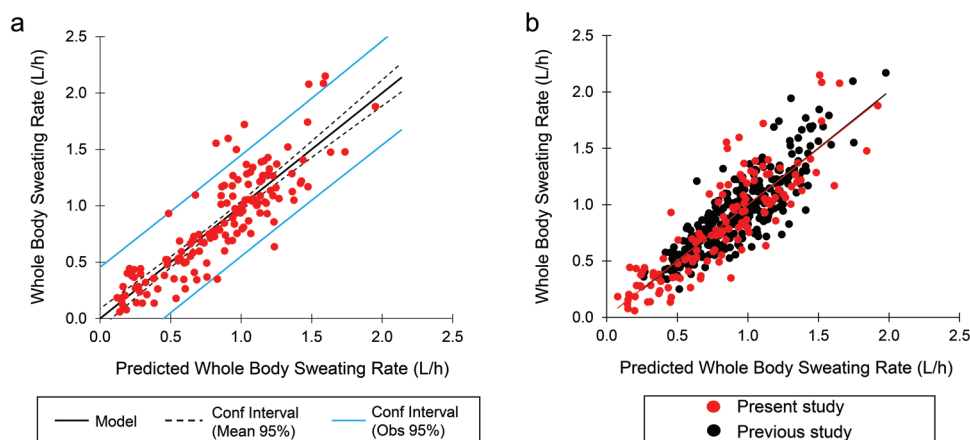


Figure 7. Scatterplots showing predicted versus actual whole body sweating rate data. Predicted values obtained with a model that includes microfluidic regional sweating rate, body mass, sex, air temperature, type of sport, exercise duration, and energy expenditure. a) Whole body sweating rate model from the present study ($n = 148$ subjects) with cycle ergometry, running, and fitness sessions ($r^2 = 0.75$, $\text{RMSE} = 0.23 \text{ L h}^{-1}$, $\text{CCC} = 0.86$, $\text{MAE} = 0.16 \text{ L h}^{-1}$, and $\text{MAPE} = 23\%$). b) Whole-body sweating rate model when data from the present study (red circles) are combined with data reported in our previous publication ($n = 312$ subjects, black circles)^[29] (reproduced with permission from Baker et al. Sci Adv 2020) with a range of team and individual sports ($n = 460$ in total) ($r^2 = 0.74$, $\text{RMSE} = 0.20 \text{ L h}^{-1}$, $\text{CCC} = 0.85$, $\text{MAE} = 0.15 \text{ L h}^{-1}$, and $\text{MAPE} = 18\%$).

microfluidic device ($n = 312$) ($r^2 = 0.74$, $RMSE = 0.20 \text{ L h}^{-1}$, $CCC = 0.85$, $MAE = 0.15 \text{ L h}^{-1}$, and $MAPE = 18\%$, $n = 460$ in total). The whole body sweating rate predictions derived from the regional measurements create opportunities for fluid and electrolyte replacement strategies, thereby enabling actionable hydration feedback to users, in real-time, without the need for advanced laboratory equipment.

3. Discussion

A series of studies were conducted to compare the wearable microfluidic platform with standard techniques for measuring sweating rate and sweat chloride concentration during physical activity across a wide range of environmental conditions. For sports science and clinical applications, the development of smartphone applications and microfluidic patch features demonstrated in this work (i.e., machine-learning based patch detection algorithm, patch graphical layer with enhanced color swatches, image processing algorithms across smartphones) are critical to enabling real-time, on-body, and non-invasive sweat biomarker measurements. Taken together, the new software features and advanced microfluidic patch designs (increased collection area for rapid sweat collection) enable naïve operators to perform these measurements on themselves and others with little to no training and in uncontrolled environmental conditions. These conditions include poor lighting (glare, low light, shadows), skew (image warping due to operator's camera angle), blur during image capture, and variations in physical characteristics of the user (e.g., arm curvature, which warps the camera image of the patch).

