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IMPACT OF SAMPLING FREQUENCY ON SKIN RESISTANCE ANALYSIS FOR COMFORT EVALUATION IN VEHICLE CABINS

Ivan VITÁZEK*[1], Rastislav KOLLÁRIK[1], Jan JANČA[2], Željko JUKIĆ[3], Vladimír MADOLA[4]

[1]Slovak University of Agriculture in Nitra, Faculty of Engineering, Institute of Agricultural Engineering, Transport and Bioenergetics, Nitra, Slovakia, xkollarik@uniag.sk
[2]Mendel University in Brno, Faculty of Agrisciences, Department of Agricultural, Food and Environmental Engineering, Brno, Czech Republic, xjanca2@mendelu.cz
[3]University of Zagreb, Faculty of Agriculture, Department of Field Crops, Forage and Grassland, Zagreb, Croatia, zjukic@agr.hr
[4]Slovak University of Agriculture in Nitra, Faculty of Engineering, Nitra, Slovakia, vladimir.madola@uniag.sk

*correspondence: ivan.vitazek@uniag.sk

The assessment of in-vehicle comfort using physiological measurements has gained increasing attention in recent years. Skin resistance (electrodermal activity, EDA) represents a promising indicator of sympathetic nervous system activity and thermal comfort perception. This study examines the influence of sampling frequency on the analysis of skin resistance in relation to cabin temperature, providing insights relevant for adaptive HVAC systems. Data were collected during winter test drives in Škoda Kodiaq in collaboration with Mendel University. Electrodermal activity was recorded in four participants at 1 Hz and subsequently subsampled to lower frequencies (0.5 Hz, 0.2 Hz, and 0.1 Hz). Analytical methods included correlation analysis, entropy, and variability assessment. The results demonstrated that reducing the sampling frequency led to lower correlation strength and diminished signal information content. Sampling frequency therefore has a significant impact on the accuracy and interpretability of physiological signal analysis. An optimal balance between data quality and computational efficiency was observed in the range of 0.2–0.5 Hz. These findings provide a valuable basis for developing intelligent HVAC systems that integrate physiological feedback.

Keywords: skin resistance; electrodermal activity; sampling frequency; vehicle comfort; HVAC systems; physiological sensing

Thermal comfort (Carrilho da Graça and Martins, 2021) is a critical factor influencing the well-being (Balková et al., 2024), safety, and performance of drivers and passengers in a vehicle cabin (Huo et al., 2025). Modern automotive (Buchecker et al., 2022) research increasingly seeks objective methods to evaluate comfort, complementing subjective questionnaires. Among physiological indicators (Mehel et al., 2023), skin resistance (electrodermal activity, EDA) has emerged as a reliable measure (Partin et al., 2006) as it reflects sympathetic nervous system activity and thus provides insights into stress levels or discomfort (Sirirat et al., 2020).

In previous studies (Kollárik and Vitázek, 2024), including our own pilot research conducted under winter conditions, EDA was analysed in relation to comfort-enhancing features such as heated seats, heated steering wheels, and the Air Care function. Most of these studies employed a fixed sampling frequency (commonly 1 Hz) (Madola et al., 2023), without critically evaluating its impact on the accuracy and interpretability of the results.

Given that adaptive Heating, Ventilation and Air-conditioning (HVAC) systems will likely need to process physiological signals in real time with computational constraints (He et al., 2024), understanding the influence of sampling frequency is crucial. This research therefore focuses on quantifying how different sampling frequencies affect the correlation between EDA and cabin temperature, entropy, and signal variability.

The main output of this manuscript is the quantitative evaluation of how sampling frequency affects the accuracy of electrodermal activity analysis in relation to cabin temperature. The novelty of this study lies in identifying the optimal frequency range (0.2–0.5 Hz) that balances information richness and computational efficiency, which is a crucial innovation for future adaptive HVAC systems relying on physiological sensing.

