Ecz -Ware: A Wearable System for Real-time Nocturnal Scratch Detection and Intervention

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***Abstract*— Eczema is a prevalent chronic skin condition in which subconscious nocturnal scratching exacerbates inflammation and delays healing. We present Ecz-Ware, a wearable that detects scratching in real time using flex sensors and an MPU6050 (accelerometer + gyroscope), processed on a Raspberry Pi Pico / Raspberry Pi 5 pipeline with a trained model for gesture classification. Upon detection, a haptic vibration motor provides subtle feedback to interrupt the itch–scratch cycle. Preliminary models achieve > 80% classification accuracy and early trials indicate meaningful reductions in scratching duration and improved sleep quality. We describe the system requirements, concept selection, modelling, prototype development, and initial evaluation.**

I. Introduction

Atopic dermatitis (eczema) is a chronic inflammatory skin disease characterized by pruritus and recurrent flares. Subconscious nocturnal scratching perpetuates the itch–scratch cycle, worsens inflammation, and impacts quality of life [1][2][3]. While moisturizers, topical therapies, and behavioral strategies offer partial relief, there remains a gap for real-time, non-invasive, user-friendly interventions [4].

Ecz-Ware addresses this gap by detecting scratching movements and delivering calibrated haptic feedback to gently interrupt the behavior without disturbing sleep. Primary beneficiaries include eczema patients (children and adults) and caregivers; anticipated outcomes are reduced scratching frequency/duration and improved sleep.

II. Proposed Approach

A. System Requirements

To ensure that Ecz-Ware meets both functional and user-centered goals, we established a comprehensive set of system requirements that guided the design, development, and evaluation process. These requirements were derived from a combination of evidence-based insights, user-centered research, and iterative prototyping. First, a review of the literature on eczema and wearable interventions provided performance benchmarks for parameters such as detection accuracy, false positives, and haptic feedback effectiveness. Next, interviews and surveys with potential users, including adults, and caregivers, highlighted practical considerations such as comfort during overnight use, ease of wear, battery life, and safety of materials in contact with skin. Finally, early prototypes were constructed and tested to evaluate sensor placement, feedback strength, and responsiveness, enabling iterative refinement of each target metric based on empirical observations. A detailed summary of these requirements, along with their target metrics, is provided in Table I.

TABLE I. SYSTEM REQUIREMENTS FOR ECZ-WARE

Requirement	Description	Target Metric
Detection Accuracy	Ability to correctly classify scratching vs. non-scratching movements	≥ 90% accuracy
Latency	Time between scratching onset and haptic feedback activation	< 1 second
False Positives	Avoid vibration during normal movement	< 5% false positives
Feedback Effectiveness	Haptic signal should interrupt scratching without waking user	≥ 70% reduction in scratching duration and frequency; < 5% sleep disturbance
Wearability and Comfort	Glove should be lightweight, breathable, and tolerable overnight	< 150g weight; breathable fabric (bamboo jersey); fit for multiple hand sizes
Battery Life	Device should last through a full night's sleep	≥ 8 hours continuous use
Safety	Materials and electronics safe for skin contact	Skin-safe, insulated, no overheating

B. Concept Selection

We explored a spectrum from restrictive eczema mittens to passive monitoring. Restrictive methods reduce compliance; purely observational solutions lack immediate intervention. Through our literature review, we also found that accelerometers and RNNs have previously been used for scratch detection [5], while wearables with haptic feedback have been proven effective in reducing scratching behavior [6]. We therefore selected a hybrid concept that prioritizes minimal intrusion with tiered responses: (i) continuous detection with an accelerometer and flex sensors, and (ii) subtle haptic feedback on detection.