The main finding in this study was that regional sweating rate and sweat chloride concentration from the microfluidic patch were significantly correlated ($r = 0.77\text{--}0.92$) with those of the standard absorbent patch technique. The within-subject CVs for the microfluidic device (9–14%) were similar to those of the reference techniques (11–13%) for both sweating rate and sweat chloride concentration, representing normal day-to-day variation. In addition, models to predict whole-body sweating rate based on microfluidic patch results and other inputs were tested under various environmental conditions. The good agreement between predicted and measured whole-body sweating rate ($r^2 = 0.75$, $CCC = 0.86$) enables personalized use in remote settings as well as real-time fluid-electrolyte intake recommendations. The current work extends the validity and reliability of the wearable microfluidic platform to much larger cohorts of everyday users, across a broad range of sweating rates and environmental conditions.

The mean sweating rate across all subjects in this study was 0.84 L h^{-1} , which is similar to the mean sweating rates previously reported in recreational exercisers during a gymnasium-based exercise session at a fitness center (0.79 L h^{-1})^[3] and hot yoga (0.81 L h^{-1}).^[30] By comparison, mean sweating rates in more competitive athletes have been reported to be $\geq 1.0 \text{ L h}^{-1}$.^[6,31] Despite lower mean sweating rates, it is noteworthy that significant inter-individual variation and high sweating rates exist among recreational exercisers, as the range in the present study was 0.1 to 2.1 L h^{-1} . Likewise, high sweating rates ($\approx 2 \text{ L h}^{-1}$) have also been reported elsewhere in

recreationally-active individuals, especially during short duration high-intensity workouts^[32] or hot environments.^[33] Recreational exercise typically involves low-moderate intensity activity over an extended period ($\approx 60\text{--}90 \text{ min}$) or high-intensity interval workouts of shorter duration ($\approx 30\text{--}45 \text{ min}$). In these scenarios total sweat volume is also generally lower than in competitive team sports or endurance athletes who train/compete at high intensities for up to two hours. Accordingly, total sweat losses were 0.67 L (ranging from 0.10 to 1.68 L) in the present study compared with 1.27 L (ranging from 0.12 to 4.16 L) in our previous study with athletes.^[29] Microfluidic device measurement capabilities across the full range of low and high sweat losses are important for hydration planning so that intake is appropriate for actual instead of perceived fluid and electrolyte needs—to prevent both significant over- and under-drinking during exercise.

Current guidelines regarding fluid replacement for the physically active recommend the prevention of modest levels of hypohydration (2% body mass deficit) while also avoiding over-hydration (body mass gain).^[1,14,15] In addition, sodium should be ingested with water when sweat sodium losses are high, which may occur when there is some combination of moderate-to-prolonged duration exercise in the heat ($>1\text{--}2 \text{ h}$), moderate-to-high sweating rates ($>1.5 \text{ L h}^{-1}$), and/or moderate-to-high sweat sodium concentrations ($>60 \text{ mmol L}^{-1}$).^[1,14,15,34,35] However, it is important to note that, even when losses are high, not all sweat sodium loss needs to be replaced during exercise. For instance, one study found that ingestion of sodium equivalent to $\approx 50\%$ of subjects' $\approx 2.8 \text{ g}$ sodium losses incurred during 2 h cycling in the heat led to better maintenance of plasma volume, stroke volume, and cycling performance than no sodium intake, but was not different from $\approx 100\%$ replacement.^[36]

Based on these guidelines a personalized fluid intake strategy could be developed from the sweat loss and electrolyte data obtained with the microfluidic patch. For example, if there are two 70-kg individuals exercising for one hour and 20 min : Person A has a sweat loss of 2.0 L and a sweat sodium concentration of 80 mmol L^{-1} (3.7 g total sodium) while Person B has a sweat loss of 0.7 L and a sweat sodium concentration of 20 mmol L^{-1} (0.3 g total sodium). During the next 1.3 h workout of similar intensity and environmental conditions, Person A would be advised to drink $\approx 0.8 \text{ L}$ of fluid to prevent 2% hypohydration or up to 2.0 L of fluid if desired. In addition, during and/or after exercise, Person A would be advised to choose a fluid or food/gel/bar with sodium to mitigate an electrolyte imbalance and promote fluid retention. On the other hand, Person B would not need to take in any fluid to avoid 2% hypohydration during the 1.3 h workout. Person B could drink to thirst but would be advised to consume no more than 0.7 L in total and a small amount of sodium could be optional depending on personal preferences related to drink palatability.

