An IoT-Based System for the Study of Neuropathic Pain in Spinal Cord Injury

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Abstract. Neuropathic pain is a difficult condition to treat and would require reliable biomarkers to personalise and optimise treatments. To date, pain levels are mostly measured with subjective scales, but research has shown that electroencephalography (EEG) and heart rate variability (HRV) can be linked to those levels. Internet of Things technology could allow embedding EEG and HRV in easy-to-use systems that patients can use at home in their daily life. We have developed a system for home monitoring that includes a portable EEG device, a tablet application to guide patients through imaginary motor tasks while recording EEG, a wearable HRV sensor and a mobile phone app to report pain levels. We are using this system in a clinical study involving 15 spinal cord injury patients for one month. Preliminary results show that relevant data are being collected, with inter and intra-patients variability for both HRV and pain levels, and that the mobile phone app is perceived as usable, of good quality and useful. However, because of its complexity, the system requires some effort from patients, is sometimes unreliable and the collected EEG signals are not always of the desired quality.

Keywords: IoT · EEG · HRV · Neuropathic pain · mobile health

1 Introduction

Neuropathic Pain (NP) is defined by the International Association for the Study of Pain as "pain caused by a lesion or disease of the somatosensory nervous system" [1] and is considered one of the most difficult painful conditions to treat [3]. NP is present, for example, in Spinal Cord Injury (SCI), with a prevalence ranging between 40% [27] and 60% [32]. Unfortunately, pharmaceutical treatments for NP have limited efficacy (<50%) [8], hence an objective and robust biomarker for NP is desirable to personalise and optimise treatments.

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The measurement of the intensity of NP is based on psychometric scales and quality of life questionnaires [6,10]. This introduces subjectivity and only a partial/static view of the wide circumstances of the patients, which also affects the estimation of the effectiveness of treatments both in clinics and trials. To avoid bias, daily records of the level of pain become a tool to complement the proper evaluation of the patient.

Given that pain causes autonomic responses, physiological variables can be measured as biomarkers for NP, such as blood pressure, skin conductance, respiration heart rate, and electroencephalography (EEG) [14,18]. Particularly heart rate variability (HRV) shows a clear link with pain [13], due to the decrease in parasympathetic activation, which causes decreased high-frequency HRV [31] and has been even associated with the subjective experience of pain [9]. In addition to HRV, a recent systematic review on biomarkers for chronic NP [19] identified EEG as a candidate method for measuring NP objectively. These findings suggest that the combined use of EEG and HRV could provide a reliable, objective quantification of NP, as proven, for example, in placebo analgesia [7].

Internet of Things technologies could provide a means to measure these quantities with high frequency and at patients' homes. HRV can nowadays be acquired continuously by inexpensive wrist-worn fitness trackers and smartwatches [20], which can share data through their companion smartphone apps. HRV, however, can be affected by several factors in addition to pain [36], and should therefore be completed with EEG, which can be delivered with modern portable EEG devices [37], and used during scheduled measurement sessions guided through a personal computer or smartphone [2].

In terms of mobile and IoT-based systems for pain measurement and management, the literature review shows a scarcity of proven solutions, notwithstanding the growing interest in the matter [21]. Typical applications include electronically delivered surveys and scales, training programs for treatment and self-management, remote consultations, rehabilitation, psychological support and therapies, medication management and adherence [16,29,30]. Similarly, systems using objective sensor data are scarce in extant research. The aim of this study is therefore to develop an IoT-based system for the study of pain in home settings using EEG and HRV as objective measurements of pain.

This paper is structured as follows: Sect. 2 describes previous work, Sect. 3 describes the developed system while Sect. 4 provides preliminary statistics collected from our running clinical study. Finally, Sect. 5 concludes the findings so far and outlines opportunities for future development.

2 Previous Work

Machine learning has been used to identify spinal cord injured participants at risk of developing central NP from multichannel EEG [35]. Three classifiers (artificial neural networks ANN, support vector machine SVM and linear discriminant analysis LDA) were shown to obtain similar results with higher than 85% classification accuracy on a full set of features. Similarly, using a Support Vector

Machine algorithm has been proven to allow differentiation between patients with chronic pain and healthy controls [34]. This showed an accuracy of >85% solely based on the brain activity of three regions of interest: somatosensory cortex and pregenual and dorsal anterior cingulate cortices.

HRV has been studied on electrocardiogram collected from healthy subjects and patients with and without NP at rest [12]. Results show that participants with NP exhibit a lower HRV, as determined by the standard deviation in R-R length. Studies of electronic systems and IoT have used wearable accelerometers to quantify daily activity in patients with pain [4,28,33]. These highlight that there are differences in activity and behaviour between patients and healthy controls, thus outlining the direction as promising.

In order to detect and quantify pain, one approach has been to measure heart rate, skin conductance, skin temperature and respiratory rate [22]. The data were then combined using an Artificial Neural Network (ANN) and a Fuzzy expert system. Additionally, this research employed a mobile phone app to collect data and provide first-hand assistance. Another example of combining multiple sensors to recognise pain level in healthy volunteers subjected to painful heat stimuli include taking signals from 3 cameras, a Kinect, facial electromyography (EMG), skin conductance level and electrocardiogram [11]. These data were used to train machine learning algorithms where ECG was used to extract features from RR intervals, similarly to how HRV is computed.

Finally, facial EMG has also been used to implement a novel sensor based on a flexible printed circuit board which naturally fits a human's face [38]. This system includes a mobile phone app to receive the sensor data through WiFi, and a cloud-based architecture where to store, review and process patients' data in almost-real time. The proposed solution is, however, impractical in the long term.