C. Concept Description

1) Electrical Design

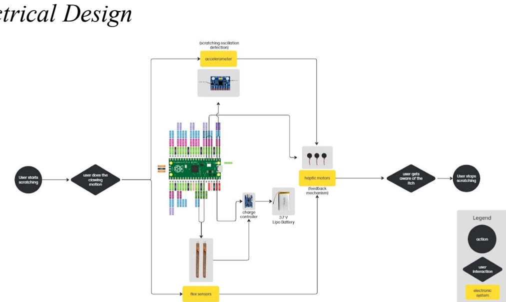


Figure 1. Functional Diagram

The device is split into two parts: the wearable, and the ItchDB. The wearable consists of a Raspberry Pi Pico W microcontroller, an MPU6050 accelerometer, 3 coin-type haptic feedback motors and a pair of flex sensors. It is powered by a 3.7V lipo battery, which charges through a TP4056 charge controller. For prototyping purposes, we used a 300mAh battery which was chosen out of easy availability. However, for a fully-fledged product, we would consider a larger capacity (~600-700mAh) and include power usage optimization features. The wearable acts as a hub for sensors and feedback. The Pico W wirelessly transmits flexion and six axes of acceleration to the ItchDB.

The ItchDB, which houses a Raspberry Pi 5, is responsible for running a KNN classification algorithm that classifies movements into scratching, resting, or other (referring to random hand movements). Once a scratch is detected, a signal is sent back to the wearable to activate the motors.

Originally, the system used sEMG signals to detect muscle movement through voltage differences across the skin [7]. For muscle flexion measurements, we used the MyoWare 2.0 Muscle Sensor during prototyping. The plan was to use STFTs (Short-Time Fourier Transforms) of the sEMG sensor data to differentiate between different kinds of muscle movement. Preliminary tests showed promise. The below spectrograms (Figure 2) depict the difference between a subject at rest (left), and a subject scratching themselves (right).

While such a setup would improve our form factor, the muscles responsible for the scratching movement (extensor digitorum and flexor digitorum) only reach the skin from underneath surrounding muscles in narrow stretches along the forearm. sEMG sensors strapped to the skin also do not account for the movement of muscles underneath the skin when the arm is twisted, and since measuring muscle activity with accuracy is highly sensitive to sensor placement, they proved to be unfeasible for our use-case.

2) Software Sub-System

Software Architecture: Overview of sensor data processing -

a) Accelerometer:

The MPU6050 is being accessed through the I2C bus on the Pico. After a few rounds of testing, we narrowed down our pipeline to read from only the registers that provide acceleration data (3 axes). The data is then run through a bandpass filter to attenuate frequencies above 200Hz to remove irrelevant data from the signal (as human movements would not occur at these frequencies). To prevent misclassification, if the I2C bus overloads, we transmit the last received data to the ItchDB while Pico resets the I2C bus.

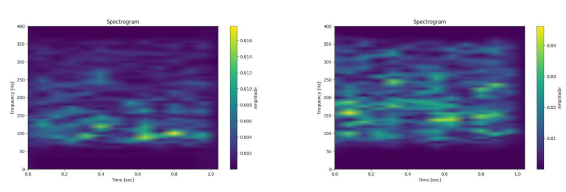


Figure 2. Spectrograms of sEMG sensor data

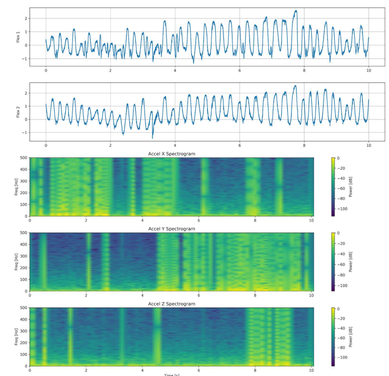


Figure 3. 1 second of scratch data from all 5 channels

b) Flex Sensors:

The flex sensors provide varying voltage values corresponding to their bending angle. These voltage values are read through the Pico's ADC ports. Together, the flex sensors and accelerometers provide 5 channels of data that are sampled at 1000Hz and transmitted to the ItchDB with a batch size of 100 samples. This value was chosen based on how fast the data could be transmitted via connections to a mobile hotspot.

The ItchDB receives batches of data and runs our classification algorithm on every 1000 samples (corresponding to 1 second) collected.

A sample used in our training data is depicted in Figure 3.

