Part III

Artificial Intelligence and Augmented Intelligence

Chapter 20

Baseline Evaluation for Enhancing Human–Robot Collaboration (HRC) in Industry 5.0 Manufacturing

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Abstract

Industry 5.0 emphasises human-robot collaboration (HRC) as a human-centred paradigm. This work establishes a psychophysiological baseline during a cobot-assisted assembly task using electroencephalography (EEG), electrodermal activity (EDA), and heart rate variability (HRV) recorded from five participants across baseline, relaxation, and repeated task cycles, complemented by a dual video stream for ergonomic analysis. The HRC task elicited reduced phasic EDA, a strong increase in tonic activity (+239%), elevated heart rate (+12%), reduced RMSSD, and a higher (low/high frequency) LF/HF ratio, reflecting sympathetic predominance and fatigue-related strain. These results show that even structured HRC tasks impose measurable physiological load. The proposed multimodal baseline enables the development of adaptive cobot strategies responsive to operator stress and workload.

Keywords: *Industry 5.0, Human–Robot Collaboration, Electroencephalography, Heart Rate, Electrodermal Activity, Adaptive Collaborative Robots*

Introduction

Industry 5.0 extends prior automation paradigms by prioritising human well-being, resilience, and sustainability alongside productivity[1]. This paradigm highlights sociotechnological collaborations between humans and machines to enhance productivity while ensuring safety, adaptability, and social responsibility[2]. Within this framework, human–robot collaboration (HRC) positions robots as cooperative partners rather than mere tools[3]. Collaborative robots (cobots) are designed to safely

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[1] Pedro Coelho et al., "Industry 5.0: The Arising of a Concept," *Procedia Computer Science* 217 (1 January 2023): 1137–44. https://doi.org/10.1016/J.PROCS.2022.12.312

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DOI: 10.18502/rq457c78_20

operate alongside humans in shared workspaces[4]. Unlike traditional industrial robots, cobots use sensing, control, and adaptive algorithms to adjust in real-time to human actions[5].

As task demands vary in HRC, operators show physiological and cognitive responses reflecting changes in workload and attention[6]. Monitoring these responses reveals how operators adapt to task complexity, while wearable sensors enable continuous, non-invasive assessment in real-world industrial settings[7]. Heart rate variability (HRV) and electrodermal activity (EDA) index autonomic regulation and sympathetic arousal[8] and electroencephalography (EEG) offers markers of attention and cognitive control[9]. Together, these measures support operator-aware multimodal assessment in HRC.

Detecting stress and workload in HRC requires being sensitive to physiological changes yet robust in real-world settings. Multimodal sensing outperforms single-signal approaches by combining complementary channels[10]. Advanced fusion methods, including deep learning, have shown high sensitivity to acute stress. However, their robustness often degrades in industrial environments due to artefacts, sensor variability, and uncertain labels[11]. Consequently, interpretable rule-based or hybrid pipelines that integrate physiological features with contextual information offer a more practical alternative[12].

This study introduces a controlled HRC (Figure **1**) paradigm that combines laboratory rigour with real-world applicability. Synchronised EEG, HRV, EDA, and video data were collected across baseline and repeated cobot-assisted tasks to support both interpretable features analysis and benchmarking of fusion models, providing a foundation for adaptive Industry 5.0 collaboration.

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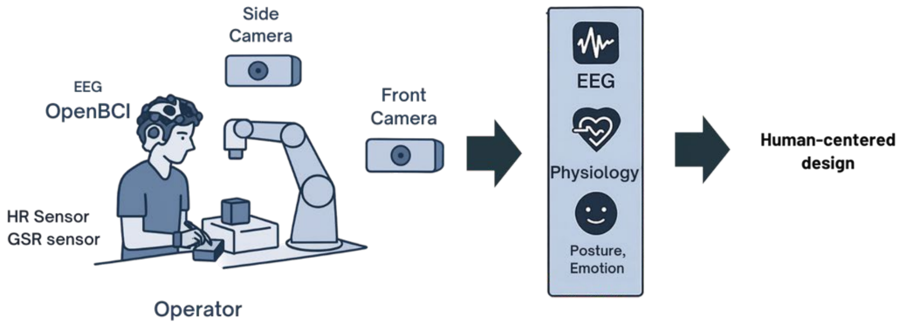


Figure 1: Experimental Setup for HRC Assembly.