Material and Methods

The study was conducted in Škoda Kodiaq during real winter driving tests in cooperation with Mendel University. The selection of a suitable car is described, for example, by Khodkam et al. (2025). Four participants (W1, W2, M1, M2) took part in the experiment (age: 20–28 years; weight: 65–92 kg; height: 163–183 cm). All were healthy adults with no signs of acute illness. The gender ratio was balanced 1 : 1.

A schematic layout of the measurement setup is provided in Fig. 2, and a photographic view of the instrumentation is shown in Fig. 1. The EDA sensor (Herceg and Herceg, 2020) operated in the range of 0–100 μS with a resolution of 0.01 μS and accuracy of ±5%. Temperature sensors had an accuracy of ±0.3 °C and resolution of 0.1 °C. The overall measurement uncertainty was evaluated at < 5% for all recorded parameters.

Fig. 1 Experimental setup in the vehicle

All participants experienced a similar level of mental load, as the measurements took place within the premises of the university campus, ensuring consistent conditions for all drives. This controlled environment helped maintain uniform experimental parameters and minimised external influences that could affect skin resistance values. The cabin temperature was gradually increased from 18 °C to 24 °C across different configurations of comfort features.

- Electrodermal activity (EDA): measured using sensors attached (Herceg and Herceg, 2020) to the distal phalanges of the fingers.
- Temperature: measured by two sensors – one near the chest (close to the body) and one mounted on the sun visor (close to the windshield).
- Comfort features tested: standard heating, heated steering wheel, heated seats, and Air Care (varied across different configurations) shown in Table 1.
- Sampling frequency: 1 Hz (original measurements).

Each participant completed a 30-minute drive along the same route. Prior to each session, the vehicle was pre-heated to operating temperature. After every measurement, the vehicle interior was ventilated for 5 minutes at the same location to ensure consistent starting conditions for all participants. The climate control system was left in automatic mode with target temperature settings.

The experimental procedure was designed in accordance with general recommendations for physiological measurements in ergonomics and automotive comfort studies (e.g., ISO 14505-2, 2006).

Data processing

Subsampling was performed on the original 1 Hz data to obtain lower frequencies:

- 0.5 Hz (every second sample),
- 0.2 Hz (every fifth sample),
- 0.1 Hz (every tenth sample).

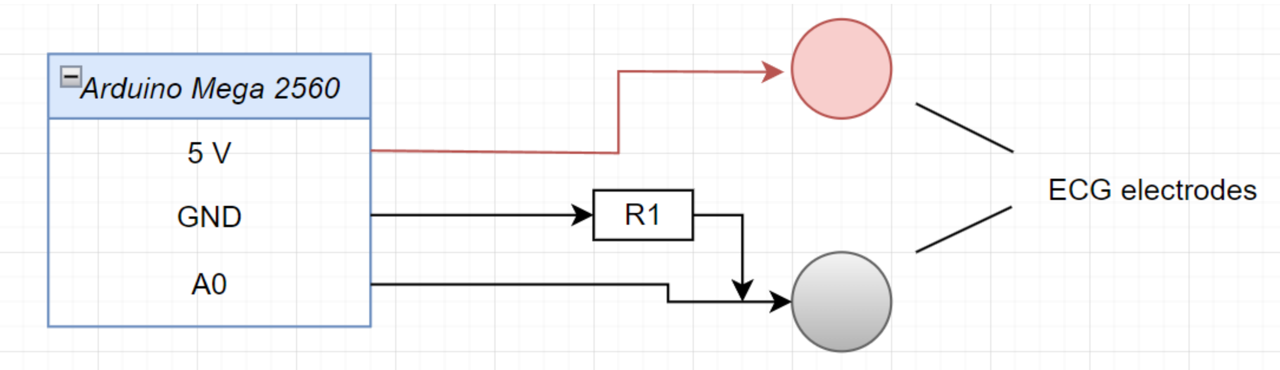

Fig. 2 A schematic layout of the measurement setup

Table 1 Comfort feature combinations

	Standard heating	Heated steering wheel	Heated seat	AirCare
Option 1	✓	☒	☒	☒
Option 2	✓	✓	☒	☒
Option 3	✓	✓	☒	✓
Option 4	✓	☒	✓	☒
Option 5	✓	✓	✓	✓

