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A comparative assessment of the simple and modified Randles cells using machine learning for optimal impedance fitting on artificial skin

Brendan B. Murphy^{1*}  and Takeshi Torita^{1*}

Abstract

Wearable devices in the healthcare space rely on electrodes interfacing with the skin to capture biosignals such as the electroencephalogram (EEG), electromyogram (EMG), and electrocardiogram (ECG), and a low electrode–skin impedance is essential for high-fidelity recording. Equivalent circuit models (ECMs) are widely used to interpret impedance data, but choosing models that balance accuracy with interpretability remains challenging. In this study, impedance spectra from seven types of commercial gelled and dry electrodes interfacing with artificial skin were fitted using two ECMs: the common Randles cell and a modified Randles cell featuring a Warburg impedance element. Both ECMs fit the impedance data well, but logistic regression (LR) using the ECM parameters revealed key differences. While either model could be used to classify electrodes as gelled or dry with > 70% accuracy, only the modified Randles cell supported multiclass differentiation among the seven electrode types with > 80% accuracy. These findings demonstrate that a Warburg-modified Randles cell results in more informative fitting results during wearable sensor characterization. More broadly, this report establishes a generalizable workflow integrating impedance fitting with supervised machine learning (ML) to optimize ECM selection, which we strongly recommend to researchers in the wearable devices field.

Keywords Equivalent circuit models (ECMs), Impedance fitting, Electrode–skin interface, Logistic regression (LR), Wearable health monitoring (WHM), Warburg impedance

Introduction

Wearable technologies for healthcare monitoring are fast becoming fixtures of our everyday lives (Rajendran et al. 2021; Kim et al. 2022; Bonato 2010; Kumar et al. 2021; Perez and Zeadally 2021; Lee et al. 2024). These devices are required to interface comfortably with the human body and collect clear biosignals that can be used to understand or decode some portion of a person's general health status at any given point in time (Rajendran et al. 2021; Kim et al. 2022; Lee et al. 2024). Many technologies in this field comprise an electrode placed in direct contact with the skin, which transduces signals

*Correspondence:

Brendan B. Murphy
m.brendan@murata.com
Takeshi Torita
t_torita@murata.com

¹Murata Manufacturing Co., Ltd., 1-10-1 Nagaokakyo-Shi, Kyoto 617-8555, Japan

such as the electroencephalogram (EEG), the electromyogram (EMG), or the electrocardiogram (ECG) from the body into the appropriate recording and processing equipment. Given such a setup, it is obvious that a low-impedance interface between the electrode and the human body is a necessary prerequisite for efficient and high-fidelity biosignal collection (Murphy et al. 2021; Ravichandran et al. 2023; Mascia et al. 2025; Hsieh et al. 2022). A variety of materials science strategies have been under investigation in recent years to ensure that the electrodes themselves are low-impedance (Kim et al. 2022; Perez and Zeadally 2021; Lee et al. 2024; Gao and Yu 2021; Sun et al. 2025; Ullah et al. 2022; Sayyad et al. 2025), but beyond these efforts, a robust and informative understanding of the electrode–skin interface itself might also bring value to next-generation designs (Murphy et al. 2021; Ehtiati et al. 2023; Wu and Zheng 2025). Indeed, impedance fitting is a common technique used to improve theoretical understanding of the charge-transfer interactions occurring at or across the interface between recording electrodes and various media, not only within the realm of wearable health monitoring (WHM), but across a wide range of applications, including in battery and fuel cell studies, during corrosion assessments, and even for cement characterization (Haeverbeke et al. 2022; Santoni et al. 2024; Zhang et al. 2024; Laschuk et al. 2021).

To date, many publications have proposed various equivalent circuit models (ECMs) to describe the electrode–skin interface in particular (Murphy et al. 2021; Ravichandran et al. 2023; Mascia et al. 2025; Ehtiati et al. 2023; Wu and Zheng 2025; Haeverbeke et al. 2022; Liu et al. 2023; Heikenfeld et al. 2018; Bora and Dasgupta 2020).

The most simple ECMs make use of a single Randles cell (Fig. 1A), which is composed of a “spreading” resistance (R_s) in series with a parallel RC circuit featuring separate branches for Faradaic reactions across a charge-transfer resistance (R_{ct}), and non-Faradaic (capacitive) reactions across a double-layer capacitance (C_{dl}). Common modifications to this ECM include a Warburg impedance element (W) added in series with R_{ct} to account for diffusion-limited Faradaic processes (Fig. 1B) (Haeverbeke et al. 2022; Laschuk et al. 2021), or a constant phase element (CPE) replacing C_{dl} and accounting for frequency-dependent capacitive behavior (Fig. 1C) (Mascia et al. 2025; Ehtiati et al. 2023; Wu and Zheng 2025; Laschuk et al. 2021). Of course, two or more Randles cells might be added in series as well (Fig. 1D), allowing for differentiation of the charge-transfer processes first from subcutaneous tissue layers (R_{sub}) to the epidermis (R_{epi} , C_{epi}), then across a gap or through a gelled coating ($R_{gap/gel}$), depending on the electrode of choice, as charges move from the epidermis into the recording electrode (Fig. 1D) (Murphy et al. 2021; Ravichandran et al. 2023; Mascia et al. 2025; Ehtiati et al. 2023; Wu and Zheng 2025; Liu et al. 2023; Heikenfeld et al. 2018).

One of the major challenges that presents itself when fitting impedance data is choosing the “right” ECM to model one’s experimental results. The most appropriate model ought to not only match the data collected from the system, but should also be easy to interpret, so that it provides a meaningful and intuitive explanation of the electrochemical processes that are likely to occur within that system (Haeverbeke et al. 2022; Zhang et al. 2024). Often, it is considered best practice to choose ECMs that are minimally complex and easily interpretable, as

