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# Wearable System for Continuous Estimation of Transepidermal Water Loss

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**Abstract:** To maintain skin moisture, we need to maintain good stratum corneum barrier function, which prevents moisture evaporation from the inside of the skin. Transepidermal water loss (TEWL), the amount of water that evaporates from the skin, indicates the state of barrier function. The barrier function of facial skin is easily damaged in daily life, and the condition of the skin becomes worse without us noticing. We should constantly monitor TEWL to prevent worsening skin conditions. In this paper, we propose a wearable device that continuously measures TEWL. We estimate TEWL using machine learning from temperature and humidity values of water evaporation from the skin and parameters that affect TEWL, such as skin surface temperature and galvanic skin response. We experimented with the prototype device in a controlled environment. We confirmed that the prototype device could estimate TEWL accurately enough to judge the skin's condition in stationary and conversational situations. Then, we experimented to verify the environmental conditions for estimating TEWL using the prototype device. The prototype device could estimate TEWL with sufficient precision in an office without airflow. However, we could not estimate TEWL in the office with airflow and outdoor.

**Keywords:** machine learning; skincare; skin barrier function; skin condition monitoring; transepidermal water loss (TEWL); wearable device



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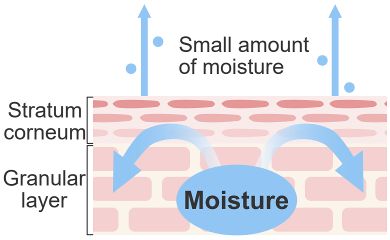
## 1. Introduction

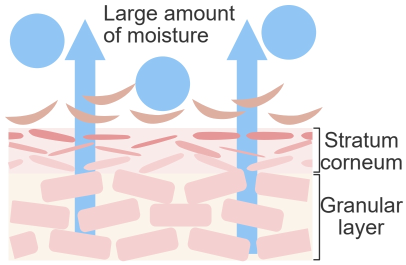
Skin moisture relates strongly to skin smoothness, translucency, and firmness [1,2]. Therefore, maintaining skin moisture is essential to keeping our skin healthy. The outermost layer of the skin is called the stratum corneum. The barrier function of the stratum corneum is a function that prevents moisture from evaporating out of the body and protects the inside of the skin from various forms of stimulation from the outside. To maintain skin moisture, we need to maintain good barrier function of the stratum corneum [3].

Many causes in daily life weaken barrier function, such as dryness, friction, ultraviolet rays, and mental stress. The facial skin's stratum corneum is thinner than that of other body parts [4]. Therefore, the condition of facial skin can become worse in a short period of time. For example, the skin may be in good condition in the morning, but in the evening, it becomes dry and dull. We need to constantly monitor the state of barrier function in our daily lives in order to find out what causes bad skin conditions.

Transepidermal water loss (TEWL), the amount of water that evaporates from the skin, indicates the state of barrier function [5]. Figure 1 shows the stratum corneum in healthy and damaged skin conditions. In a healthy skin state with good barrier function, as shown in Figure 1a, the stratum corneum neatly covers the skin surface and prevents moisture evaporation. Therefore, the amount of TEWL is small. Once the barrier function becomes worse, as shown in Figure 1b, the stratum corneum collapses, and moisture evaporates from the skin surface, increasing TEWL. If we leave the skin in a worse state of barrier function, the skin will dry out, causing skin redness and roughness. We need to take care of our skin at the proper timing, even during the day, in order to prevent the worsening of the barrier function.




(**a**) Healthy skin state.




(**b**) Damaged skin state.

**Figure 1.** The stratum corneum in healthy and damaged skin states.

To monitor the state of barrier function, we need to measure TEWL constantly. By constantly measuring TEWL, we may encourage users to take care of their skin before the skin condition becomes worse. We may also reveal what makes barrier function worse in our daily lives. In many studies of skin, Tewameter [6] is used as the standard instrument for measuring TEWL. However, we can only use Tewameter in controlled environments because it is easily affected by ambient airflow. Tewameter is a stationary device that connects to a PC. The sensor device contains as many as 30 temperature and humidity sensors, which are too large for us to wear on our face constantly. When we measure TEWL using Tewameter, we need to hold the sensor device in our hand and place it on the skin. The skin surface on which the sensor is placed must be horizontal, limiting the measurement postures. For these reasons, Tewameter is not suited for constant measurement in daily life. The device that constantly measures TEWL should be simple and small enough to be worn on the face in our daily lives and should consider the effects of ambient airflow.

In this study, we propose a wearable device that constantly measures TEWL. The proposed device is smaller than standard devices; it reduces the number of temperature and humidity sensors. In addition, we use machine learning to estimate TEWL. We attempt to improve the estimation accuracy by using parameters that affect TEWL in machine learning, such as a skin surface temperature (SST) sensor that measures changes in skin temperature due to inflammation, and a galvanic skin response (GSR) sensor that measures electrical resistivity, which is proportional to the amount of moisture on the skin surface.