✓ – enabled; ☒ – not enabled

Table 2 Effect of sampling frequency on the correlation between EDA and chest temperature

Frequency	Mean ρ (EDA vs. T_chest)	Variance
1 Hz	-0.79	0.03
0.5 Hz	-0.74	0.04
0.2 Hz	-0.65	0.07
0.1 Hz	-0.58	0.10

Table 3 Effect of sampling frequency on entropy and variability of EDA signals

Frequency	Entropy (bits)	Standard Deviation
1 Hz	2.71	1.29
0.5 Hz	2.48	1.12
0.2 Hz	2.12	0.94
0.1 Hz	1.78	0.72

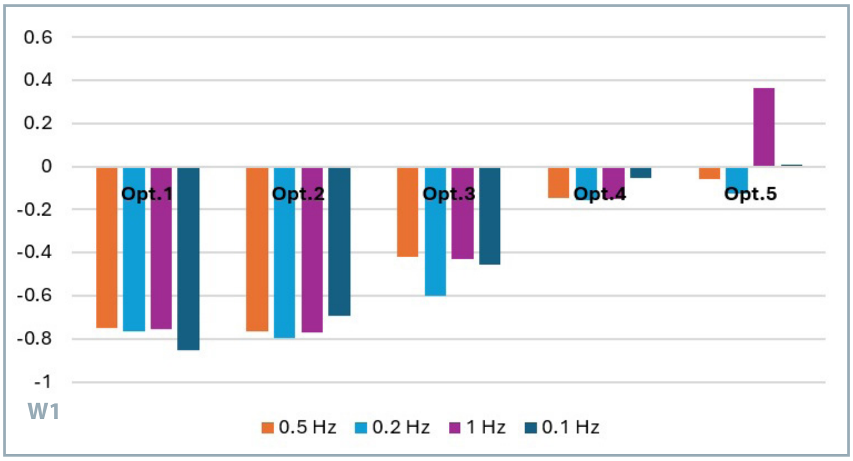

Fig. 3 Correlation coefficients across sampling frequencies for Subject 1 (Options 1–5)

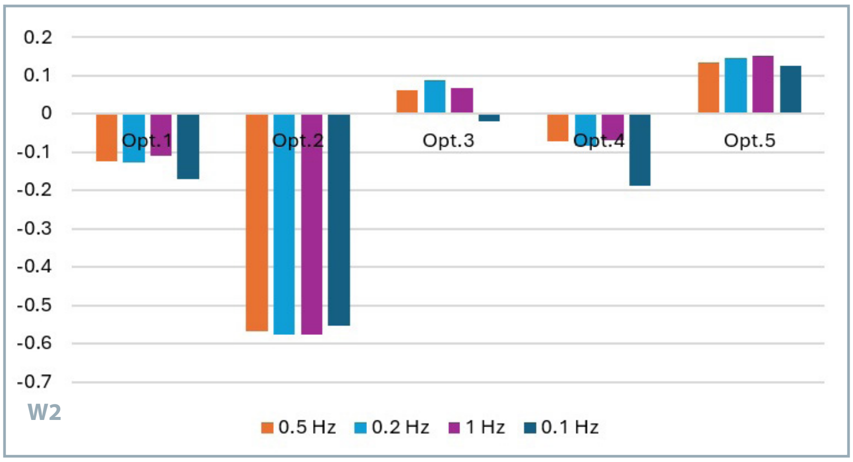

Fig. 4 Correlation coefficients across sampling frequencies for Subject 2 (Options 1–5)

Analytical methods

Normality test: Shapiro-Wilk test, confirming non-normal distribution (Reynolds et al., 2025).