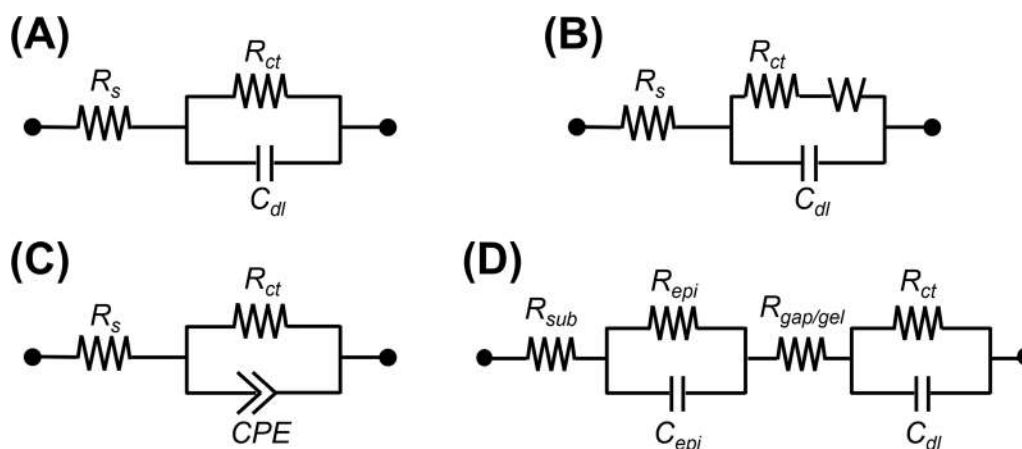


Fig. 1 Common equivalent circuit models (ECMs) used for wearable health monitoring (WHM) and in other applications. **A** The simple Randles cell, the most common ECM. The specific circuit parameters are: R_s = “spreading” resistance; R_{ct} = charge-transfer resistance; C_{dl} = double-layer capacitance. **B** A modified Randles cell, with a Warburg impedance element in series with R_{ct} to describe diffusion-limited charge-transfer reactions. **C** An alternative modified Randles cell, which replaces C_{dl} with a frequency-dependent constant phase element (CPE). **D** An expanded ECM to describe an electrode interfacing with human skin, as used in Murphy et al. (2021). This model comprises two simple Randles cells in series, with the first (R_{sub} , R_{epi} , C_{epi}) describing charge-transfer processes occurring from the subcutaneous fat layers up until the epidermis, and the second ($R_{gap/gel}$, R_{ct} , C_{dl}) describing processes across a gap or through a gelled coating, then through the main recording electrode

such models avoid “overfitting” the measured data with unnecessary or opaque parameters (Wu and Zheng 2025; Hershkovitz et al. 2011; Sgura and Bozzini 2005). Even so, for most situations, impedance fitting requires extensive trial and error to refine and optimize model parameters (Ehtiati et al. 2023; Wu and Zheng 2025; Haeverbeke et al. 2022; Zhang et al. 2024). Constraints are usually set on the ECM elements themselves, to ensure that physically possible values are obtained (Murphy et al. 2021; Ehtiati et al. 2023). More generally, though, the overall accuracy or “correctness” of an ECM is best described with a goodness of fit measure, typically a chi-squared value (χ^2) based on a nonlinear-least-squares (NLLS) analysis (Murphy et al. 2021; Mascia et al. 2025; Wu and Zheng 2025; Hershkovitz et al. 2011; Sgura and Bozzini 2005). In this regard, Mascia et al. have recently used MATLAB®’s built-in NLLS function, *lsqnonlin()*, to compare a variety of ECMs used for fitting the skin impedance of ultra-thin tattoo electrodes (Mascia et al. 2025). In more recent publications, though, advanced machine learning (ML) techniques have been adopted to identify the optimal ECM based on large amounts of collected data (Wu and Zheng 2025; Furugori and Katayama 2024; Zhu et al. 2019; Zulueta et al. 2023; Bongiorno et al. 2022; Schaeffer et al. 2023; Chen et al. 2025). For example, using a support vector machine (SVM) algorithm, Zhu et al. trained a model to automatically select the most suitable ECM among five types commonly used to describe lithium-ion batteries at various stages in their lifetime (Zhu et al. 2019). Random forests were used by Chen et al. to simplify ECM selection and impedance fitting of corrosion data for low-carbon steel, ultimately enabling estimation of mass losses from atmospheric corrosion processes (Chen et al. 2025). Elsewhere, both Zulueta et al. (Zulueta et al. 2023) and Bongiorno et al. (Bongiorno et al. 2022) have used artificial neural networks (ANN) to aid in ECM selection, as well as to estimate specific circuit parameters, for lead-acid battery and corrosion studies, respectively. In each of these instances, although the use of ML techniques has sped up ECM selection and optimization overall, given the complexity of the ML methods themselves, very large (typically > 500) impedance datasets have been necessary for successful implementation of the proposed algorithms, which increases the experimental burden (Mascia et al. 2025; Zhu et al. 2019; Bongiorno et al. 2022; Schaeffer et al. 2023). Unlike the abovementioned battery studies, impedance studies in the biomedical field typically do not allow for the collection of large datasets (Murphy et al. 2021; Mascia et al. 2025; Bora and Dasgupta 2020). Nevertheless, given the complexities of the electrode–skin interface, a methodology that might support faster ECM selection would be highly desirable. And while the NLLS method is a valuable example of how to optimize the ECM selection process, such analysis

does not readily lend itself to comparisons *between* models, so much as comparisons *within* a single model across different datasets (Mascia et al. 2025; Sgura and Bozzini 2005). Accordingly, it may be said that there is a need for a simplified ML paradigm that is applicable even when considering smaller impedance datasets.

In this report, we recorded impedance from seven different types of electrodes interfacing with an artificial skin sample under ambient conditions, exploring both gelled and dry electrode technologies. Recent work has shown that real-world human skin conditions can be reliably simulated by controlling the composition of artificial skin samples (Ehtiati et al. 2023; Goyal et al. 2022; Shimizu and Nonomura 2018; Dąbrowska et al. 2016; Bublex et al. 2025), and in particular, polyvinyl alcohol (PVA)-based phantoms are reliable substrates to mimic both the mechanical and electrical properties of the skin and deeper tissue layers (Goyal et al. 2022; Bublex et al. 2025). Accordingly, the choice of an artificial skin substrate here not only saved experimental time, but still provided meaningful results that have applicability in the real-world. After impedance measurements, we employed two ECMs for impedance fitting: (1) the simple Randles cell (Fig. 1A) and (2) a modified Randles cell featuring a Warburg impedance element (Fig. 1B). These ECMs were chosen because of their simplicity. The Randles cell contains the minimum number of resistors and capacitors needed to model most impedance behavior (Haeverbeke et al. 2022), and in the case of the modified Randles cell, the Warburg impedance is a well-defined Faradaic component with only a single factor (the Warburg constant, W) to optimize when fitting (Haeverbeke et al. 2022; Lazanas and Prodromidis 2023). The CPE-modified Randles cell (Fig. 1C) was not considered because the CPE itself was deemed too complex, having two parameters that require optimization during fitting (an admittance, Y_0 , and a unitless coefficient, n or α , ranging from -1 to 1) (Haeverbeke et al. 2022; Lazanas and Prodromidis 2023). Interpretation of the CPE’s unitless coefficient, in particular, can pose challenges after fitting (Haeverbeke et al. 2022; Lazanas and Prodromidis 2023; Magar et al. 2021). Meanwhile, the extended ECM shown in Fig. 1D was deemed to have an excessive number of components for the present study, increasing the chances for overfitting. We therefore compared only the simple and Warburg-modified Randles cells, first from a simple statistical standpoint, but thereafter, we also employed logistic regression (LR) to train ML models that used the ECM parameters and the impedance moduli at 10 Hz as inputs for predicting on the electrode type. While impedance fitting resulted in accurate modeling of the frequency response when using either of the two ECMs, deciding which ECM was best could not be done from fitting results alone. Subsequent

implementation of our simple ML algorithms highlighted clear distinctions between the ECMs, with the modified Randles cell demonstrating higher accuracies (>80%) at correctly predicting electrode type, indicating that this ECM is the superior choice for describing the complex electrode-artificial skin interface. In total, this report demonstrates a novel yet simple methodology leveraging simple ML methods for a retrospective comparison of different ECMs when fitting electrode impedances. Furthermore, by adopting the methodology proposed here, it is possible to conclude that a modified Randles cell may in every case be more useful for impedance analysis of the electrode-skin interface than a simple Randles cell, which has significant implications for researchers seeking to understand and improve the performance of next-generation wearable technologies before their deployment in specific use cases.