In our previous microfluidic patch study, we found that lower regional sweat flow rates ($\leq 0.4 \text{ mg cm}^{-2} \text{ min}^{-1}$) made it difficult in some cases to collect sufficient sweat volume to assess the regional sweating rate and chloride concentration.^[29] Design changes demonstrated in the present study enabled sweat profile measurements during short duration exercise (as low as 25 min) or relatively low regional sweat flow rates (as low as $\approx 0.2 \text{ mg cm}^{-2} \text{ min}^{-1}$). However, it is important to note

that the device is not intended for very low exercise intensity, activities of daily living, or cool-cold weather; as these conditions may not produce sufficient sweat for analysis, particularly for chloride measurement. For example, during cool weather (8–13 °C) testing with fitness exercisers, although sweating rate assessment was successful, several subjects did not sweat enough to produce a colorimetric reaction for chloride measurement. However, individualized electrolyte replacement planning is less important when overall sweat losses are very low ($<0.3 \text{ L h}^{-1}$ in subjects for which chloride could not be measured).^[1,14] The device successfully measured sweat chloride concentrations across the full physiological range ($\approx 5\text{--}90 \text{ mmol L}^{-1}$) for individuals with low-moderate sweating rates ($0.3\text{--}1.0 \text{ L h}^{-1}$) in cool weather (8–13 °C) and in all subjects tested in temperate to warm conditions (17–32 °C).

4. Conclusion

The microfluidic patch and image processing software system enable real-time assessment of sweating rate and sweat chloride concentration in everyday users during typical exercise activities at home or in remote environments. Collection of sweating rate and sweat electrolyte loss data using this low-cost wearable sensing approach could improve the accessibility of sweat analytics in real-world settings, with applications not only in athletic performance but also in providing insights into appropriate hydration planning to prevent significant dehydration and overhydration in fitness enthusiasts and recreational exercisers. Future research should explore further broadening the applicability of similar microfluidic wearable systems, such as in occupational settings where physical labor and heat stress can induce significant fluid/electrolyte imbalances and pose a risk to worker safety and productivity.

5. Experimental Section

Three trials were conducted to compare the microfluidic sweat patch with standard methods for sweat testing. The objective of Trial 1 was to compare the microfluidic patch and absorbent patch results for regional sweating rate and sweat chloride concentration during indoor recreational exercise. The within-subject CV of the patches was also determined in Trial 1. The objective of Trial 2 was to compare the microfluidic patch and absorbent patch results for regional sweating rate and sweat chloride concentration during outdoor recreational exercise. Finally, in Trial 3 the objective was to develop a whole-body sweating rate predictive model.

This research (Clinical Trial Identifier: NCT04240951; Jan 27, 2020) was approved by the Sterling Institutional Review Board (Atlanta, GA) for the protection of human study participants (Sterling IRB ID: 6004). Each participant and his/her parent or guardian (for subjects under 18 years) were informed of the experimental procedures and associated risks before providing written informed consent. Figures S3–S5, Supporting Information, show the CONSORT flow diagrams for study enrollment, participant exclusion, and data exclusion details for Trials 1–3. In total, data from 148 subjects ($n = 93$ male, $n = 55$ female; 17–48 years) were analyzed. Table S1, Supporting Information, provides summary data of subject characteristics for each trial.

Fabrication of Wearable Microfluidic Devices: The microfluidic patch fabrication steps were previously published.^[29] Briefly, a multi-layered stack of thin-film polymeric materials (polyurethane film; Aline Inc., CA, USA) with laser-cut regions creates the micro-channels and inlet

ports. Pressure-sensitive adhesive bonds the intermediate fluidic layer with the top graphics and subjacent skin adhesive layers (polyethylene film; 3M, MN, USA). Laser-cut inlet windows in the adhesive layer create openings to define the two sweat collection regions for microchannel 1 and microchannel 2. For colorimetric analysis of microchannel 1, a dehydrated colored dye ($\approx 4 \mu\text{L}$) was deposited in an assay well region and used to mix with sweat, providing an optical method to measure regional sweat volume and sweating rate. Microchannel 2 was embedded with a mixture of silver chloranilate and polyhydroxyethylmethacrylate (pHEMA; Sigma-Aldrich, MO, USA) hydrogel placed near the assay well region to mix with sweat for chloride concentration analysis.^[29] Microchannel 1 has a volume of about $112 \mu\text{L}$ while microchannel 2 has a volume of about $20 \mu\text{L}$.