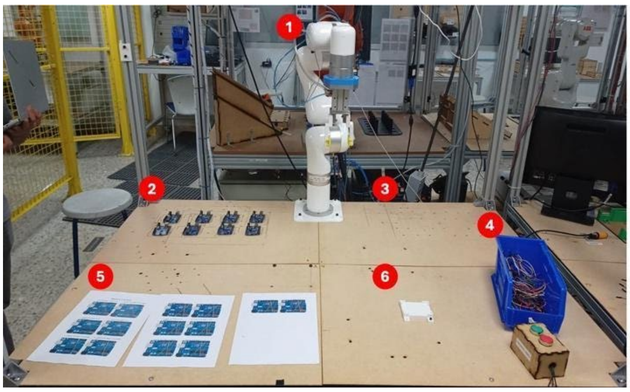
Methods

Participants and Setting

The study was conducted at the FrED Factory Lab (25 °C, 102 kPa). Five engineering undergraduates (19-21 years; four male, one female; right-handed) participated. Three had prior cobot exposure. None reported neurological or cardiovascular disorders or medication affecting automatic function. Informed consent was obtained.

Experimental Protocol

Participants completed two seated baselines (90 s each): eyes open and eyes closed. They then performed six consecutive cobot-assisted assembly trials (~35 min total). An xArm 6 XI1202 delivered an Arduino Uno board; participants connected 14 jumper wires following visual instructions and signalled completion for retrieval. The full session lasted ~1 hour (Figure **2**).



1. **Cobot**
2. **Pre-Assembly Arduinos**
3. **Post-Assembly Arduinos**
4. **Jumper Container**
5. **Instruction Manual**
6. **Push-buttons**

Figure 2: Overview of the workstation.

Data Acquisition

EEG was recorded using an OpenBCI Ultracortex Mark IV (8 dry electrodes: FP1, FP2, C3, C4, P3, P4, T5, T6). Cardiac activity was captured via Polar H10 (HR at 1 Hz). EDA was measured with a Grove GSR sensor (~5.5 Hz) embedded in open-finger gloves and streamed via an ESP32. Two synchronised video streams (frontal and lateral) supported behavioural and ergonomic analysis. All modalities were time-synchronised and stored for offline analysis (Figure **3**).

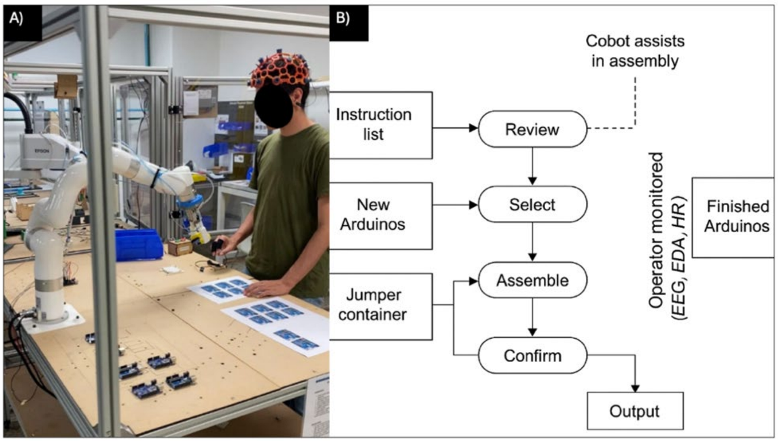


Figure 3: Experimental execution in the non-adaptive condition: (a) participant and (b) workload.

Analysis

EDA was decomposed into tonic and phasic components, with features including SCR peaks/min and band power. Cardiac metrics included mean HR, RMSSD, and frequency-domain LF/HF components. Ergonomic analysis extracted joint angles (shoulder, elbow, wrist, neck, trunk) and time spent in low-, medium-, and high-risk postural bands.

Results

Electrodermal Activity

Relative to the eyes-open baseline, eyes-closed relaxation reduced SCRs modestly (-11%). During HRC, SCRs decreased substantially (-42%), while tonic EDA increased progressively from baseline to eyes closed (+40%) and peaked during HRC (+239%). Phasic power increased slightly during eyes-closed relaxation (+12%) but decreased during HRC (-17%), indicating a shift from transient reactivity to sustained sympathetic activation. Figure **4** presents the 3D GSR spectrograms across conditions for a representative participant.