The contributions of this study are as follows:

- We propose and implemented a wearable device that constantly estimates TEWL.
- We confirm that the proposed device could estimate TEWL with sufficient accuracy to determine the skin condition in a controlled environment.

This paper is organized as follows. Section 2 introduces related research, and Section 3 describes the proposed device. Section 4 describes evaluation experiments conducted in a controlled environment using a prototype of the proposed device. Section 5 describes evaluation experiments conducted in an environment similar to that in daily life using an improved prototype device, and Section 6 summarizes the paper.

## 2. Related Works

### *2.1. Research on Skin Properties and Skin Condition Measurement*

Skin characteristics depend on the individual, and various factors of daily life influence skin condition. Hu et al. suggest that many skin diseases can be prevented or mitigated by improving lifestyle habits, such as diet, sleep, exercise, stress, alcohol, and smoking [7]. Sözener et al. also suggest that allergens in the air, cleansers, and exhaust gases damage the skin's barrier function [8].

Some studies evaluated and examined the causes of skin translucency, skin redness, and pore size based on skin characteristics. Jiang et al. investigated the relationship between skin moisture and skin optical properties [9]. The study found that the skin's spectral reflectance and scattering coefficient increased when the skin was dry and decreased when the skin was moist. In other words, skin translucency increases as skin moisture increases. Galzote et al. evaluated the effects of summer and winter weather on women's skin in Asia based on parameters of stratum corneum water content, TEWL, and skin pH [10]. Results of the study showed that low temperatures, low humidity, and reduced exposure to sunlight during the winter months increase TEWL.

In many studies about skin, Tewameter is used as a standard instrument for measuring TEWL. Cheng et al. used Tewameter and other measurement devices to investigate the skin's physiological changes after applying skin care cosmetics [11]. Nakamura et al. also investigated seasonal and facial site-specific skin changes due to long-term mask wear using Tewameter and several other instruments [12]. The study revealed that long-term mask use during the winter season impairs the skin barrier function of the cheeks. As mentioned above, many studies on the skin have used Tewameter to measure TEWL. However, Tewameter is limited to use in controlled environments and is unsuitable for constant daily measurement.

### *2.2. Beauty Devices and Research Using Skin Condition Sensing*

Many beauty devices use skin sensing. The Photo PLUS Shiny NEO, a facial machine by Ya-Man, has a temperature sensor [13]. If the temperature sensor recognizes that the skin has reached a specific temperature, the device reduces the output of RF waves that accelerate blood circulation in the skin to prevent overheating. My Skin Track Ph, a patch-type wearable sensor from L'Oreal, measures the pH value of the skin, which is a parameter related to inflammation and dryness [14]. The user can check the measurement results using a dedicated application and select cosmetics that match their skin's pH. SONY's Beauty Explorer uses near-infrared light to capture images of inner skin [15]. This device analyzes not only the surface but also the invisible internal conditions of the skin from these images. VISIA by CANFIELD is a skin analysis machine used in many beauty clinics [16]. VISIA takes pictures of the face from three angles (right, left, and front) and can analyze wrinkles and texture and detect pigmentation and inflammation. It can also simulate the appearance of aging and cosmetic surgery treatments from the images.

There are also studies about devices for measuring skin conditions. Smeton et al. proposed a method for testing cosmetics products using images taken by ordinary subjects themselves with their smartphones [17]. Conventional product testing methods require measurement of the skin during product use at a dedicated facility. They used image processing to capture changes in skin tone and wrinkles during cosmetic use, even from images taken with a smartphone. Nakagawa et al. propose a remote skin counseling system using life logs [18]. This system is a dresser-type device that acquires skin care logs, such as photos of skin texture, photos of the entire face, and history of skin care cosmetics use, from regular skin care activities, without discomfort. Based on the acquired data, the system presents suitable information about skin care for each user. Ali et al. proposed a tag-type sensor device that measures TEWL and skin wetness using temperature and humidity sensors [19]. They realized a compact sensor device that can acquire and transmit sensor values without a power supply. They used NFC installed in smartphones to measure skin conditions easily anywhere. Tobar et al. developed Skinly, a handheld device that uses machine learning to evaluate an individual's skin characteristics from multiple skin parameters [20]. Skinly can take pictures of a user's skin in three different LED modes. Using those three images, they proposed a system that uses machine learning to output parameters related to skin appearance, such as skin age, skin color evenness, and wrinkle depth. Xiong et al. proposed Eye Vis, a system to visualize makeup residue around the eyes for eliminating skin problems caused by incomplete makeup removal around the eyes in Chinese operas [21]. The system captured the outline of the eye by taking a picture of the eye area with a smartphone and detecting the edges of the image. By filtering with a specific range of hues and saturations around the outline, the system could visualize residuals around the eyes.