Machine Learning Algorithm for Automated Image Capture: A machine-learning algorithm was developed to analyze live video from the smartphone camera to detect the presence and location of the patch, an identifying logo, and a set of color swatches used for lighting correction. To optimize performance for real-time processing, this algorithm was built and trained using the YOLOv2 framework before being exported as a CoreML model to leverage hardware acceleration on the iPhone. The training set consisted of 570 images of microfluidic patches taken on the forearms at the beginning and end of exercise, collected as part of a previous study.^[29] Annotations for the locations of the patch, logo, and swatches were recorded as bounding boxes drawn manually around these features in each image. Because of the small number of images available for training, a pre-processing step was applied to each image to generate 5 additional images with random variations in horizontal and vertical position (up to 10%), rotation angle (up to 30°), shear (up to 0.5°), zoom (80–120%), and brightness (up to 20% increase, but no decrease allowed). The annotations for these artificial images were derived by applying these same spatial transformations to the original image annotations. The model was trained using 80% of the resulting set of annotated images, and tested with the remaining 20%. The model was integrated into the smartphone app so that an outline of the patch used to guide the user in capturing the photo turned green when the model detected a patch (Figure S1, Supporting Information). In addition, if the model detected the patch in 15 consecutive image frames and the location of the patch did not change by a pre-defined limit (i.e., the image was stable), the app automatically triggered photo capture. Field tests showed that the app automatically triggered photo capture in 244 of 259 capture sessions (94%).

Smartphone Colorimetric Analysis of Sweating Rate and Chloride Concentration: Smartphone colorimetric analysis was previously published under controlled and ambient lighting conditions.^[29] Briefly, photos of microfluidic patches were captured using a smartphone application (iPhone 8, Apple Inc.) in laboratory and uncontrolled outdoor settings. Images were captured at the time of absorbent patch removal at the end of recreational exercise, prior to removal of the microfluidic patch. The image was captured as a RAW image, allowing a well-defined, repeatable conversion from the sensor readout to RGB color values. The resulting image and machine-learning-model-detected bounding boxes were passed to an algorithm based on traditional computer vision techniques. This approach allowed to combine the speed of machine-learning-based approaches to automate image capture with the precision of traditional methods for quantifying image features.

Because the size and aspect ratio of the live camera preview differ from those of the final captured image in ways that can vary by phone model, the machine-learning-detected bounding boxes were used to constrain a more precise hexagonal bounding shape for the patch. This more precise shape was used to account for perspective shifts (e.g., if the phone and arm were not parallel then the patch will appear bigger on the closer side) and to support mapping between the image and known patch geometry (e.g., to determine if a given pixel was inside a microfluidic channel). The machine-learning-detected bounding box for the patch was used to constrain the overall size and position of this hexagon. The detected logo and swatch locations were used to determine if the resulting hexagon captured the entire patch (e.g., the logo should be near the right center of the patch shape).

To derive this hexagonal shape, the image was first converted to CIELAB color space, where the axes were lightness L^* and the color axes a^* (green/red) and b^* (yellow/blue). Since it was assumed that the patch was roughly centered in the image, the brightest 10% of pixels (L^* channel) in the center 1/8 of the image were used to determine the median and standard deviation of the white color of the patch in the a^*b^* color plane. A second derived image was then made by attenuating the L^* value of pixels based on their vector distance from the patch white color in the a^*b^* plane; this served to enhance the contrast between the patch and surround. For both derived images as well as the RGB image, the Canny edge detection algorithm^[37] was applied with multiple thresholds to obtain a set of edge images.