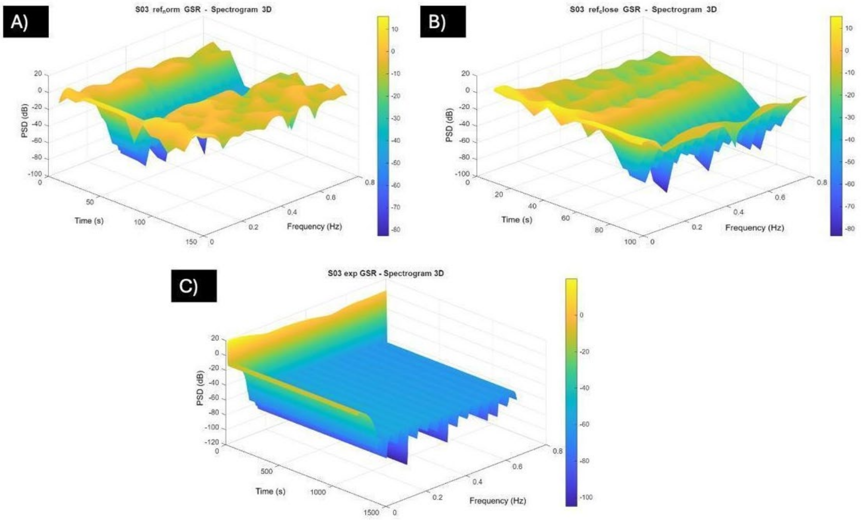


Figure 4: Subject 3: A) eyes open, B) eyes closed, C) experience. 3D spectrograms showing the power spectral density (PSD).

Figure **5** shows the distribution of skin conductance responses (SCRs) per minute across eyes-open, experimental, and eyes-closed conditions.

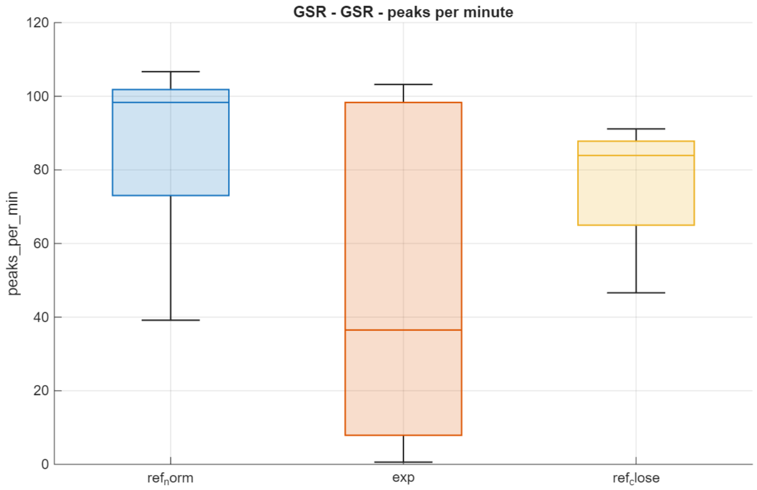


Figure 5: Box plot of GSR peaks per minute.

Figure **6** shows changes in tonic and phasic GSR components across conditions. Tonic activity was low at the eyes-open baseline, increased during eyes-closed rest (+40%), and rose markedly during the HRC task (+239%).