As mentioned above, several studies and developments of beauty devices use skin sensing, and measurement of skin condition is essential for beauty. However, there are no devices that constantly measure TEWL in daily life. In this study, we propose a wearable device that supports maintaining healthy skin by constantly measuring TEWL daily.

### *2.3. Research on Body State Estimation Using Wearable Devices and Machine Learning*

Many studies use machine learning algorithms to estimate the physical state of daily life using sensor values acquired by wearable sensors and machine learning. Kodama et al. proposed a eyeglass-type wearable device that recognizes the user's breathing and actions [22]. The proposed device consists of a pair of eyeglass frames and a nose mask. The device measures the temperature inside the nostrils with a temperature sensor placed in the nose mask, and sends the data wirelessly to a smartphone via a microcomputer installed in the eyeglass frames. This study uses machine learning to estimate eight breathing and movement patterns that occur in daily life based on sensor values acquired by the device. Jia et al. proposed a system for estimating the degree of perceived sweat based on the value of a textile sensor that can continuously measure the amount of sweat [23]. The textile sensor consists of three conductive threads and estimates the amount of sweat based on their resistance, which changes with the amount of moisture between them. They embedded the sensor in clothing and allowed constant measurement without limiting the wearer's activities. Maritsa et al. proposed a system that detects the wearer's breathing state during sleep based on environmental and breathing sound data acquired by a wearable device [24]. The wearable device uses two types of microphones: a contact microphone placed close to the neck to acquire breathing sounds and an open-air microphone to acquire environmental sounds. Machine learning is used to detect the state of sleep from sound data. Hong et al. estimated changes in blood glucose levels before and after exercise based on the amount of glucose in sweat and physiological data that could be obtained noninvasively with the Smart Band [25]. Post-exercise blood glucose measurement is essential for diabetes management, but invasive methods are standard. They reduced the stress on the person being measured by noninvasively measuring glucose levels in sweat, heart rate, blood oxygen saturation, and exercise data with the smart band, using machine learning to estimate blood glucose levels before and after exercise.

From these studies, we found that we could detect with commercially available measurement devices using machine learning with data measured with wearable devices. In this study, we apply these methods to measure humidity near the skin using a wearable device and estimate TEWL using machine learning.

## 3. Proposed Device

In this study, we propose a device that we can always wear in our daily lives and that can continuously output accurate TEWL values. We first describe the conventional method of measuring TEWL, and then describe the prototype device.

### *3.1. Conventional Method of TEWL Measurement*

TEWL refers to the amount of water that has transpired from the body through the stratum corneum, expressed as the weight of water (g) per unit area ($m^2$) and per unit time (h), that is, $g/m^2h$. TEWL is an indicator that reflects the barrier function of the stratum corneum. As barrier function decreases, TEWL increases.

Tewameter [6] from Courage+Khazaka is a representative standard instrument for measuring TEWL. The measurement image using Tewameter is shown in Figure 2. Temperature and humidity sensors are lined up at equal intervals in a cylindrical chamber. The temperature and humidity differences between the sensors can be used to measure the concentration distribution of water vapor in the chamber. TEWL is calculated using Fick's law, which concerns the concentration distribution of water vapor in the chamber and the spreading velocity of materials [26]. The measurement repeatability (confidence interval 99%) is $\pm(0.15\ g/m^2h + 1.0\%)$ and the measurement uncertainty is $\pm(0.15\ g/m^2h + 5.0\%)$ with Tewameter.