Contours and convex hulls were derived from these edge images and evaluated for size (33–90% of image area), orientation, aspect ratio (near 1.4), and comparison to the machine-learning-detected bounding box. The resulting convex hulls were approximated by hexagons that were then evaluated by the relative lengths of all 6 sides (4 long, 2 short), the angles between adjacent sides, and the angles between opposite sides. Contours were sorted by an error metric derived from these measurements, and those with an error more than 20% larger than the minimum were discarded. Of the remaining contours, the largest was chosen based on early testing results. Patch orientation was determined by the relative position of the machine-learning-detected logo. This contour was then used to derive a perspective transform between the image and an idealized model of patch geometry. This process compensated for perspective errors (e.g., camera tilt, arm curvature) as well as scaling, translation, and rotation. In addition, as explained in detail below the subsequent processing steps do not rely on the precise location of this boundary.

The size and location of the color swatches depend on the accuracy of the derived patch outline as well as manufacturing tolerances. To identify the swatches, successive scan lines parallel to the lower-right patch outline edge were analyzed. For each scan line, leading and trailing running sums were computed, with the sum length determined by the expected height of each swatch. The difference between these sums was used to identify the boundaries of each color swatch. The resulting set of boundaries was used to fit parallelograms to each set of color swatches. The median color in these parallelograms was measured to determine the swatch colors.

The filled volume of the patch was determined by the furthest extent of orange dye in microchannel 1. Because the orange dye can get depleted so that sweat entering the patch later may have faded or no color (e.g., Figure 3a), color thresholding followed by pixel counting was not sufficient. Instead, 50 scan lines evenly spaced across each of the width and height of the patch were analyzed. For each scan line, leading and trailing running sums were computed over roughly 1 mm lengths. A location was tagged when the difference between these sums exceeded a threshold determined by the orange swatch color and then exceeded the negative threshold within 1.5 mm (i.e., the running sum entered and then left an orange region). Locations that did not map to known channel positions were discarded, and the fill volume was computed for all remaining locations based on known patch geometry. Spurious points were rejected by discarding any locations that did not have at least 5 other points with a fill volume within 1 μL of the maximum, along with any points within 0.5 mm of the orange color swatches. The largest remaining fill volume was reported.

For microchannel 2, the purple color intensity maps monotonically to chloride concentration over the physiological range (5–100 mmol L^{-1}). To correct for color variations due to lighting conditions (e.g., color temperature), swatches with known colors printed on the patch surface were located and measured in the image. Colors were corrected in CIELAB color space by deriving an affine transform between the measured swatch colors and the known color values. Sweat NaCl concentrations change in direct proportion with sweating rate, which in turn was primarily dictated by exercise intensity. Thus, at the beginning of exercise, sweat chloride concentration gradually increased concomitant with the ramp up in sweating rate. After reaching a steady state, sweating rate and sweat NaCl were constant if exercise intensity was uniform throughout the course of exercise, which was generally the

case with endurance activity.^[38] However, with intermittent activity (such as fitness exercise) fluctuations in sweat NaCl can occur.^[39,40] The intent of the microfluidic patch was to use one measure of central tendency that represents sweat chloride concentration over the course of the entire exercise session, similar to the approach used with the traditional absorbent patch method. Thus, the colors of microchannel 2 and the adjacent patch background were measured along the channel length to determine the median chloride value. The difference in corrected color between microchannel 2 and the patch background was calculated and projected onto a vector representing the expected purple color. Values, where this projection reduced the vector length by more than 10%, were rejected. The length of each projection was then mapped to chloride concentration using a power-law relationship determined experimentally. Chloride values were rejected if they were below 50% of the mean upstream value, or if the distance to the nearest valid upstream measurement was >25% of the channel length. The median value of the remaining measurements was reported as the estimate of central tendency for chloride concentration over the course of exercise in direct comparison to absorbent patch analyses. A variety of checks were added to this process to avoid commonly observed failure modes; for example, chloride measurements were discarded when the measured volume of microchannel 1 was below 10 μL . Figure S1D, Supporting Information, shows the locations of various image features detected and measured during this analysis. The performance of this process was evaluated by comparing the measured volume and chloride concentration to values measured manually from the same images (Figure 2).