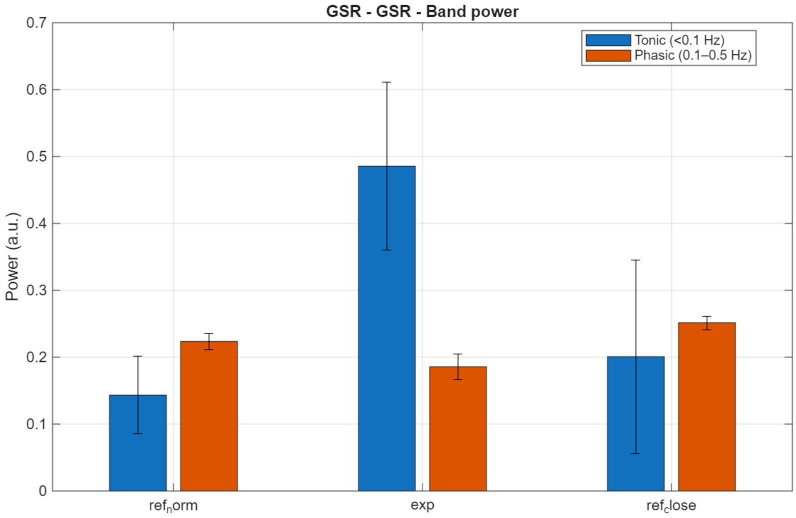


Figure 6: Box plots of GSR band power.

Table **1** summarises GSR features across conditions**.** SCRs decreased from baseline to the HRC task, while tonic power increased and phasic power declined, indicating sustained sympathetic activation.

Table 1: GSR metrics by condition.

Metric	Ref (eyes open)	Ref (eyes closed)	Experimental
Peaks per min (GSR)	85.73 ± 27.29	76.39 ± 20.16	49.46 ± 47.97
Tonic power	0.14 ± 0.13	0.20 ± 0.29	0.49 ± 0.28
Phasic power	0.22 ± 0.03	0.25 ± 0.02	0.19 ± 0.04
Min	-1.38 ± 0.45	-1.38 ± 0.37	-1.06 ± 1.11
Max	1.64 ± 0.20	1.55 ± 0.12	5.22 ± 7.43

Cardiac Measures

Mean HR remained stable at baseline (~77 bpm), increased slightly during eyes-closed relaxation (+3%), and rose during HRC (+12%). RMSSD decreased during HRC, indicating reduced parasympathetic modulation. Frequency-domain analysis showed increases in both LF (+28%) and HF (+26%) during HRC, with a higher LF/HF ratio consistent with sympathetic predominance. Figure **7** compares the distribution of average cardiac activity across the same three conditions (*ref_norm, exp, and ref_close*).

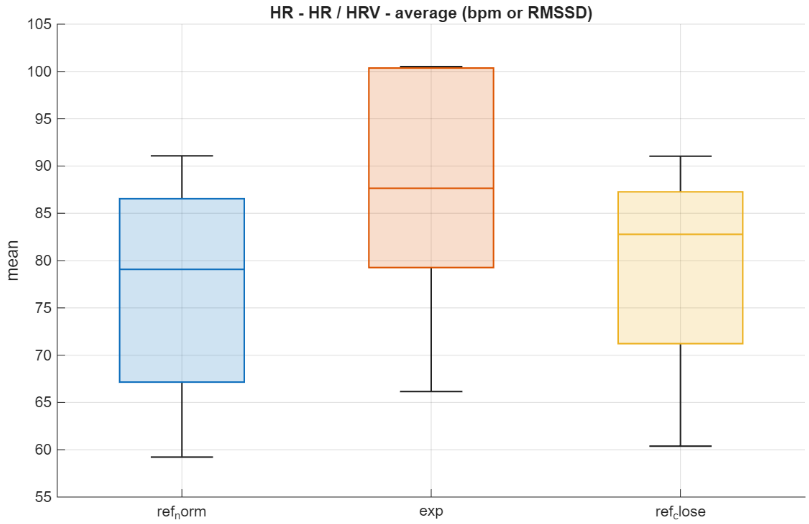


Figure 7: Box plot of HR/HRV average.

Figure **8** shows increased LF and HF power with a higher LF/HF ratio during HRC, indicating sympathetic dominance.