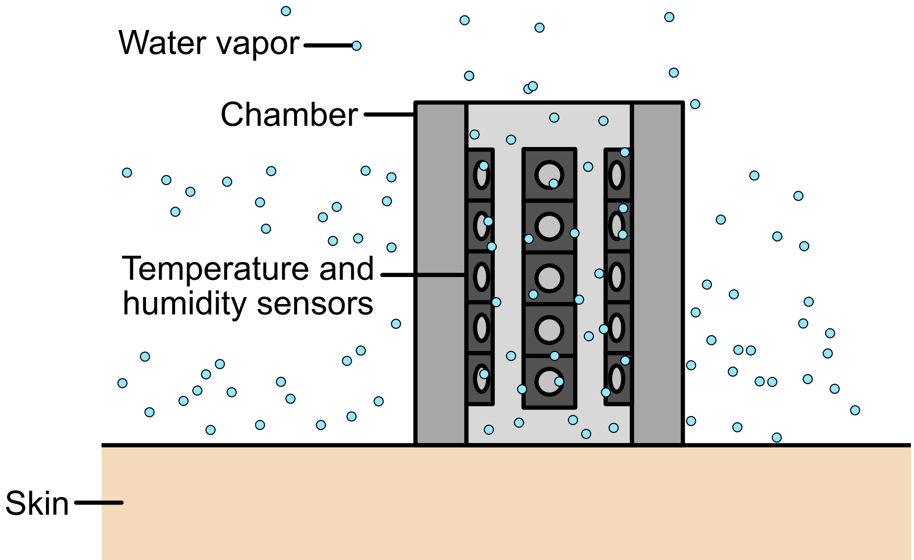



**Figure 2.** Measurement image using Tewameter.

Tewameter is a stationary device that connects to a PC and contains as many as 30 temperature and humidity sensors, which are too large to wear on our face constantly. Tewameter allows consecutive measurements because the air in the chamber is constantly released to the outside air. However, ambient airflow and weather greatly affect the measurement results because outside air directly flows into the chamber. We should use Tewameter in an artificial weather environment without airflow, which limits its usage situations. In addition, the measurement surface of Tewameter must be horizontal because water vapor diffuses upward. When we measure the face's surface with Tewameter, we need to keep our face tilted.

### *3.2. Prototype Device*

Before designing a device to continuously measure TEWL, we need to confirm that we can estimate TEWL in various daily situations with a simple device. Therefore, as shown in Figure 3, we created a prototype device. Since the optimal combination of sensors has not yet been determined, we will design the prototype device to attach a variety of sensors freely. The size of the prototype device is large for the above reasons, but we plan to reduce the size of the proposed device to be created in the future by reducing the number of sensors to the minimum necessary. Furthermore, the device must integrate socially and not interfere with the wearer's movements. We should design the device so that TEWL can be measured at the normal angle of the wearer's face.

The prototype device's measurement area is the cheek, which is the area where pores become more visible due to the worsening of the skin condition. The prototype device consists of a chamber with four temperature and humidity sensors, a SST sensor, a GSR sensor, a microcomputer, and a PC. We placed the temperature and humidity sensors (TH1, TH2, TH3, and TH4) on the inner wall of the chamber as shown in Figure 4, referring to the standard instrument for measuring TEWL.

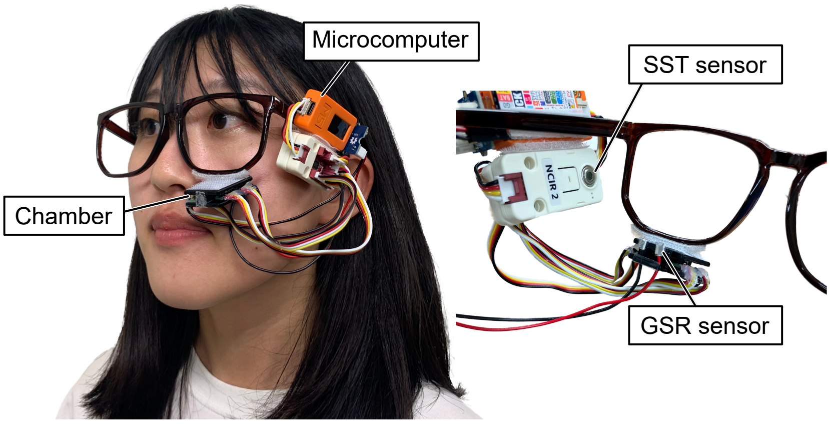



**Figure 3.** Prototype device.

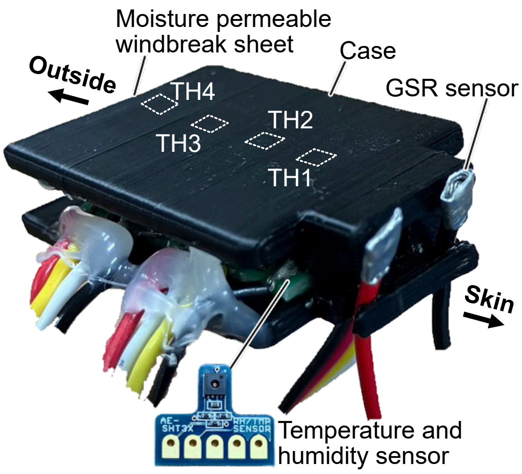



**Figure 4.** Sensor arrangement of the chamber.

Figure 5 shows a block diagram of the prototype device. The prototype device measures the temperature and humidity of the water vapor emitted from the skin, the skin surface temperature, and the skin's electrical resistance. Water vapour released from the skin flows through the chamber from the skin surface to the outside air. Four temperature and humidity sensors are placed in a row at 7 mm intervals from the skin surface to the outside for measuring temperature and humidity differences in the chamber and TEWL is estimated from these values using machine learning. We also attach a SST sensor to the glasses' temples to measure both the skin surface temperature and the outside air temperature. We attach a GSR sensor to the skin side of the chamber to measure the skin's electrical resistance. The microcomputer wirelessly transmits each sensor's values to the PC for processing. The PC estimates TEWL using machine learning from the sensor values received by each sensor. The temperature and humidity sensor is SHT35-DIS (Typical accuracy of ±1.5%RH and ±0.1 °C) from SENSIRION (Stäfa, Switzerlant), and the microcomputer is M5Stick-C from M5Stack (Shenzhen, China).