Regional Sweating Rate and Sweat Chloride Concentration Measurements: Consistent methodology was used in each trial to measure regional sweating rate (Trials 1–3) and regional sweat chloride concentration (Trials 1–2). Sweat was collected from the right and left ventral forearms with an absorbent patch (TegadermTM+Pad, 3M, St. Paul, MN; pad size 11.9 cm^2) and the wearable microfluidic patch, respectively. The literature suggests there were no significant bilateral differences in forearm sweating rate and sweat electrolyte concentrations,^[41–45] with CVs reported to be ≈ 12 –13%. The day-to-day CV in ventral forearm sweating rate and sweat chloride concentration was ≈ 9 –13%.^[41]

Before patch application, the ventral forearms were wiped clean with alcohol pads followed by deionized water and dried with electrolyte-free gauze (4 × 4 in; Thermo Fisher Scientific, Waltham, MA). For optimal patch adhesion to the skin, the ventral forearms were shaved if needed to remove hair. The microfluidic patch was applied to the left ventral forearm about 5 cm below the elbow crease. No effort was made to precisely control or calibrate this positioning for individual subjects. The ventral forearm was chosen because of the significant correlation with whole body sweating rate and electrolyte concentrations.^[41] This location was also convenient for users to photograph with their smartphone and tends to have less hair than other sites. An elastic net dressing (Surgilast; Derma Sciences, Princeton, NJ) was placed over the right forearm to ensure the absorbent patch remained affixed to the skin. Upon removal, the absorbent pad was immediately separated from the Tegaderm using clean forceps and placed in an air-tight plastic tube (Sarstedt Salivette, Nümbrecht Germany). Regional sweating rate (in $\text{mg cm}^{-2} \text{min}^{-1}$) was determined from the mass of sweat absorbed in the pad (to the nearest 0.001 g using an analytical balance; Mettler Toledo Balance XS204, Columbus, OH), the pad surface area, and the time the patch was on the skin. Sweat from the absorbent patch was extracted using centrifugation and was subsequently analyzed for $[\text{Cl}^-]$ in duplicate by ion chromatography (Dionex ICS-6000).

Whole-Body Sweating Rate: For Trials 1, 2, and 3, whole-body sweating rate was calculated from the difference in pre- to post-exercise body mass, corrected for food/fluid intake, urine/stool loss, respiratory water loss, and weight loss due to substrate oxidation,^[46] divided by exercise duration. The within-subject CV for whole body sweating rate was measured in the repeat subjects of Trial 1 was 2%.

Trial Design and Protocols: Additional details of experimental procedures for each trial are described below. Table S2, Supporting Information, provides a summary of descriptive data related to the exercise conditions, environment, and physiological measures in each trial.

Trial 1: For the first objective sweat was collected with microfluidic and absorbent patches during indoor exercise. Subjects either cycled ($n = 5$ male and 1 female; 32 ± 6 years; 82.05 ± 11.56 kg) on an ergometer (Velotron SRAM, Pro, Chicago, IL) or ran ($n = 5$ male and 4 female; 31 ± 8 years; 64.52 ± 8.79 kg) on a treadmill (1% grade, HPCosmos, Cosmed T170, Nußdorf Germany) at moderate intensity ($83 \pm 10\%$ maximum heart rate) in a climate-controlled chamber (32°C , 50% relative humidity measured via QUESTemp 36, Quest Technologies). Exercise duration was 90 min or the time it took to nearly reach the capacity of the microfluidic patch, whichever came first (range was 35–90 min). Heart rate was monitored using telemetry (Polar Electro RS400; Lake Success, NY) and power output (watts) and cadence or treadmill speed were recorded every 10 min. Energy expenditure (kcal) was calculated from the cycling work rate^[47] or run distance and body mass.^[48] Subjects were provided a commercially available 6% carbohydrate-electrolyte solution to drink ad libitum during exercise. Bottles were weighed (Mettler Toledo PG6002-S, Columbus OH) before and after the trial to determine the amount consumed. Immediately before and after exercise, nude body mass was recorded using a digital platform scale (KCC300 platform and IND439 reader; Mettler Toledo, Columbus, OH) to the nearest 0.01 kg. Subjects were asked to towel dry before each body mass measurement.