Materials and methods

Overall methods are summarized graphically in Fig. 2. Electrochemical impedance spectroscopy (EIS) was completed using an AUTOLAB PGSTAT302N and FRA32M module (Metrohm AG Instrument) in Potentiostatic mode, with a three-electrode configuration under ambient conditions (24°C, 50–60% relative humidity). Each test electrode was used as the working electrode, while standard disposable ground plate Ag/AgCl electrodes (Natus®, Product No. 019-400500) were used as the reference and counter electrodes in every measurement to ensure a static reference potential. Electrode impedances were measured in response to a 10 mV_{RMS} sinusoidal input, sweeping the frequency from 0.1 Hz to 10 kHz at a resolution of 10 points per decade. The recording medium used for all measurements was a two-layer sheet-type artificial skin model suitable for practicing incisions and sutures of the human body (Product No. OHMTS01212, WetLab Inc.). The primary material of this artificial skin was PVA, and the

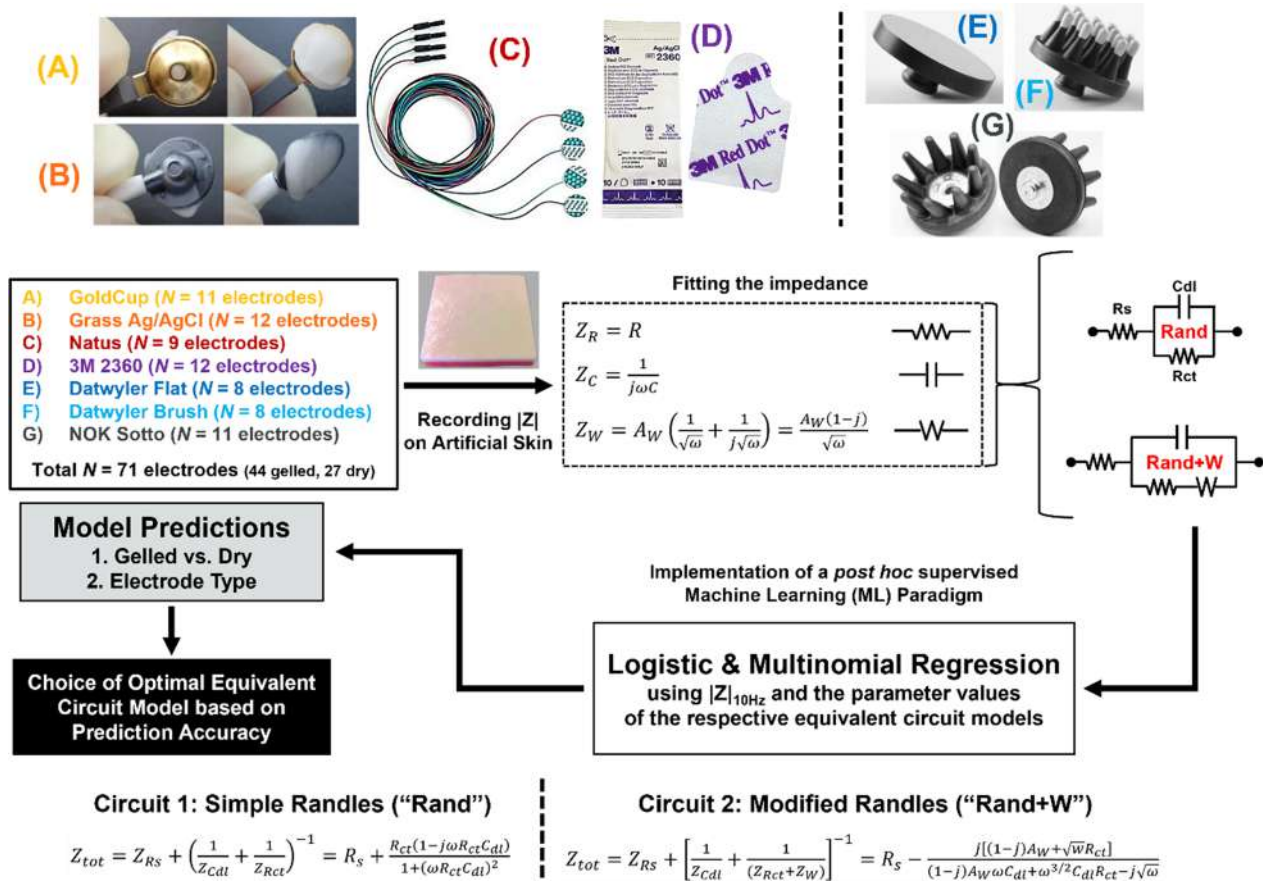


Fig. 2 Summary of the study design. We recorded impedance from a variety of electrodes, both gelled and dry, using an artificial skin substrate. Thereafter, the impedance was fitted using two equivalent circuit models (ECMs): the simple Randles cell ("Rand") and a modified Randles cell featuring a Warburg impedance element ("Rand+W"). Next, we completed logistic and multinomial regression using the 10 Hz impedance moduli and the values of the respective ECM parameters, to identify which ECM resulted in better predictions for the original type of electrode used in the initial impedance measurements

dimensions were length x width x thickness ($L \times W \times t$) = 85 mm × 85 mm × 15 mm.

The specific electrodes tested here are summarized in Table 1. They included four separate types of gelled electrodes (Grass® reusable “GoldCup” electrodes and disposable Ag/AgCl electrodes; Natus® disposable adhesive electrodes; 3 M RedDot™ 2360 resting-state ECG electrodes) and three types of dry electrodes (SoftPulse™ Flat and Brush Medium electrodes from Datwyler Holding Inc.; “Sotto” elastomer electrodes from NOK Corporation). The two Grass® electrodes considered here are typically used for EEG recording, and require application of a conductive paste before use. Accordingly, we used the standard Ten20® conductive paste sold by Weaver and Company when characterizing the Grass® electrodes here. In total, the impedance of 71 separate test electrodes was measured, comprising 44 gelled electrodes (62% of the total dataset) and 27 dry electrodes (38% of the total dataset). However, comparable numbers of each test electrode were measured so that no individual electrode type made up >20% of the total dataset (see the final column of Table 1).