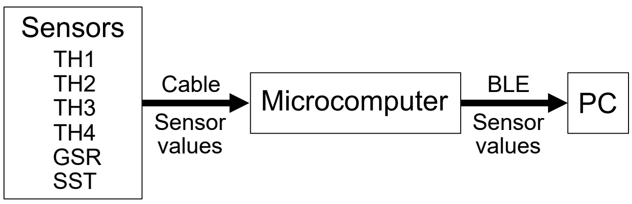



**Figure 5.** Block diagram of the prototype device.

To reduce the number of sensors and downsize the device without decreasing the measurement accuracy from the conventional device, we combine multiple types of sensors and use machine learning to estimate TEWL. We use 17 features for machine learning: 4 temperature and humidity sensor values, differences in humidity values between temperature and humidity sensors, skin surface temperature values, ambient temperature values, and skin electrical resistance values.

The humidity difference in the chamber reveals the flow of water vapor evaporated from the skin. Therefore, the humidity difference due to moisture evaporated from the skin in the chamber is especially important for accurate estimation of TEWL. However, when outside air flows in through the chamber opening, the outside air and the air in the chamber mix. As a result, the humidity difference inside the chamber is lost. Even if the chamber is completely sealed to prevent the inflow of outside air, the water vapor inside the chamber becomes saturated and the humidity difference is lost. To maintain the humidity difference due to moisture transpired from the skin inside the chamber, we install a moisture-permeable windbreak sheet at the chamber opening. This sheet prevents the inflow of outside air, but does not prevent water vapor in the chamber from flowing outside, thus maintaining a humidity difference in the chamber.

## 4. Experiment in Controlled Environment

To design the device to measure TEWL continuously, we need to confirm that the prototype device shape is sufficient to estimate TEWL. We also have to confirm a valid sensor combination. Therefore, we first experimented to confirm that the prototype device could estimate TEWL using the prototype device in a controlled environment.

### *4.1. Experimental Method*

The experimental environment was a space controlled at a temperature of 25 °C and humidity of 45%. We also avoided air flow around the subjects. To confirm that estimation is possible for various skin conditions, we collected data for the following three different skin conditions:

**Low evaporated state:** Vaseline is applied to the participant's skin, reducing moisture evaporation from the skin.
**Normal state:** Skin is washed and dried.
**High-moisture transpiration state:** The skin surface is peeled off with tape, and the barrier function of the stratum corneum is significantly low.

To confirm the influence of the participants' behavior on the estimation of skin condition, we measured skin condition in a sitting still condition and in a conversational condition with slight air flow around the participants. Thus, there were six situations, each with three trials. To estimate the correct data, we used linear regression (LR) [27], support vector machine regression (SVR) [28], and Random Forest Regression (RFR) [29] as machine learning algorithms. The participants were five men and women in their 20s and 30s.

In the experiment, we first measured the TEWL of the participant's skin with Tewameter, as shown in Figure 6, and then measured with the prototype device. The participant sat still for 60 s after the start of the measurement to stabilize the sensor values, and then we took the sensor values when they were sitting still or talking in 60 s, which formed one trial. We assumed that the skin condition would not change during this trial. Therefore, the Tewameter value obtained at the beginning of the trial was the correct value for this trial. In this experiment, we wanted to determine whether the proposed device can distinguish healthy skin conditions (TEWL: 10–15 $g/m^2h$) and damaged skin conditions (TEWL: 25–30 $g/m^2h$), as shown in Table 1, which provides guideline values for skin conditions based on TEWL measurements taken with Tewameter. Therefore, we aimed for an estimation error within 5 $g/m^2h$. This experiment was approved by the Ethics Committee of Kobe University Graduate School of Engineering for research involving human participants (Approval No. 05-30).