Five additional subjects ($n = 4$ male and 1 female; 33 ± 5 years; 87.17 ± 17.84 kg) completed two identical trials in standardized conditions 3–7 days apart at the same time of day to determine day-to-day reliability of regional sweating rate and sweat chloride concentration measured with the microfluidic patch and absorbent patch. To ensure consistency between trials, subjects reported to the laboratory after abstaining from caffeine, alcohol, and vigorous exercise for 24 h and food for 2 h. In addition, subjects were asked to consume a consistent diet in the 48 h preceding each trial and record all food and fluid intake in that time frame. Diets were analyzed using Nutribase Software (NB19Pro+; CyberSoft, Inc.; Phoenix, AZ). Subjects were asked to drink 500 mL of water 2 h before the trials. A urine sample was collected for assessment of baseline urine-specific gravity (USG; Atago Pen Refractometer, 3741-E03, Tokyo Japan). Subjects either cycled ($n = 4$) on an ergometer (Velotron SRAM, Pro, Chicago, IL) or ran ($n = 1$) on a treadmill (1% grade) at moderate intensity in a climate-controlled chamber as described above. Exercise duration was 90 min or the time it took to nearly reach the capacity of the microfluidic patch, whichever came first (range was 51–90 min among subjects, but was consistent within subjects). Dietary analysis confirmed that energy (4102 ± 1244 kcal vs 4103 ± 1243 kcal), water (5.91 ± 2.10 L vs 5.89 ± 2.13 L), and sodium intake (8391 ± 3453 mg vs 8436 ± 3410 mg) were consistent ($p > 0.05$) in the 48 h leading up to each trial. There was no difference in baseline USG (1.016 ± 0.009 vs 1.014 ± 0.008) or body mass (87.17 ± 17.84 kg vs 87.06 ± 17.99 kg) between trials. Fluid intake during exercise (0.597 ± 0.490 L vs 0.586 ± 0.481 L) and net fluid balance (-1.05 ± 0.40 vs $-0.98 \pm 0.34\%$) were consistent between trials. As expected, there were also no differences ($p > 0.05$) in relative intensity ($87 \pm 3\%$ vs $85 \pm 3\%$ maximum heart rate) or environmental conditions ($31.9 \pm 0.3^\circ\text{C}$ vs $31.8 \pm 0.4^\circ\text{C}$; $53 \pm 2\%$ vs $52 \pm 1\%$ relative humidity) between trials.

Trial 2: Sweat was collected with the microfluidic and absorbent patches during outdoor running ($n = 19$ male and 6 female; 31 ± 5 years; 78.4 ± 11.7 kg) and fitness exercise sessions ($n = 6$ male and 3 female; 30 ± 5 years; 80.8 ± 15.2 kg). The running sessions took place on a 0.4 mile loop, where subjects were asked to run at their desired pace for 30–60 min (mean was 52 ± 7 min). The fitness workouts were 60 min in duration, led by a certified fitness instructor, and consisted of intermittent bouts of low-to-moderate intensity activities such as walking/jogging/running, lunges, squats, pushups, and other lower and upper body resistance exercises. The environmental conditions were 17 – 22°C and 31 – 87% relative humidity during the running sessions and 8 – 13°C and 38 – 60% relative humidity during the fitness sessions (measured via Kestrel 5400 Nielsen-Kellerman Co., Boothwyn, PA). Body mass was measured before and after exercise to the nearest 0.05 kg on a digital platform scale (Tanita BC-350, Arlington Heights, IL) while subjects wore minimal clothing (i.e., compression shorts/sports bra).

Subjects were asked to towel dry before each body mass measurement. Subjects were allowed to consume water or other drink of their choice ad libitum during exercise. All drink bottles were massed before and after exercise (to the nearest 1 g; Ohaus CS2000; Parsippany, NJ). When necessary, athlete's urine loss during exercise was collected using a pre-weighed container and later massed (to the nearest 1 g; Ohaus CS2000; Parsippany, NJ). Each participant's energy expenditure during exercise was estimated using a global positioning system device equipped with a digital 3-axis accelerometer and wrist-based heart rate sensor (Garmin Forerunner 245, Garmin International, Inc. Olathe, KS).