Classification Strategy:

a) The Model:

The pipeline extracts time-domain features from the flex sensor data to characterize bending patterns over each analysis window. These include mean absolute value (MAV), root mean square (RMS), waveform length (WL), zero-crossing rate (ZCR), and slope sign changes (SSC). Each metric captures a different aspect of the flex signal, from overall bending intensity and variation to rapid changes in direction and shape.

Furthermore, our pipeline extracts spectral domain features of the data after performing an STFT on the accelerometer data. Due to our sensor placement, patterns of spectral energy appear at selected bands (0-5Hz, 5-20Hz, 20-50Hz, 50-120Hz, 120-300Hz) corresponding to different kinds of movement.

A total of 34 features are extracted from the sensors, and then put through a PCA dimensionality reduction, which selects 9 parameters that vary most consistently with varying classes of movement. These 9 parameters are then used in a K-nearest neighbours classifier.

Our dataset was created by recording 3 subjects performing our 3 classes of movement for extended periods of time. Our movement classes (scratching and other) were collected in 2.5-minute intervals with 60 seconds of break in between to allow the subject to rest. Our non-movement class (resting) was collected at 5-minute intervals to best represent extended periods of low movement. This gave us a total of 5 minutes per class per subject. With 3 subjects, we trained our model on 45 minutes of data.

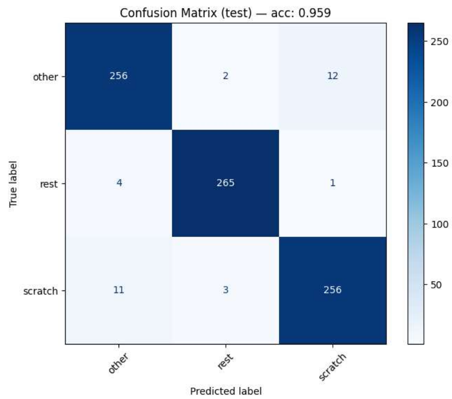


Figure 4. Confusion Matrix for the K-means classifier

After preprocessing, we first split the dataset into a combined training and validation set and a test set, with 15% reserved for testing. The remaining 85% was then split again, with 15% allocated for validation, ensuring stratification to maintain class balance.

We performed a search over different values of k, distance metrics, and weights, using the validation set to identify the best hyperparameters. The optimal parameters were k = 1, p = 1, with uniform weights, achieving a best cross-validation score of approximately 95.08%.

On the validation set, the model achieved an accuracy of 95.07%, and on the unseen test set, it reached 95.93%. The classification report shows balanced performance across all three classes, each achieving around 94–98% precision, recall, and F1-scores.

2) Feedback Mechanism:

Our choice of haptic feedback as the intervention mechanism was driven by the goal of establishing a subtle, non-disruptive cue to interrupt the itch–scratch cycle without disturbing sleep. The wearable incorporates three coin-type vibration motors positioned in the interdigital folds (spaces between the knuckles), chosen for their proximity to the joints responsible for initiating scratching motions. These motors are activated only when scratching is confirmed by the combined accelerometer and flex sensor classification pipeline, ensuring high specificity and avoiding false triggers from unrelated movements. Motor intensity and duration were calibrated through preliminary trials to provide perceptible feedback strong enough to prompt behavioral interruption, yet gentle

Figures 6 and 7. Prototype iterations

enough to avoid waking the user. Sleep study results indicated that this balance effectively reduced scratching episodes while maintaining sleep continuity (see Section IV).

The electrical design is illustrated in Figure 1.

3) Mechanical Design

a) Design of wearable:

Our priority was to design a glove that was comfortable to encourage compliance, and as such restrictive designs like mittens were not considered. Our designs also had to accommodate the above electronic and power systems. Our choice of fabric was bamboo jersey, due to its breathability, temperature regulation and antibacterial nature [8].
An early concept integrated a tension-based system for both scratch detection and prevention, which we found cumbersome.