**Figure 6.** How to obtain correct data.

**Table 1.** Guideline values for skin conditions by TEWL.

| TEWL [g/m$^2$h] | TEWL Guideline Values |
|---|---|
| 0–10 | Very healthy |
| 10–15 | Healthy |
| 15–25 | Normal |
| 25–30 | Damaged |
| $\geq 30$ | Seriously damaged |

### *4.2. Results*

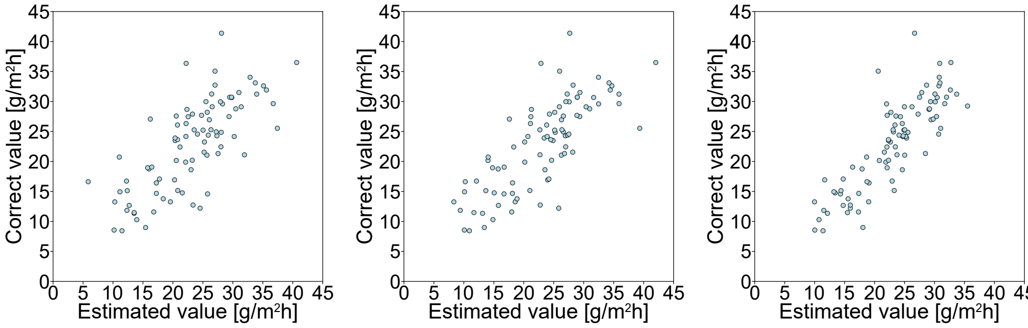
The sensor values of the proposed device were stable regardless of the participants' behavior. Therefore, we estimated TEWL by machine learning without dividing the data by behavior conditions.

In this experiment, we used LR, SVR, and RFR as algorithms for estimating the correct data and conducted within-individual three-fold cross validation divided by trial. Table 2 shows the estimation accuracy of TEWL using all the sensors on the prototype device. In addition, scatter plots of the relationship between the estimated value and the correct value for each trial are shown in Figure 7. The average mean absolute error (MAE) across the participants was 4.43 g/m$^2$h with LR, 4.23 g/m$^2$h with SVR and 2.92 g/m$^2$h with RFR. The average MAEs across the participants of the three classifiers for estimating TEWL were all within 5 g/m$^2$h, which was smaller than the range of TEWL values for healthy skin and damaged skin shown in Table 1. Therefore, the prototype device could estimate TEWL with sufficient accuracy. In addition, the estimated values by RFR in Figure 7c had the highest correlation with the correct values and showed the least variability among the three machine learning algorithms. Therefore, RFR was the most suitable algorithm for this evaluation experiment. We will select RFR as the algorithm to be used for estimation in future evaluations, because it had the highest estimation accuracy.

**Table 2.** MAE estimated TEWL using all sensors.

| | MAE [g/(m$^2$h)] |
|---|---|
| LR | 4.43 |
| SVR | 4.23 |
| RFR | 2.92 |

In measuring TEWL using Tewameter, we needed to keep the measurement surface horizontal and the chamber vertical, as shown in Figure 6. The results of this experiment showed that TEWL can be estimated with sufficient accuracy even when the face is vertical and the chamber is horizontal. This result contributes to ease of fitting and greater flexibility in device design. Therefore, we will design the device to mount the chamber horizontally in the following sections of this paper. We also found that the chamber's permeable windbreak sheet reduced the outside air's effect on conversations.




(**a**) LR. (**b**) SVR. (**c**) RFR.

**Figure 7.** The relationship between the estimated and correct values for each algorithm.

We compared the estimation accuracy using machine learning for all six sensor combinations used in the prototype device to reduce the device size while keeping the estimation accuracy. There were 63 combinations of six sensors. Using RFR, we performed machine learning estimations for each combination. Table 3 shows the top three sensor combinations with the smallest average MAEs across the participants and their estimation accuracy. The sensor combination with the highest estimation accuracy was the combination of the TH1 temperature and humidity sensor located on the most skin side of the chamber, the TH4 temperature and humidity sensor located on the most outside air side, and the skin surface temperature sensor.

**Table 3.** Combination of sensors with small average MAEs across the participants.

| | **MAE [g/(m$^2$h)]** |
|---|---|
| TH1, TH4, SST | 2.72 |
| TH1, TH4, SST, GSR | 2.74 |
| TH1, TH2, TH4, SST, GSR | 2.77 |

### *4.3. Problems with the Prototype Device*

**Chamber digs into the skin and hurts:**

During the experiment, subjects wore the chamber in close contact with their skin. However, some participants pointed out that the chambers cut into their skin and hurt. We should find out how to avoid damaging the wearer's skin by wearing the device. In addition, since the device may be worn for long time, we need to remove as much discomfort as possible while wearing the device. To solve this problem, we will attach a soft gel to the part of the chamber that touches the skin.

**Keep distance of non-contact skin surface temperature sensor from the skin surface:**

In this experiment, we used a non-contact SST sensor to measure the skin surface temperature. However, we considered that a non-contact SST sensor is inappropriate for constant measurement because the distance between the measurement surface and the non-contact skin surface temperature sensor varies depending on how the user wears the device. Therefore, we will measure the skin surface temperature by contacting the thermistor with the skin.