Trial 3: Microfluidic regional sweating rate and whole body sweating rate were measured in 148 subjects (93 male and 55 female; 32 ± 6 years; 77.3 ± 13.6 kg) to develop a whole body sweating rate prediction equation. This data set included all subjects in Trial 1 ($n = 20$) and Trial 2 ($n = 34$) as well as an additional $n = 36$ runners (28 male and 8 female; 36 ± 5 years; 76.2 ± 10.7 kg) and $n = 58$ fitness class participants (26 male and 32 female; 31 ± 6 years; 77.6 ± 15.2 kg). Exercise duration for the additional $n = 36$ runners was 25–60 min and for the additional $n = 58$ fitness participants was 29–60 min. Environmental conditions during the additional sessions were 17 – 29°C and 27 – 87% relative humidity for the $n = 36$ runners and 8 – 25°C and 38 – 77% relative humidity for the $n = 58$ fitness participants. The entire data set ranged from 25 to 90 min duration of exercise in conditions of 8 to 32°C and 27 to 87% relative humidity. Additional details can be found in Tables S1 and S2, Supporting Information. Experimental procedures in the laboratory and field were the same as described above for Trial 1 and Trial 2, respectively.

Statistical Analysis: Analyses were carried out using Statistical Analysis Software version 9.4 (SAS Institute, Cary, NC), Minitab 17 Statistical Software (Minitab, State College, PA), and JMP Pro version 15.1 (SAS Institute, Cary, NC). The significance level for all statistical tests was set at $\alpha = 0.05$. Shapiro-Wilk tests were conducted to assess the normality of the data and Levene's tests were used to assess homogeneity of variance. Data were shown as mean $\pm$ standard deviation. Paired t-tests (two-sided) were used to determine mean differences between microfluidic and absorbent patch measures of regional sweating rate and sweat chloride concentration. CVs were used to assess the intra-method test-retest variability. Pearson product-moment correlations were conducted to determine the relations between the microfluidic patch and absorbent patch as well as between regional and whole-body sweating rates.

Multiple regressions with diagnostic tests on residuals were used to develop prediction models for whole-body sweating rate. The prediction strength of regression models was assessed via coefficients of determination (r^2).^[49] Quantitative agreement between predicted and measured was assessed using the concordance correlation coefficient (CCC), which measures the degree of departure between x-axis and y-axis values relative to the line of identity.^[50] A CCC > 0.80 was considered very good agreement.^[51] Prediction model error was quantified using mean absolute error, mean absolute percentage error, and root mean square error.

Supporting Information

Supporting Information is available from the Wiley Online Library or from the author.

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Conflict of Interest

L.B.B., M.A.K., S.D.B., K.A.B., P.D.D., S.Q., J.A., A.S.W., J.R.S., and J.M.C. are employed by PepsiCo R&D. M.S.S., J.B.M., D.E.W., S.P.L., J.W., W.L., J.A.W., A.J.A., and R.G. are employed by Epicore Biosystems. J.A. and T.F. are employed by Smart Design Inc. R.G., J.B.M., S.P.L., A.J.A., and J.A.R. are co-founders of Epicore Biosystems.

Author Contributions

Study conceptualization: L.B.B., J.A.R., A.J.A., and R.G.; methodology: L.B.B. and S.D.B.; data collection: L.B.B., M.A.K., S.D.B., K.A.B., P.D.D., A.S.W., J.R.S., M.S.S., J.B.M., J.W., and A.J.A.; data curation: L.B.B., M.S.S., A.J.A., and R.G.; data analysis: L.B.B., P.D.D., S.Q., J.A., T.F., A.J.A., S.P.L., J.A., D.E.W., W.L., D.S.Y., and S.L.; project administration: L.B.B. and R.G.; supervision: L.B.B., J.R.S., J.M.C., J.A.R., and R.G.; writing—original draft preparation: L.B.B., J.A.W., A.J.A., and R.G.; writing—review and editing: L.B.B., D.S.Y., S.L., A.J.A., M.S.S., J.A.R., R.G., and J.M.C.; manuscript visualization/data presentation: L.B.B., M.S.S., A.J.A., J.A.W., J.A.R., and R.G.

Data Availability Statement

The data that support the findings of this study are available in the supplementary material of this article.

Keywords

electrolytes, fitness, hydration, microfluidics, wearables

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