Table 1 Electrode summary

Electrode	Gelled or dry	Sensing material	Contact area (mm ²)	Company reference	N (% of Total)
Grass® Reusable Stamp-Cup Electrodes (“GoldCup”) (Part No. 019-477500)	Gelled	Au	78.54	Natus	11 (15%)
Grass® Disposable Cup Electrodes (Part No. 019-477200)	Gelled	Ag/AgCl	78.54	Natus	12 (17%)
Natus® Disposable Adhesive Electrodes (Part No. 019-400400)	Gelled	Ag/AgCl	314.16	Natus	9 (14%)
3M RedDot™ ECG resting electrodes 2360	Gelled	Ag/AgCl	400.00	Solventum	12 (17%)
SoftPulse™ flat	Dry	Ag/AgCl	132.73	Datwyler	8 (11%)
SoftPulse™ brush medium	Dry	Ag/AgCl	11.80	Datwyler	8 (11%)
NOK Corp. “Sotto” brain-wave rubber electrode	Dry	Carbon rubber	15.90	NOK株式会社	11 (15%)

After EIS measurements, equivalent circuit models (ECMs) were created using the NOVA 2.1.4 software (Metrohm AG Instrument). The circuit descriptions for the simple Randles cell (“Rand”) and the modified Randles cell with a Warburg impedance element (“Rand + W”) were “R(RC)” and “[R(C[RW])]”, respectively. Impedance fitting procedures, as well as calculations of the goodness of fit (χ^2) for each fit, were also completed in NOVA 2.1.4, employing the NLLS method. The maximum number of iterations allowed for each fitting procedure was 500, while the maximum number of iterations allowed without improvement in average χ^2 value was 50.

Following impedance fitting, we first applied two-sample Student’s *t*-tests to test for statistical differences in the 10 Hz impedance moduli ($|Z|_{10 \text{ Hz}}$) of all electrodes. The significance level for these comparisons was set to $p < 0.05$ for each electrode pair under consideration. Afterwards, we employed a one-way analysis of variance (ANOVA) to test for differences in the means of the specific parameter values between the two ECMs. Where significant differences were found from ANOVA, we used Tukey’s honestly significant difference (HSD) post hoc test for multiple comparisons to assess the exact nature of that difference. After these analyses, the $|Z|_{10 \text{ Hz}}$ and ECM parameter values were used to train ML models in two scenarios. In the first instance, we used logistic regression (LR) to predict whether an electrode was gelled or dry, while in the second case, we used multinomial logistic regression (MnLR) to predict which of the original seven electrode types was used. LR is a widely used supervised ML method allowing for multivariate analysis of a binary dependent variable, which ensures reliable predictions that are only marginally improved by more complex methods such as SVM or ANN (Issitt et al. Feb. 2022; Singh et al. 2016). Here, our first scenario classified electrodes according to a binary condition (gelled = 0 or dry = 1), so an LR model was deemed appropriate. In the second scenario, however, since the dependent variable consisted of seven different categories, corresponding to the seven different test electrode types, a maximum likelihood estimator was deemed more appropriate, necessitating the MnLR approach (Liang et al. 2020). A standard 70–30 train-test split was used for both models, and the mean squared error (MSE) and overall prediction accuracy (PA) were calculated in 10 cross-validation (CV) folds to allow for comparisons between predictions based on different model inputs. We trained three separate LR and MnLR models (six models total), based on the following inputs: (1) $|Z|_{10 \text{ Hz}}$ data alone; (2) $|Z|_{10 \text{ Hz}}$ data plus the “Rand” parameters (R_s , R_{ct} , and C_{dl}); and (3) $|Z|_{10 \text{ Hz}}$ data plus the “Rand + W” parameters (R_s , R_{ct} , C_{dl} , and W).

All statistical and ML analyses were completed using custom-made scripts in MATLAB®, and making

exclusive use of built-in functions found in the Statistics and Machine Learning Toolbox. Two-sample Student's *t*-tests were completed using *ttest2()*. One-way ANOVA was completed with *anova1()*, and Tukey's HSD test was implemented with *multcompare()*, calling 'CriticalValueType' = 'tukey-kramer' to ensure protection against pairwise comparisons. Test-train splitting and tenfold CV for the respective ML models were both implemented using *cvpartition()*. LR was completed with *fitglm()*, specifying 'Link' = 'logit' and using a Poisson distribution, while MnLR was implemented using *fitmnr()*. Model predictions were obtained using *predict()*, while each model's MSE and PA were calculated using standard expressions, as provided in (1) and (2).

$$\text{MeanSquaredError (MSE)} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (1)$$

for predictions y_i and true values $\hat{y}_i$

$$\text{Prediction Accuracy (PA)} = \left[\frac{\text{True Positives (TP)}}{\text{Total Number of Predictions}} \right] \times 100\% \quad (2)$$

Results and discussion

All electrodes made use of silver/silver-chloride (Ag/AgCl) as the primary sensing material, except for the GoldCup samples (gold) and the NOK Sotto samples (carbon elastomer). Ag/AgCl is the most common option for biosignal electrodes because it is low-noise, low-impedance, and generally non-polarizable (Albulbul 2016). Even so, different manufacturers have different methods for realizing Ag/AgCl electrodes, and as a result, although the same primary sensing material may be used, different impedance responses may be seen (Lee et al. 2022). This was true here, as is clear from the Nyquist and Bode plots of each electrode's average impedance magnitude and phase (Fig. 3A–D). Almost all Ag/AgCl electrodes had impedance moduli between 10^2 and $10^4 \Omega$ across the frequencies investigated (Fig. 3C), but each type of test electrode exhibited a unique phase response (Fig. 3D), especially below 10 Hz. GoldCup electrodes had similar impedance magnitudes to the Ag/AgCl samples, but their phase response was distinguishable from all Ag/AgCl samples below 1 kHz. Meanwhile, NOK Sotto electrodes had a significantly higher average impedance magnitude than all other electrodes, and an obviously distinct phase response.

For many healthcare applications, 10 Hz is a meaningful reference frequency (Murphy et al. 2021; Wu and Zheng 2025; Boehler et al. 2020), so here, we used the average 10 Hz impedance modulus, $|Z|_{10 \text{ Hz}}$, to compare the seven test electrode types in pairwise fashion (Fig. 3E). All gelled electrodes, including GoldCup, exhibited similar $|Z|_{10 \text{ Hz}} < 1 \text{ k}\Omega$, with average values ranging from a minimum of 214 Ω (for GoldCup), to a maximum of 576 Ω (for Natus). Furthermore, no statistically significant

difference was observed between the $|Z|_{10 \text{ Hz}}$ of any of the gelled electrodes ($p > 0.05$ for all pairs). However, the dry electrodes each exhibited significantly higher $|Z|_{10 \text{ Hz}}$ than every gelled electrode. Specifically, the SoftPulse™ Flat electrodes had average $|Z|_{10 \text{ Hz}}$ of $3.64 \pm 2.93 \text{ k}\Omega$, which was significantly higher than all gelled electrodes ($p < 0.001$ for every pairwise comparison). The SoftPulse™ Brush electrodes had $|Z|_{10 \text{ Hz}}$ of $7.08 \pm 4.30 \text{ k}\Omega$, which was also significantly higher than every gelled electrode ($p < 0.001$ for every pair). The two SoftPulse™ electrodes, despite being of different geometric surface areas (see Table 1), did not have significantly different $|Z|_{10 \text{ Hz}}$ when compared to one another ($p = 0.099$), although this might be because they are both made by the same manufacturer and feature the same materials. Finally, NOK Sotto electrodes had significantly higher $|Z|_{10 \text{ Hz}}$ ($4.86 \pm 4.31 \text{ M}\Omega$) not only compared to all gelled electrodes ($p < 0.001$ for every pair) but also compared to the SoftPulse™ Flat ($p < 0.001$) and Brush electrodes ($p < 0.05$). The high impedance of the NOK electrodes can most likely be ascribed to the fact that the main sensing material, carbon rubber, is significantly less conductive than Ag/AgCl or gold.