**Downsizing of the device:**

Regarding device downsizing, sensors TH1 and TH4 were the temperature and humidity sensors used in this experiment's combination of sensors with the highest estimation accuracy. However, the estimation accuracy was lower when we used two directly next to each other. This indicates that the distance between TH1 and TH4 may affect the estimation accuracy. Therefore, the device will not be small even if we use only TH1 and TH4. In addition, this experiment showed that the GSR sensor does not affect the accuracy of the estimation. We will improve the device by keeping the number of temperature and humidity sensors and not using the GSR sensor.

We improved the prototype to solve the above problems. Figure 8 shows images of an improved version of the prototype device and the chamber. We attached a gel to the mouth of the chamber to soften the parts of the skin touching it. We also mounted a thermistor at the mouth of the chamber to measure the skin surface temperature. The estimation of TEWL in a actual environment is performed under more severe conditions than in this experiment. Therefore, we used four sensors in our improved prototype device as well.

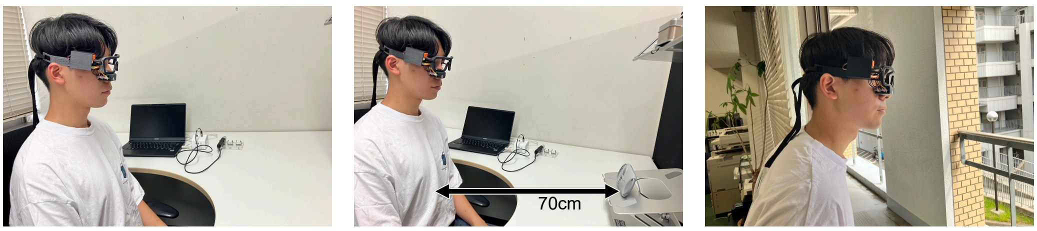

**Figure 8.** The chamber of the improved prototype device.

## 5. Experiment in Uncontrolled Environment

To design a device that can constantly measure TEWL in a actual environment, we need to find out in what environment the improved prototype device can estimate TEWL. We experiment with the improved prototype device in three environments that are close to the uncontrolled actual use environment.

### 5.1. Experimental Method

We experiment on the improved prototype device's ability to estimate TEWL in an office environment, which is similar to a controlled environment, as well as in an environment with air currents and in an outdoor environment, shown in Figure 9.




(**a**) Office without airflow. (**b**) Office with airflow. (**c**) Outdoor.

**Figure 9.** Three environments of the experiment.

- **Office without airflow**: A controlled office environment where the airflow from the air conditioner does not directly hit the participants. Vaseline is applied to the participant's skin, reducing moisture evaporation from the skin.
- **Office with airflow**: The airflow from a small fan hits the participant's skin. We plac this fan about 70 cm away from the participant.

- **Outdoor:** Participants face out the office window, and their skin is exposed to the outdoor air.

The office temperature was between 27.2 °C and 28.8 °C, and the humidity was between 35% and 49% during the experiment. The outdoor temperature was between 30 °C and 33 °C, and the humidity was between 45% and 60% during the experiment. We took our measurements in the three skin conditions mentioned in Section 4: a low-evaporation state, normal state, and high-moisture transpiration state. We took our measurements four times in the office without airflow, twice each in the office with airflow, and outdoor, in each skin condition. The participants were eight men and women in their 20s and 30s.

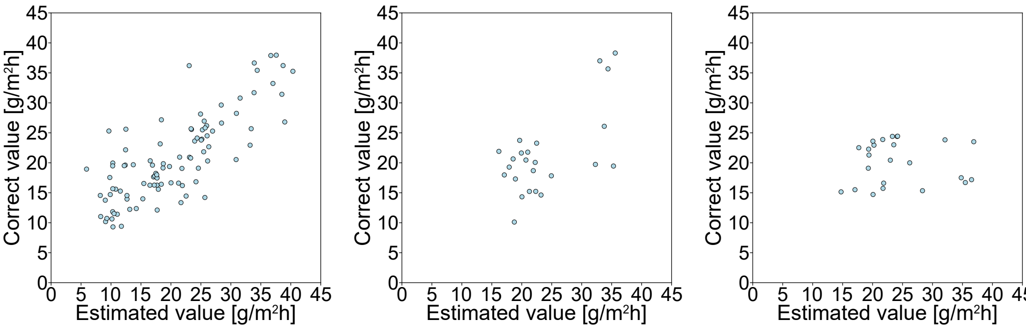
Participants first measured TEWL with Tewameter in an office without airflow and then wore the improved prototype device in each environment. The participants stayed sitting still for 60 s to allow the sensor values to stabilize, and then we took the sensor values for 60 s. Then, we measured TEWL again with Tewameter in an office without airflow. The above was one trial.

In the next experiment, we used RFR as the algorithm to estimate the correct data. We conducted a four-part cross-validation for the office without airflow. We estimated TEWL for offices with airflow and outdoors by using the data acquired in the office without airflow as training data.