After further ideation, we pivoted to haptic and pneumatic feedback systems, with sEMG sensors and an accelerometer as our detection systems. This meant our wearable had to extend from the fingers to the upper forearm. However, sEMG integration faced significant issues: the muscles involved in scratching were small and shifting of electrodes with any movement hindered placement, while environmental noise made sEMGs unfeasible to use in non-shielded conditions. We had also experimented with using gel electrodes, which were messy, as well as dry electrodes, which were more ideal for our use case but more susceptible to noise.

After extensive testing and daily design adjustments, the pneumatic component was dropped and sEMG was replaced with flex sensors, requiring finger slots for detection. Electronics were embedded between interfacing fabric for durability, with snap closures for washability and ease of maintenance.

Figure 5. Disassembled View of Prototype

Figure 8. 3D Model of the Prototype

III. MODELLING

A. *Component Selection*

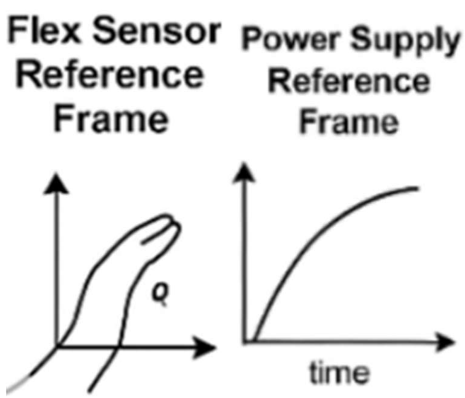
1) Common assumptions across all models:

(i) The signal will be stationary when there is no movement.
(ii) Sampling rate fs =1000 Hz (sufficient for human hand kinematics up to ~50 Hz).
(iii) Battery: single LiPo unit where C=2200 mAh, V_{no} = 3.7 V.
(iv) No technical factors like crosstalk affecting the relationship between the normal force and the flex sensor signal.

2) Common goals:

(i) Detection objective: To ensure positive detect “scratching” gestures of at least 80% at an acceptable false-alarm rate (P(fa)) ≤ 10^ (-3) and end-to-end latency ≤ 5 m/s.
(ii) Haptic objective: deliver a perceivable vibration amplitude (subjective threshold) while limiting each burst to ≤ 0.09 mJ so battery life meets user requirements.
(iii) Battery objective: operate for at least 2 hours of typical daily use without recharge.

3) Mechanism reference frames



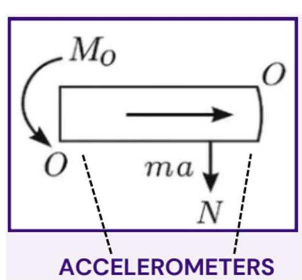


Figure 9. Accelerometer

TABLE II. DEFINITION OF KEY VARIABLES

VARIABLE	UNIT	DEFINITION
θ = bend angle	rad or °	Angle of a physical bend or flex.
a = acceleration vector	m/s^(2)	Vector quantity that describes the rate of change of an object’s velocity over time.
V = applied voltage	Volts (V)	The electric potential difference between two points in the electrical circuit.
R(θ) = resistance at bend angle θ	Ohms (Ω)	Function of when the electrical resistance of the flex sensor changes as the bend angle changes.

B. *Performance Predictions*

These models should target your system requirements. Brief description of your assumptions and variables. Present your predictions using Figures and or Tables.