Next, we considered the ECM parameters extracted from fitting each test electrode's impedance spectrum with either the simple or the Warburg-modified Randles cell (Table 2a, b and Fig. 4). The simple Randles cell ("Rand") provided a consistent fit to the experimental data for all electrodes, with the goodness of fit ranging between $\chi^2 = 1.94\text{e-}02$ and $\chi^2 = 6.43\text{e-}02$ (Pearson's χ^2 test with $df = 2$ degrees of freedom). The modified Randles cell ("Rand + W") likewise provided reliable fits to the experimental data across electrode types, with χ^2 lying between $1.14\text{e-}02$ and $5.86\text{e-}02$ (Pearson's χ^2 test, $df = 3$). We next completed a one-way ANOVA, which allowed us to examine more closely whether there were any significant differences between the average values of the individual parameters common to both ECMs (*i.e.*, R_s , R_{ct} , and C_{dl}). This test revealed that there was a statistically significant difference in the model parameters between at least two groups ($F(5,420) = 69.01$, $p = 1.44\text{e-}52$, see Table 3). Tukey's HSD post hoc test found that the mean values of R_s , R_{ct} , and C_{dl} were significantly different amongst each other, which is to be expected since these parameters describe different and distinct electrochemical processes. However, only the mean values of C_{dl} were statistically significantly different from one another based on the specific choice of ECM ($p = 2.10\text{e-}12$). Specifically, C_{dl} was significantly lower for every electrode when using the "Rand + W" ECM (Fig. 4C). Meanwhile, there was no significant difference between the R_s or R_{ct} values, regardless of the choice of ECM ($p > 0.05$ in both cases). The Warburg impedances (W) were held out from ANOVA testing since they only featured in the "Rand + W" model.

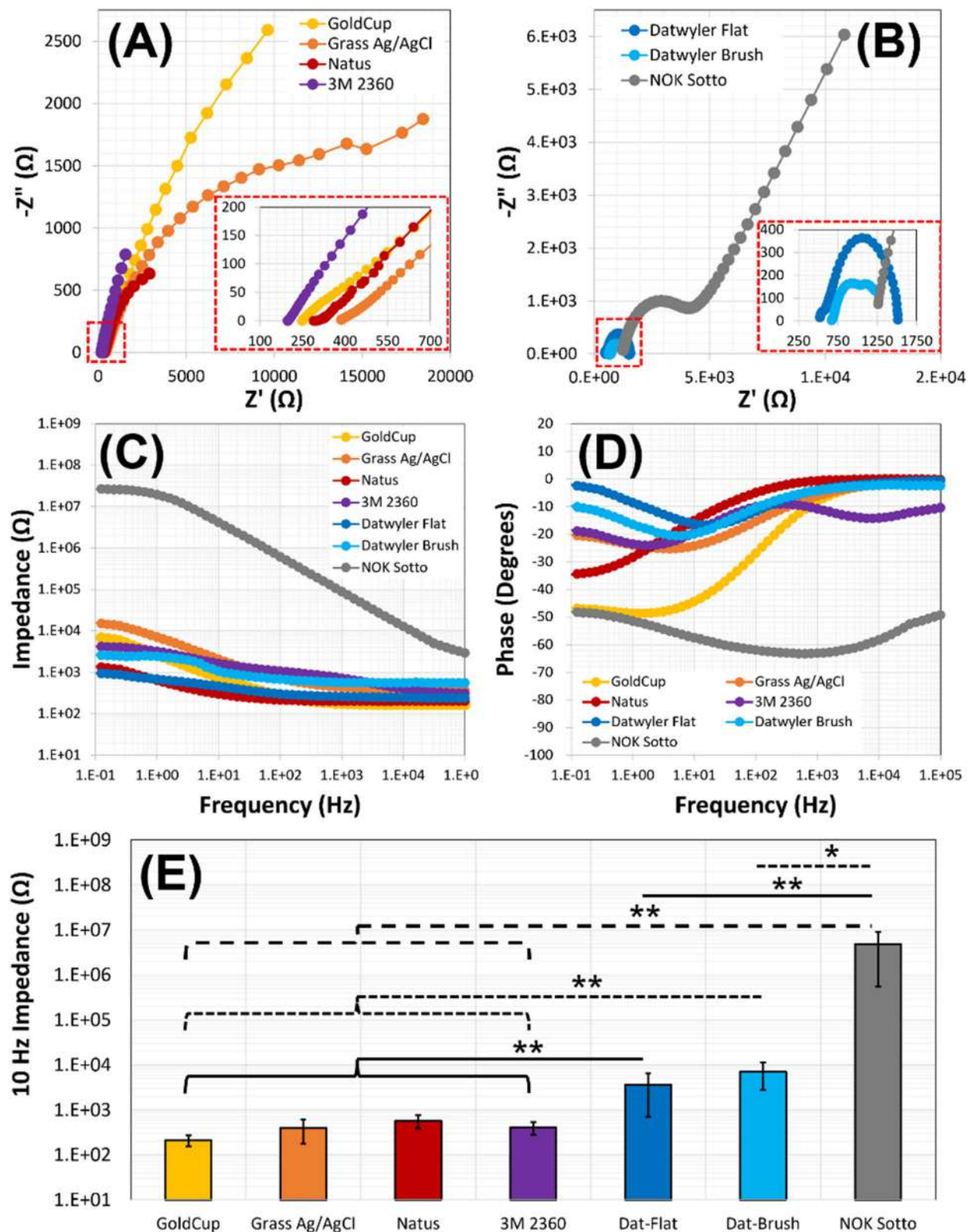


Fig. 3 Nyquist impedance plots for the gelled (A) and dry (B) electrodes. Plotted data were averaged across all electrodes of each type. The data in the dashed red boxes are shown in the insets. Bode plots of the impedance modulus (C) and phase (D) for each electrode type, averaged across all electrodes of each type. The average impedance moduli at 10 Hz (E) were examined in pairwise fashion to test for statistically significant differences between different electrode types. Bars represent averages, while errorbars are standard deviations. Significance levels: (*) denotes $p < 0.05$, (**) denotes $p < 0.001$. "Dat-Flat" denotes the "Datwyler Flat" electrodes, while "Dat-Brush" denotes the "Datwyler Brush" electrodes

Table 2 a Summary of fitting parameters extracted from the simple Randles cell (“Rand”). Values are reported as avg. $\pm$ std. dev. for N electrodes, where N is provided in parentheses in the “Electrode” column. **b** Summary of fitting parameters extracted from the modified Randles cell (“Rand + W”). Values are reported as avg. $\pm$ std. dev. for N electrodes, where N is provided in parentheses in the “Electrode” column