We should consider temporal changes in the skin due to environmental factors. For this reason, we used the TEWL correctness data as Tewameter values taken at the beginning and end of the trial, linearly connected by time on the x-axis and TEWL on the y-axis. As in Section 4.1, the target estimation accuracy for this experiment is within 5 $g/m^2h$. This experiment was approved by the Ethics Committee of Kobe University Graduate School of Engineering for research involving human participants (Approval No. 06-10).

### 5.2. Results

Table 4 shows the estimation accuracy of TEWL in this experiment. In addition, scatter plots of the relationship between the estimated value and the average correct value for each trial are shown in Figure 10. The average participant's mean percentage increase in skin temperature before and after wearing the prototype device was 1.87%. The average MAE across the participants was 3.84 $g/m^2h$ for the office without airflow, 6.64 $g/m^2h$ for the office with airflow, and 6.38 $g/m^2h$ for outdoor. In the office without airflow, the average MAE across the participants was within 5 $g/m^2h$, and the improved prototype device could estimate TEWL with sufficient accuracy. In addition, the estimated values in the office without airflow in Figure 10a had the highest correlation with the correct values among the three environments. However, the average MAE across the participants in the office with airflow and outdoors was greater than 5, which did not meet the accuracy requirement.




(**a**) Office without airflow. (**b**) Office with airflow. (**c**) Outdoor.

**Figure 10.** The relationship between the estimated and correct values for each environment.

**Table 4.** MAE-estimated TEWL using the improved prototype device.

| | **MAE [g/(m$^2$h)]** |
|---|---|
| Office without airflow | 3.84 |
| Office with airflow | 6.64 |
| Outdoor | 6.38 |

### *5.3. Future Developments*

The improved prototype device often estimated constant values outdoor despite different skin conditions. Reviewing the sensor data, we found that the temperature and humidity values taken outdoors were generally higher than those taken in the office. Because the training data did not include outdoor data, the machine learning algorithm may have failed to capture the characteristics of the sensor values for each skin condition sufficiently for estimation. To increase the number of environments covered by the device, we will create learning models from data taken in various environments.

The estimated values sometimes rose and fell significantly in an office with airflow. Since skin conditions change gradually and TEWL values should also change gradually, discontinuous jumps in the estimated values are most likely due to airflow outside the chamber. We reviewed the sensor values when the estimates jumped discontinuously. We found that the difference between the humidity values of each sensor was very small compared to normal when the estimates jumped discontinuously. At this time, airflow from outside the chamber may have entered the chamber at this time. The air in the chamber is not suitable for estimation because the air is not water vapor-evaporated from the skin. After the air in the chamber was replaced, the temperature and humidity sensor values returned to their previous state in approximately 20 s. To achieve constant measurement in actual use, we will not use the sensor values for 20 s after the difference between the humidity values of each sensor becomes very small for the estimation and instead supplement TEWL during that time by connecting the values before and after with a straight line. We consider that introducing this method of eliminating irregular jumps in the estimates would allow the device to be used consistently in an office with airflow and outdoor. As a further improvement of the wearing experience, we should make the weight of the device evenly balanced on the left and right sides for more stability.

Regarding the results of the experiment in an office without airflow, MAE was within the 5 g/m$^2$h, which was the target accuracy. However, the Bland–Altman plot demonstrated that the mean different (bias) was $-0.27$ g/m$^2$h, with 95% limits if the agreement was calculated as $-10.63$ g/m$^2$h to 10.08 g/m$^2$h. This indicates that the reliability of the prototype device is challenged, which is a limitation of this study. The prototype device was not shaped to accommodate individual differences in the shape of the wearer's face, which may have contributed to its unreliability. In the future, we will personalize the shape of the device to accommodate individual differences and improve the reliability.

## 6. Conclusions

In this paper, we proposed a simple and compact wearable device that constantly measures TEWL and conducted evaluation experiments to evaluate whether the prototype device can estimate TEWL in a controlled environment. This experiment showed that the prototype device could estimate TEWL with sufficient accuracy within 5 g/m$^2$h for sitting still and talking. Then, we improved the prototype device and conducted experiments to examine the environmental conditions for estimating TEWL using it. The improved prototype device could estimate TEWL with sufficient accuracy in an office without airflow. However, we could not estimate TEWL with sufficient accuracy outdoors. To increase the number of environments the device covers, we need to create learning models from data taken in various environments. We also analyzed sensor values in situations unsuitable for estimation and investigated how to detect them and process the data. In the future, we will propose optimal skincare methods for each user based on TEWL values estimated by the proposed device and provide skincare support suited to individual lifestyles and skin types.

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**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** Data are available on request due to the privacy restriction.

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