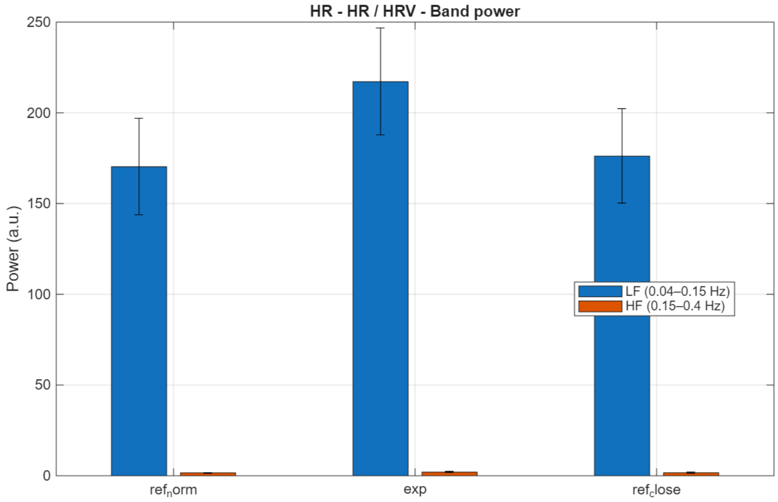


Figure 8: Box plots of HR/HRV band power.

Table **2** summarises cardiac indices across conditions. Mean HR and LF/HF increased during HRC, indicating sympathetic predominance, whereas the eyes-closed baseline showed a more balanced autonomic profile.

Table 2: HR / HRV metrics.

Metric	Ref (eyes open)	Ref (eyes closed)	Experimental
Mean	76.84 ± 12.60	79.24 ± 13.18	87.65 ± 14.17
SD	3.41 ± 2.35	2.76 ± 0.80	3.81 ± 0.97
Tonic power	170.29 ± 59.43	176.14 ± 52.09	217.18 ± 65.77
Phasic power	1.61 ± 0.56	1.66 ± 0.52	2.03 ± 0.64

Ergonomic Assessment

Most joints operated within low-risk ranges. Shoulder elevation and trunk flexion remained low and stable; elbow flexion showed moderate variability. Wrist flexion exhibited frequent deviations, and neck flexion consistently occupied high-risk bands, identifying primary ergonomic concerns during the task. Figure **9** shows the frontal and lateral views of the operator while performing an assembly task with a cobot.

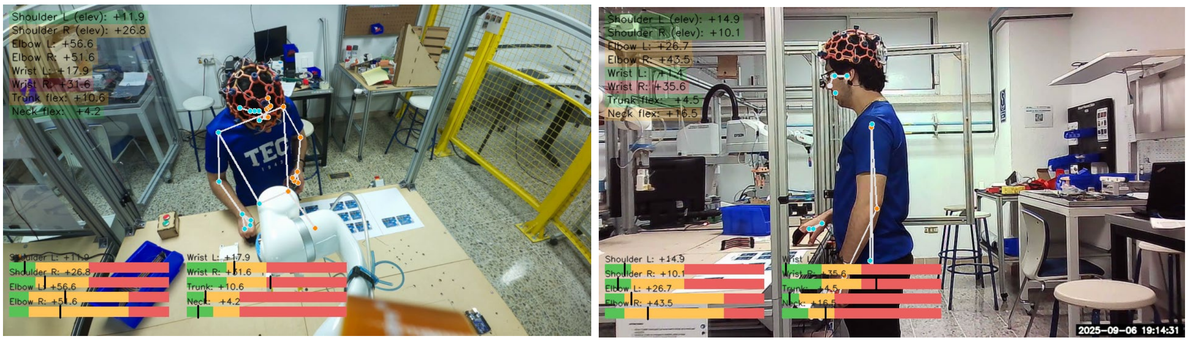


Figure 9: Ergonomic analysis of the operator.

Figure **10** illustrates the distribution of joint angles recorded during the task.

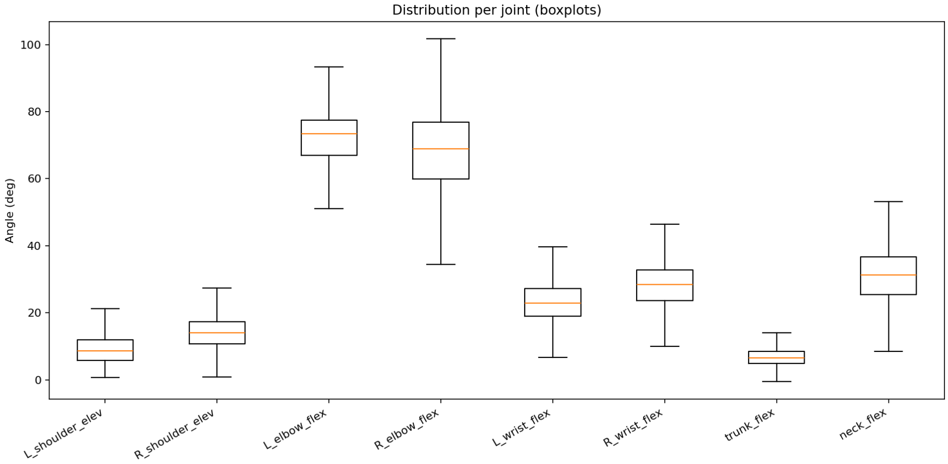


Figure 10: Distribution per joint: shoulders, elbows, wrists, trunk, and neck.