(a)					
Electrode	R_s (k Ω)	R_{ct} (k Ω)	C_{dl} (μ F)		Model χ^2 (df=2)
GoldCup (N=11)	0.32 $\pm$ 0.06	6.47 $\pm$ 2.26	28.62 $\pm$ 9.87		(5.26 $\pm$ 4.46)e-02
Grass Ag/AgCl (N=12)	0.85 $\pm$ 0.27	7.94 $\pm$ 4.71	21.85 $\pm$ 7.22		(5.87 $\pm$ 0.91)e-02
Natus (N=9)	0.41 $\pm$ 0.17	10.02 $\pm$ 2.36	18.72 $\pm$ 3.79		(6.43 $\pm$ 1.69)e-02
3 M 2360 (N=12)	0.91 $\pm$ 0.21	6.43 $\pm$ 0.83	15.84 $\pm$ 1.54		(4.04 $\pm$ 2.45)e-02
Datwyler Flat (N=8)	0.51 $\pm$ 0.02	11.38 $\pm$ 1.37	35.23 $\pm$ 18.28		(1.94 $\pm$ 1.32)e-02
Datwyler Brush (N=8)	1.15 $\pm$ 0.16	17.78 $\pm$ 1.57	51.07 $\pm$ 9.46		(3.55 $\pm$ 2.23)e-02
NOK Sotto (N=11)	0.81 $\pm$ 0.19	30.08 $\pm$ 2.30	71.69 $\pm$ 13.30		(4.17 $\pm$ 3.32)e-02
(b)					
Electrode	R_s (k Ω)	R_{ct} (k Ω)	C_{dl} (μ F)	W (k Ω s $^{-1/2}$)	Model χ^2 (df=3)
GoldCup (N=11)	0.28 $\pm$ 0.07	5.80 $\pm$ 0.55	6.21 $\pm$ 0.15	0.18 $\pm$ 0.06	(3.18 $\pm$ 2.42)e-02
Grass Ag/AgCl (N=12)	0.33 $\pm$ 0.14	6.57 $\pm$ 0.25	5.55 $\pm$ 0.04	0.51 $\pm$ 0.31	(5.41 $\pm$ 2.73)e-02
Natus (N=9)	0.54 $\pm$ 0.16	8.11 $\pm$ 1.68	5.26 $\pm$ 0.08	0.14 $\pm$ 0.05	(5.86 $\pm$ 4.37)e-02
3 M 2360 (N=12)	0.99 $\pm$ 0.29	5.88 $\pm$ 0.05	8.86 $\pm$ 0.96	0.26 $\pm$ 0.14	(1.14 $\pm$ 1.31)e-02
Datwyler Flat (N=8)	0.44 $\pm$ 0.02	10.90 $\pm$ 4.60	29.46 $\pm$ 15.86	7.61 $\pm$ 0.90	(3.31 $\pm$ 2.58)e-02
Datwyler Brush (N=8)	0.85 $\pm$ 0.24	20.27 $\pm$ 4.14	32.30 $\pm$ 8.26	9.33 $\pm$ 3.40	(1.50 $\pm$ 2.16)e-02
NOK Sotto (N=11)	0.87 $\pm$ 0.16	31.30 $\pm$ 2.40	43.94 $\pm$ 13.75	(1.64 $\pm$ 0.31)e+03	(2.66 $\pm$ 1.82)e-02

For this parameter, units of Ω -s $^{-1/2}$ are most commonly used (Haeverbeke et al. 2022; Lazanas and Prodromidis 2023), and for analysis, we completed another set of pairwise Student’s t -tests across the seven electrode types. The results of this analysis were the same as those obtained for the $|Z|_{10\text{ Hz}}$ values: first, no significant difference was found between W values among the gelled electrodes ($p > 0.05$ for all pairs). Meanwhile, the SoftPulse™ Flat and Brush electrodes had significantly higher W than every gelled electrode ($p < 0.001$ for both electrodes, for all pairwise comparisons), but they did not have significantly different W from each other ($p > 0.05$). Finally, NOK Sotto electrodes had higher W than every gelled electrode ($p < 0.001$ for all pairs), as well as higher W than the SoftPulse™ Flat ($p < 0.001$) and Brush electrodes ($p < 0.001$).

Now, these results tell us that *either* the “Rand” model *or* the “Rand + W” model can be used to fit the electrode impedance data on artificial skin. Using the “Rand + W” model results in statistically significantly lower C_{dl} than using the “Rand” model, but this might be explained as due to the presence of the Warburg impedance itself. After all, while W typically models diffusion-limited reactions, it may also be used to describe non-ideal, pseudocapacitive behavior at the electrode-artificial skin interface (Haeverbeke et al. 2022; Laschuk et al. 2021; Dong et al. 2022; Mainka et al. 2022; Chen et al. 2023; Naranjo-Hernández et al. 2019). Applying the Warburg impedance element as a non-ideal pseudocapacitor, then, we have two elements in the “Rand + W” model that describe some portion of the total “capacitive” behavior of each electrode, and it may be reasonably expected that

the “ideal” or traditional capacitance should decrease as a consequence of the presence of “non-ideal” pseudocapacitance. This serves to explain why the C_{dl} values were lower for the “Rand + W” model. In effect, though, our interpretation of the electrochemical processes occurring between the electrode and the recording medium may change based on the ECM we choose to use, but the basic “correctness” of either model is unaffected by that choice. Especially given the similar ranges of χ^2 values obtained from both models, and the lack of any significant differences in the R_s or R_{ct} parameters between the two ECMs, it is difficult to conclude from these results alone which model is better at fitting the impedance data here. We therefore decided to employ a simple post hoc ML paradigm, in which the impedance and ECM parameters were used to predict on the original electrode type. From this exercise, we expected that differences between the “Rand” and “Rand + W” ECMs would become more apparent, allowing us to more confidently decide which model is best for describing the dynamics of the electrode-artificial skin interface.

Accordingly, we next trained first an LR model to predict whether an electrode was gelled or dry. Then we trained an MnLR model to predict on the specific electrode type. The two ML model types were fed three separate datasets as inputs: (1) $|Z|_{10\text{ Hz}}$ data only, (2) $|Z|_{10\text{ Hz}}$ data plus the “Rand” parameter values, or (3) $|Z|_{10\text{ Hz}}$ data plus the “Rand + W” parameter values. We compared model performances in terms of MSE and PA (Fig. 5).