Correlation analysis: Spearman's rank correlation between EDA and cabin temperature (Lyu et al., 2024).

Signal entropy: Shannon entropy as a measure of information density.

Variability analysis: standard deviation of the signal (Takefuji, 2025).

Results and Discussion

Correlation analysis

The strongest correlations were found at higher frequencies shown in Table 2. Below 0.2 Hz, the signal lost sensitivity to short-term physiological responses, leading to weaker or even altered correlation patterns.

Entropy and variability

Entropy and variability both decreased consistently with lower sampling frequencies, reflecting the loss of finer details in EDA signals. Results are shown in Table 3.

Individual variability

Notable differences between subjects were observed. For example:

- Subject 1 (W1): The correlations across all options were predominantly negative (Fig. 3), with relatively high variability depending on sampling frequency. In Option 1 and Option 2, correlations remained consistently strong and negative (ρ ≈ -0.75 to -0.85). In Option 3, values were moderately negative (around -0.42 to -0.46), while in Option 4, correlations weakened substantially (ρ ≈ -0.05 to -0.15). The most pronounced variability was observed in Option 5, where the correlation changed direction depending on frequency: ranging from weakly negative (–0.05) to positive (ρ = 0.37 at 1 Hz).
- Subject 2 (W2): This subject demonstrated a different pattern compared to others. Correlations were mostly weak to moderate (Fig. 4), with some paradoxical increases at lower frequencies. For Option 1 and Option 2, correlations stayed consistently negative (around -0.11 to -0.57). In Option 3, however,

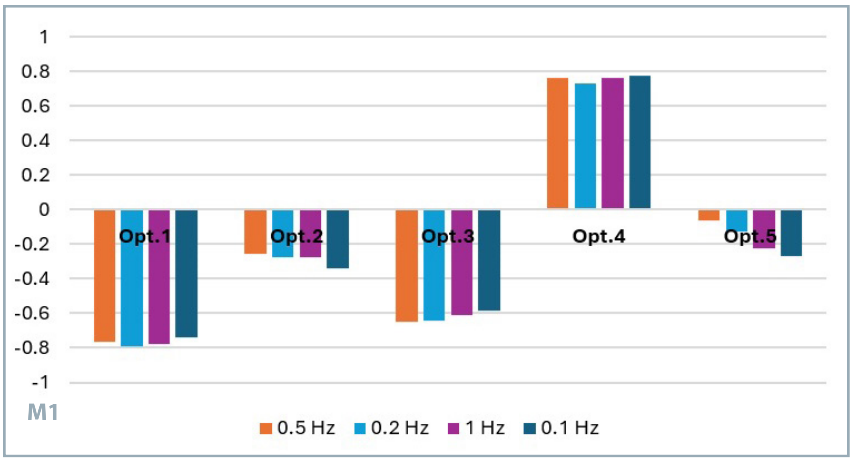

Fig. 5 Correlation coefficients across sampling frequencies for Subject 3 (Options 1–5)