Figure **11** highlights neck and wrist postures as the main ergonomic risk factors during the task.

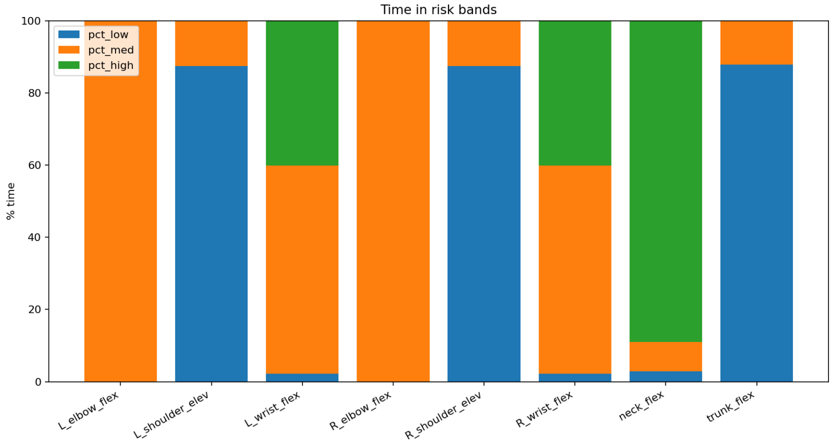


Figure 11: Percentage of task duration for each joint.

Discussion

This study shows that repetitive HRC elicits stress- and fatigue-related psychophysiological signatures, characterised by reduced phasic EDA (−42%) and elevated tonic activation (+239%), indicating sustained sympathetic arousal, a pattern commonly linked to cumulative stress and mental fatigue[13] [14]. Together, these findings indicate that even predictable cobot-assisted tasks impose a measurable physiological load on operators.

These results align with prior work showing that physiological stress markers can emerge without conscious awareness, as demonstrated by rule-based GSR approaches[15], and with studies highlighting the effectiveness of multimodal biosensing for stress detection[16]. While deep-learning approaches emphasise classification accuracy, the present study prioritises interpretable physiological markers to better characterise the operator stage during HRC.

Ergonomic analysis identified neck flexion and wrist deviation as primary risk factors, consistent with links between sustained postures, autonomic stress, and altered HRV [17]. This convergence suggests a dual risk of physical strain and stress during HRC tasks.

Conclusions and Future Work

This study establishes a concise multimodal baseline for assessing stress, fatigue, and ergonomic risk in HRC, aligned with Industry 5.0 principles. HRC tasks elicited sustained sympathetic activation relative

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[14] Hugo F. Posada–Quintero et al., “Elevation of spectral components of electrodermal activity precedes central nervous system oxygen toxicity symptoms in divers,” *Communications Medicine* 4, no. 1 (2024): 1–11.10.1038/s43856-024-00688-4

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[16] Jing Zhang et al., “Real-time mental stress detection using multimodality expressions with a deep learning framework,” *Frontiers in Neuroscience*, 16, (2022): 947168. 10.3389/fnins.2022.947168

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to baseline, while ergonomic analysis highlighted risks to the neck and wrist. These insights support adaptive cobot strategies that adjust behaviour based on operator state, potentially improving safety, performance, and well-being. Future work will integrate real-time EEG features and adaptive control to personalise collaboration.

Acknowledgements

The authors acknowledge the FrED Factory Lab at Tecnológico de Monterrey and thank Dr. Manuel Cebral, Dr. Mauricio Ramirez, and Iñaki García Bárcena García for their support.

Supplementary Information

Ethics and Consent: Ethical approval was waived due to the absence of identifiable data. Informed consent was obtained from all participants.

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