Our LR model achieved a low MSE (0.165 $\pm$ 0.088) and high PA (86%) when using just $|Z|_{10\text{ Hz}}$ data. This suggests that impedance data alone is more than sufficient

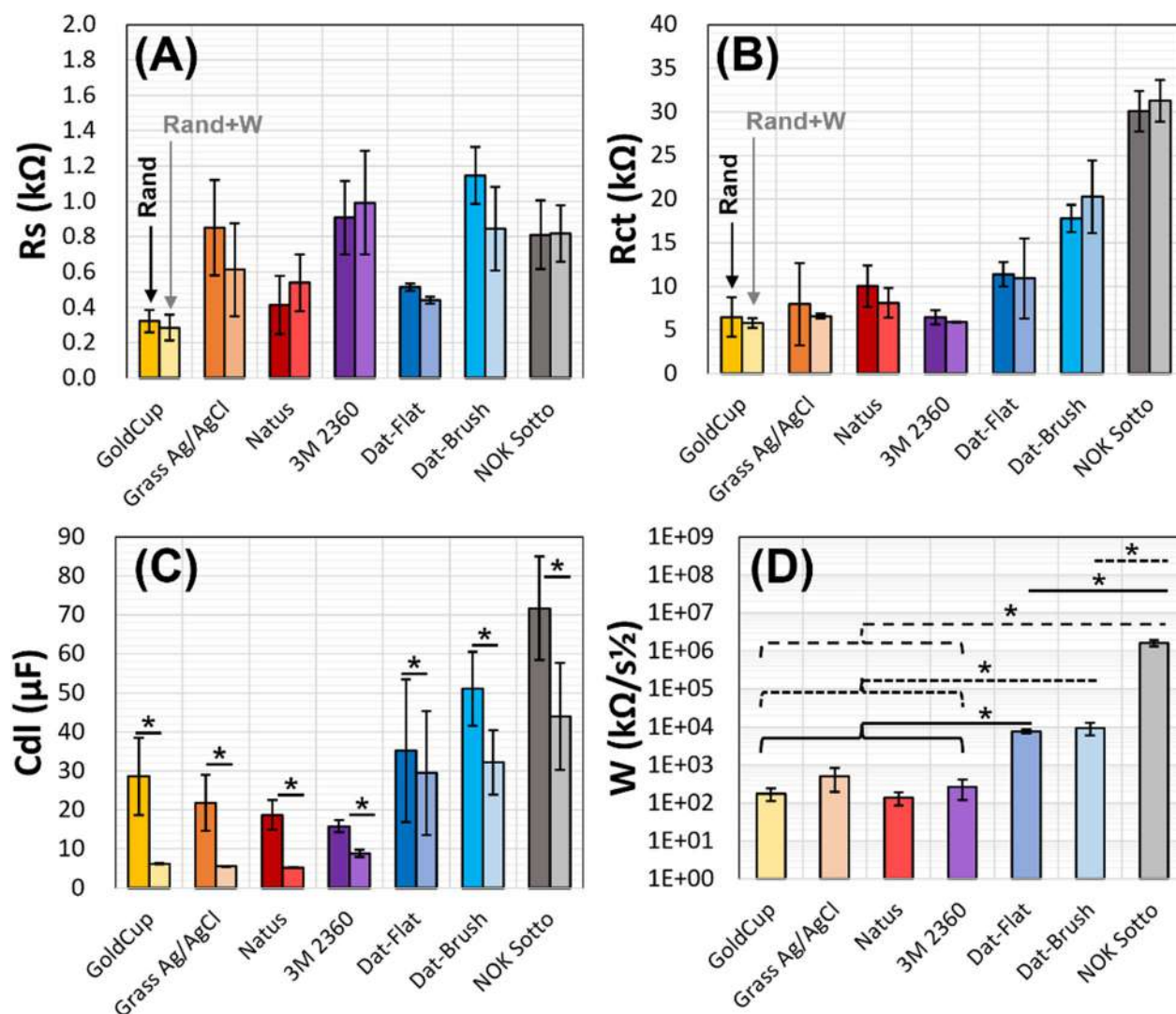


Fig. 4 Average equivalent circuit model (ECM) parameters for all electrodes. “Rand” denotes values from fitting with the simple Randles cell, while “Rand + W” denotes values obtained from fitting with the modified Randles cell. **A** Spreading resistances (R_s). **B** Charge-transfer resistances (R_{ct}). **C** Double-layer capacitances (C_{dl}). **D** Warburg impedances (W), displayed for the modified Randles cell (“Rand + W”) only. In all panels, bars are averages and errorbars are standard deviations. Asterisks (*) in panels C and D denote statistical significance at $p < 0.001$

Table 3 We completed a one-way ANOVA to compare the effect of the choice of equivalent circuit model (“Rand” vs. “Rand + W”) on the values of the model parameters common to both circuits (R_s , R_{ct} , and C_{dl})

Source	SS	df	MS	F-score	p-value
Between groups	5.66e+04	5.00	1.13e+04	69.01	1.44e-52
Within groups	6.89e+04	420.00	1.64e+02		
Total	1.25e+05	425.00			

to allow one to distinguish between gelled and dry electrodes. Adding the “Rand” parameters (R_s , R_{ct} , and C_{dl}) to the training dataset did not improve the LR model PA (86%), however it did result in a slightly larger MSE value (0.191 ± 0.070). Conversely, when using the parameters from the “Rand + W” ECM (R_s , R_{ct} , C_{dl} , and W), there was a decrease in MSE (0.102 ± 0.024) with an improvement

in overall PA (92%). It is possible that both the “Rand” and “Rand + W” ECMs introduce new factors that are highly correlated with the $|Z|_{10 \text{ Hz}}$ data, thus increasing the overall multicollinearity of the simple LR model. This might explain the differences in MSE observed, despite consistently high (*i.e.*, > 80%) overall accuracies, especially since multicollinearity is not expected to impact the predictions themselves, only their interpretability (Vatcheva and Lee 2016; Shieh 2010; Kim 2019). To improve the LR model MSEs in future studies, ridge regression using robust estimators may be beneficial (Lukman et al. 2024; Akhtar and Alharthi 2025), however, since we applied ML here in a retrospective fashion, we do not consider interpretation to be a major challenge. Especially given what are already known of the statistical differences between the