Refer to Figures 1-3 for the various predictions

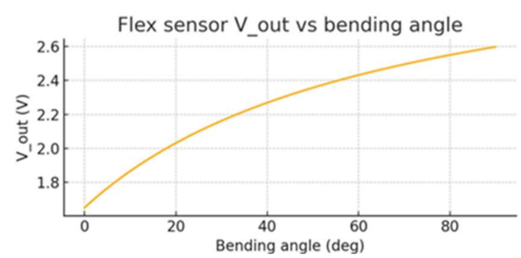


Figure 10: Flex sensor data prediction

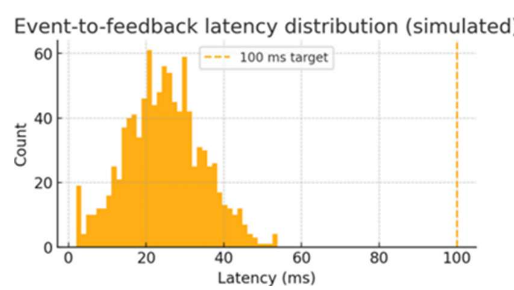


Figure 11: Latency prediction

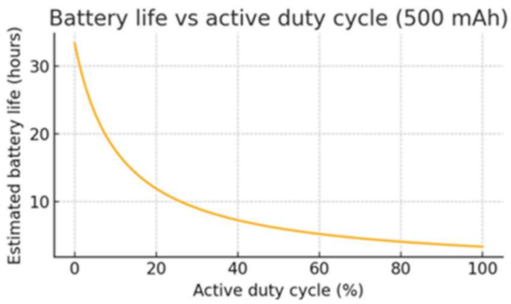


Figure 12. Battery life prediction

IV. RESULTS

A. Prototypes

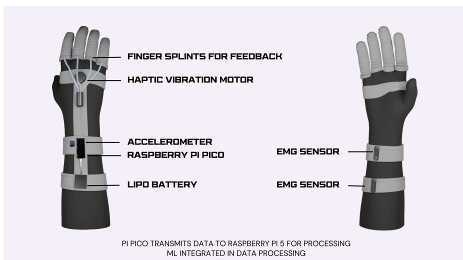


Figure 13: Component breakdown of early proposed system

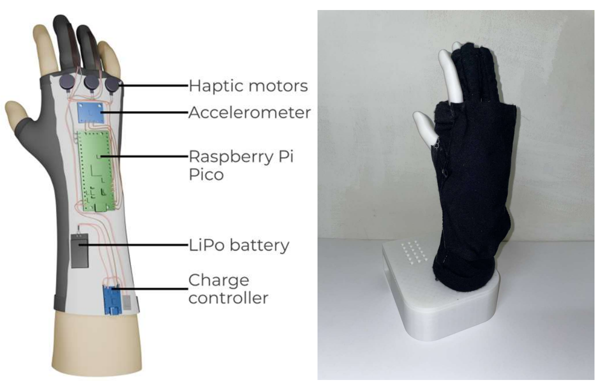


Figure 14&15: Component breakdown of system & Glove mounted on ItchDB

B. Experiments

A sleep study was conducted to evaluate *Ecz-ware*, combining a single-subject sleep trial with broader user feedback from 16 participants.

For the sleep trial, the subject was recorded for two hours during sleep using a video camera. An initial control session was conducted with no intervention (no *ecz-ware*), followed by a session in which the subject wore the device. To further assess detection accuracy, the participant was also provided with a handheld logger to record the number of true and false positives encountered during daily activities. This additional measure supplemented the sleep recordings by capturing real-world performance data. The experimental results, including detection accuracy, false positives, and user feedback, are summarized in Table III, while our feedback is summarized in Figure 13.

TABLE III. EXPERIMENTAL RESULTS OF ECZ-WARE

Itch Region	Without Ecz-Ware			With Ecz-Ware		
	Duration (mins)	Intensity	Frequency	*Duration (mins)*	Intensity	Frequency
Elbow	0.58	3	6	0.2	1	4
Shins	1.88	4	4	1.00	3	2
Under Knees	1.77	4	5	0.08	2	5
Hand	1.00	4	3	1.00	3	4
All	5.16	4	18	2.20	2.25	15