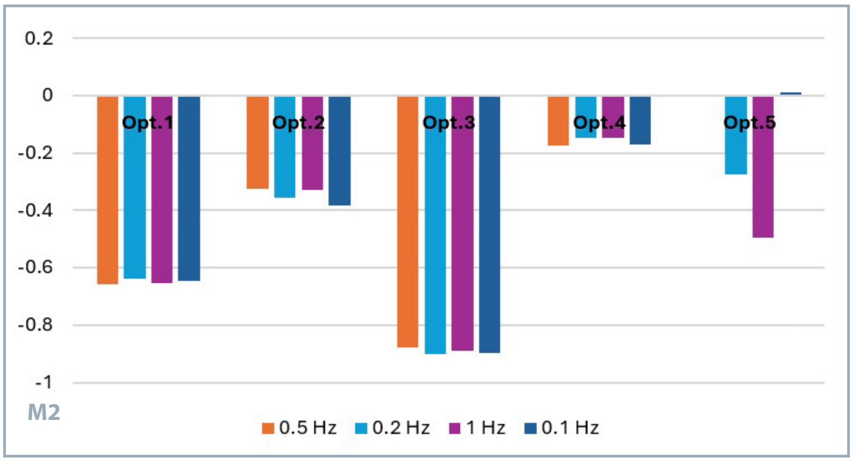

Fig. 6 Correlation coefficients across sampling frequencies for Subject 4 (Options 1–5)

the correlation shifted: while most frequencies showed slightly positive associations (ρ ≈ 0.06), at 0.1 Hz the relationship became negative (ρ = -0.02). Option 4 produced only weak negative correlations (-0.06 to -0.18). In Option 5, correlations were small but positive across all frequencies, suggesting a subject-specific dynamic response.

– Subject 3 (M1): This subject displayed (Fig. 5) strong and stable negative correlations across Options 1, 2, and 3 (ρ ≈ -0.52 to -0.78), with minor variation across frequencies. A contrasting behaviour was observed in Option 4, where consistently strong positive correlations were found (ρ ≈ 0.76). Option 5 yielded predominantly negative correlations, ranging from -0.06 to -0.27, with a tendency toward stronger negativity at lower frequencies.
– Subject 4 (M2): The correlations for Subject 4 were characterised by extremely strong negative values (Fig. 6), especially in Option 3 (ρ ≈ -0.88 to -0.90 across all frequencies). Option 1 and Option 2 also produced moderate to strong negative correlations (ρ ≈ -0.32 to -0.65). In Option 4, correlations were weak and negative (-0.09 to -0.17), while Option 5 showed very weak or inconsistent associations, ranging from slightly positive (ρ = 0.01 at 0.1 Hz) to strongly negative (ρ = -0.49 at 1 Hz).

This research confirms that sampling frequency substantially affects the interpretability of EDA signals in vehicle comfort research (Mercier et al., 2022). Higher frequencies (1 Hz) provide more detailed insights into short-term fluctuations (Basarkod et al., 2024), but require more storage and processing capacity (Geck et al., 2024). Lower frequencies reduce computational load (Chen et al., 2023), but at the cost of information loss.

The observed individual differences suggest that a one-size-fits-all approach may not be sufficient (Dogan and Acarman, 2025). Adaptive strategies could be necessary (Juuse et al., 2024) where sampling frequency dynamically adjusts depending on both system constraints and the stability of individual responses (Beloev et al., 2021). This would be particularly beneficial in future HVAC systems (Kristanto and Leephakpreeda, 2018) where real-time comfort evaluation must balance accuracy and efficiency.

The results are consistent with previous pilot research conducted in winter conditions (Kollárik and Vitázek, 2024), reinforcing the notion that the 0.2–0.5 Hz range represents a pragmatic compromise between information richness and practical feasibility. Below 0.2 Hz, the suppression of short-term physiological responses limits the ability to detect subtle changes in comfort perception.

Conclusion

This research demonstrated that lowering the sampling frequency of electrodermal activity (EDA) signals reduces the strength of correlations with cabin temperature, as well as signal entropy and variability. While some subjects maintained relatively robust responses even at lower frequencies, the general trend confirmed significant information loss when reducing resolution.

From a practical perspective, the range of 0.2–0.5 Hz can be considered a compromise, as it substantially decreases computational demands and data storage requirements. However, this reduction comes at the cost of weakened sensitivity to short-term physiological changes, thereby lowering the credibility and precision of the results.

For future applications in intelligent HVAC systems, it is recommended to adapt sampling strategies dynamically: using higher frequencies (around 1 Hz) when detailed comfort assessment is critical and applying reduced frequencies (0.2–0.5 Hz) when system resources are limited or when long-term monitoring is prioritised.

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