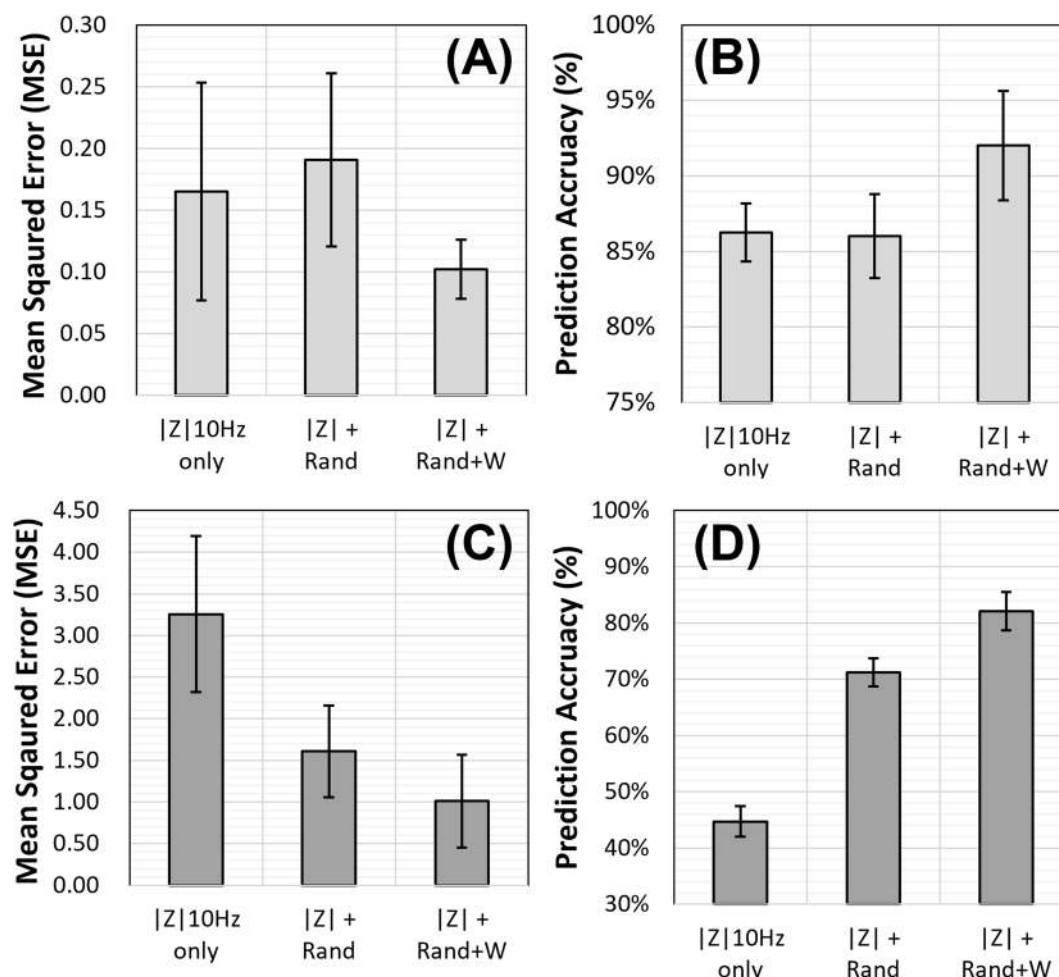


Fig. 5 Summary of results from a post hoc machine learning (ML) study using impedance and equivalent circuit model (ECM) parameter data. Bar graphs show the mean squared error (MSE) (A, C) and prediction accuracy (PA) (B, D) for a logistic regression (LR) model (A, B) and a multinomial logistic regression (MnLR) model (C, D) trained on different sets of input data. In all panels, bars are averages and errorbars are standard deviations across $N=10$ cross-validation trials (each with a 70–30 training–testing split)

two ECMs in question, as described above, the LR model results would seem to simply suggest that fitting the impedance data with *either* ECM does not greatly hinder us from distinguishing between gelled or dry electrodes.

Moving on, then, in the MnLR instance, rather than classifying electrodes as gelled or dry, we sought to predict which individual electrode type was used among the seven brands considered, making for a significantly more complex prediction scenario. Impedance alone was insufficient for such multiclass differentiation: the MSE was large (3.26 ± 0.94), and the PA was less than chance (45%) when using $|Z|_{10\text{ Hz}}$ data only. The inclusion of the “Rand” ECM parameters improved the model MSE (1.61 ± 0.55) and PA (71%) notably, which indicates that fitting the electrode impedance data with the simple Randles cell can lead to a better understanding of the distinguishing characteristics between different technologies. Nonetheless, it was the inclusion of the “Rand+W” parameters alongside the electrode $|Z|_{10\text{ Hz}}$ data that resulted

in the highest PA achieved with the MnLR model: 82% accuracy, with an MSE of 1.01 ± 0.56 . With this result, we could clearly assert that the modified Randles cell is a more robust ECM for understanding charge-transfer dynamics at the electrode-artificial skin interface, even across a variety of gelled and dry electrode technologies. To improve the model accuracy, we could include more impedance data (for example, the 1 Hz or 1 kHz magnitudes), but we expect that more complex ML models might also be considered, in which case previous literature has demonstrated the value of using SVM (Zhu et al. 2019), random forest approaches (Chen et al. 2025), or neural networks (Zulueta et al. 2023; Bongiorno et al. 2022).

Conclusions

In this report, we recorded impedance from a variety of commercially-available electrodes interfacing with artificial skin under ambient conditions. The samples

comprised both gelled and dry technologies and are examples of common electrodes used in a range of WHM applications. The impedance data was subsequently fitted using the common Randles cell, and a modified Randles cell which added a single Warburg impedance element to the overall design. Both models fit the impedance data well for all electrodes, as evidenced by similar ranges of χ^2 values. Furthermore, statistical assessments revealed that only a single model parameter (the double-layer capacitance, C_{dl}) was significantly different between the two models, although this difference could be easily ascribed to the presence of the Warburg element itself in the modified Randles cell. Accordingly, it was possible to assert that *either* ECM could be used to appropriately fit the impedance data collected, making interpretation of the results a matter of human (user) preference.

In an attempt to provide better assurances of selection “correctness,” we next completed a post hoc ML study, which used the $|Z|_{10\text{ Hz}}$ values and ECM parameters as inputs and predicted on the specific electrode type. In the first part of this exercise, LR was used for a binary classification to distinguish between gelled or dry electrodes. We found that *either* ECM could help with this classification, though impedance data alone was more than sufficient to achieve prediction accuracies above 80%. In the second scenario, using MnLR, we found that while the parameters of the simple Randles cell could be used alongside impedance moduli to improve prediction accuracies for a model that accurately predicted the electrode manufacturer, accuracies above 80% were only achieved when using the modified Randles cell parameters. This strongly suggests that the modified Randles cell provides unique, electrode-specific information which is critical for distinguishing not just between gelled and dry electrodes, but between different technologies altogether, such as the seven electrode types considered here.

While previous work has applied complex ML methods to assist with ECM selection, here we employed straightforward supervised learning approaches (LR and MnLR) to directly compare two common ECMs. This analysis supports the Warburg-modified Randles cell as the superior circuit model for impedance fitting with artificial skin, and, by extension, for studying electrode interactions with human skin; we therefore specifically recommend the Warburg-modified Randles cell for accurate electrode–skin characterizations. Beyond identifying the optimal ECM, this work has also outlined a practical methodology for evaluating competing ECMs using post hoc, supervised learning ML techniques which are easy to implement and to interpret. We strongly encourage others to adopt a similar approach when developing their own WHM technologies for next-generation healthcare applications.

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Authors' contributions

Conceptualization, B.B.M.; methodology, B.B.M.; investigation, B.B.M.; formal analysis, B.B.M.; resources, T.T.; writing—original draft preparation, B.B.M.; writing—review and editing, B.B.M. and T.T.; visualization, B.B.M.; supervision, T.T.; project administration, T.T.; budget acquisition, T.T. All authors have read and agreed to the published version of this manuscript.

Availability of data and materials

Please contact the corresponding authors with questions regarding data availability or sharing.

Declarations

Competing interests

The authors declare no conflicts of interest.

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