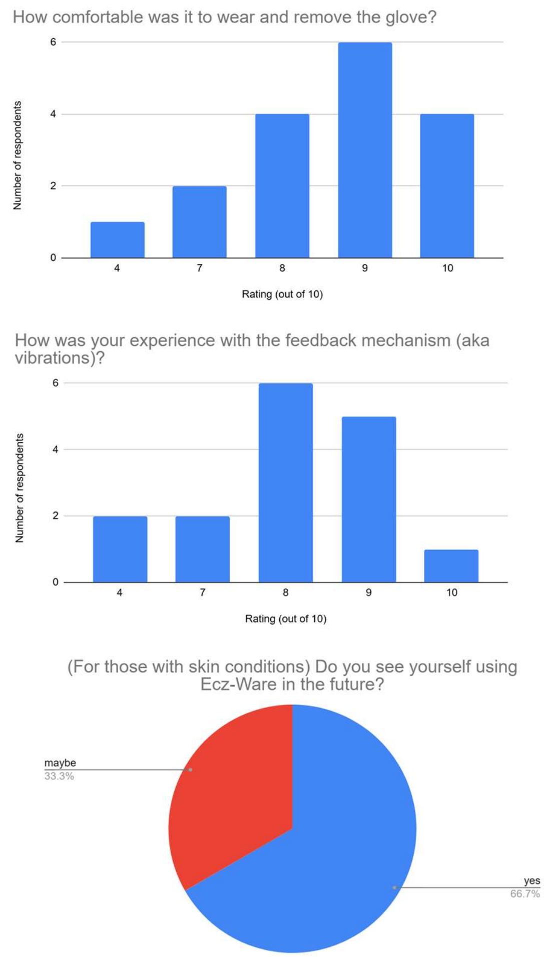


Figure 16: User Reviews

V. DISCUSSION

Our data collection and experimentation were limited by our short time frame and limited ability to find participants as a result.

Broader user feedback found that all but one user found Ecz-Ware comfortable to wear and remove (ranking it 7-10 out of 10), and all but one were satisfied with the vibration mechanism. Furthermore, when asked about whether they would consider using Ecz-Ware again, all users with skin conditions responded with either “Yes” or “Maybe”.

Although further testing would be ideal for the sleep trial, the results show a definite reduction in scratching duration and frequency.

As such, we can conclude the success of our system according to user feedback.

VI. CONCLUSIONS

We successfully proposed and prototyped **Ecz-Ware**, a real-time wearable system for detecting and interrupting nocturnal scratching. By integrating lightweight sensing with tiered feedback, it provided effective scratch detection while maintaining user comfort. The platform design enabled development and evaluation without reliance on complex clinical setups, allowing us to validate key functions including motion classification, low-latency response, and user-tolerable feedback mechanisms. It also served as a foundation for designing ergonomic wearable forms, leveraging insights gained during early trials. This approach bridges the gap between lab-based prototypes and real-world overnight use, while enabling future extensions such as longitudinal trials, mobile app integration, personalization algorithms, and alternative actuation methods (e.g., low-profile pneumatic impedance).

Future Improvements include:

- Conduct battery sizing optimisation to minimise weight and reduce dependence on hotspot connectivity.
- Design and fabricate a custom flexible PCB to improve glove integration and ergonomics.
- Refine glove design to fit a wider range of hand sizes for improved comfort and usability.
- Incorporate adjustable vibration settings to accommodate individual comfort levels and sensitivity.
- Implement a reward system to encourage compliance, particularly for children, as part of early behavioural intervention strategies.

APPENDIX

COMPONENT	VENDOR	MODEL/TYPE	COST
ACCELEROMETER	KURIOSITY	MPU 6050	$8.40
HAPTIC MOTORS	CONTINENTAL ELECTRONICS	VIBRATION MOTOR COIN 1030	$4.00
MICROCONTROLLER	CONTINENTAL ELECTRONICS	RASPBERRY PI PICO WI-FI	$19.00
	KURIOSITY	RASPBERRY PI 5	$109.80
TOTAL			**$140.4**

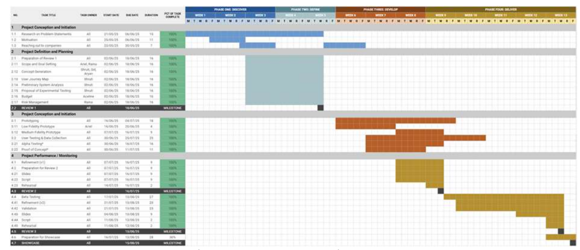


Figure 17. Gantt Chart

ACKNOWLEDGMENT

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