While the literature review shows a supportive stance on the idea of combining several sensors' data to measure pain, the majority of proposed systems are prototypes tested with healthy individuals subject to induced pain. Very few have been clinically validated with patients with NP and no studies were found where EEG and HRV are combined in those patients.

3 Methods

We have developed an IoT-based system for the collection of HRV, EEG data, and self-assessment of pain level, which is being used in a clinical study with SCI patients.

3.1 Study Protocol

We are recruiting 15 SCI patients for one month each. Subjects are recruited at the National Hospital for Paraplegics, Toledo, Spain. To include a representative and ample sample of the SCI population, the inclusion criteria are age between 18 and 75 years, any aetiology, any level of injury, minimum time post-SCI of 6 weeks, presence of pain for more than 4 weeks, and a pain level between 2 and 8. The exclusion criteria are severe psychiatric disorders, regular drug use, and the impossibility of using the app. This experimental protocol was approved by the ethics committee of the University Hospital Complex of Toledo (No. CEIC-621) and conducted according to the Declaration of Helsinki.

Patients are asked to record their pain level 3 times a day using a mobile-phone-based Visual Analogue Scale (VAS) [5]. The VAS scale is filled in at least 3 times a day (reminders are sent at 8:00, at 14:00, and at 20:00), but patients are also asked to fill in pain levels when they recognise that the pain is increasing, in accordance with a momentary assessment method [23]. Additionally, patients are asked to wear a smartwatch to measure heart rate variability continuously. Patients record their EEG activity once per day (30 days) guided by a tablet application that defines when to rest or perform an imaginary motor task. Fifteen days after starting the study, patients are asked to answer a usability [15] and technology acceptance [17] questionnaire, delivered through the app.

3.2 IoT System

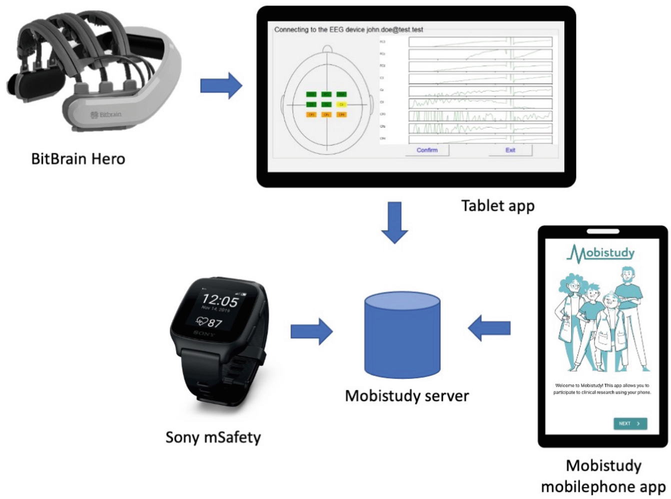

Fig. 1. IoT-base system architecture including sensors (Sony mSafety and BitBrain Hero), user applications (Mobistudy app and tablet app) and server.

We developed an IoT system with four modules (see Fig. 1). First, we use the Mobistudy app [25] to allow patients to record their pain levels. Through the app, patients can create a profile and join the PainApp study using an invitation code. The app sends reminders to ask patients to fill in the VAS scale when a task is due, but patients are also able to report their pain level at any time. The

VAS scale was implemented using a horizontal slider with values from 0 to 100. To allow patients to focus on the visual scale rather than the numerical value, the actual chosen value is not shown on the interface. Usability and acceptance questionnaires are also delivered through the app, using its configurable "forms" feature [24].

Second, we use a smartwatch used for collecting HRV data. We use the Sony mSafety wearable device, which is able to measure steps, heart rate, heart rate variability and activity type. We configured the device to measure HRV every 15 min. The data is sent by the watch to data storage using an embedded LTE CAT-M1 radio communication module. Messages are encrypted when sent and unencrypted when downloaded from the mSafety infrastructure.

Third, a tablet application allows patients to perform imaginary motor tasks while measuring brain activity through EEG. As EEG device, we use the wearable and mobile BitBrain Hero EEG headset, with 9 dry electrodes. The tablet application connects to the Hero through a USB or Bluetooth connection, collects the raw EEG data, and guides the user through the tasks defined according to the protocol [26].

Fourth, a backend server collects all data from applications and devices, using the Mobistudy REST API. The mobile phone and tablet applications are integrated with the server, and the data from smartwatches are downloaded from the mSafety infrastructure through a webhook.

4 Preliminary Results and Discussion

The clinical study is still running at the time of writing. As more than half of the patients have completed the study, we present preliminary statistics about usage and information useful to evaluate the reliability and usability of the system, based on the data collected.

Eighteen patients have been involved so far, with 12 having concluded the study and 3 having dropped out for technical reasons: two users could not register EEG data with enough quality and 1 patient did not receive notifications on the phone. Five patients are female and 13 are male. The average age is 46.5 with an 8.7 standard deviation.

Ten patients have contributed with 218 EEG sessions in total. Thirteen patients have contributed with 653 pain level reports using the app and 8 patients have contributed with 5673 HRV measurements since the start of the study.

During the execution of the study, a bug was identified in the Mobistudy app that prevented scheduled notifications to be sent after the first 3 days of participation. The bug has not been completely fixed yet, but, 3 months after the beginning of the study, patients were made aware of it and instructed about how to temporarily circumvent it. This issue had an impact on the number of responses received (which is difficult to quantify) and led to one patient ceasing to report pain levels completely.

A box plot of the received VAS pain levels recorded through the app is shown in Fig. 2. It can be observed that pain levels vary considerably among patients (inter-patient variation) with some patients having wider variations than others (intra-patient variation). The inter-patient variation is promising for associating EEG and HRV features with pain levels as greater variability will facilitate the development and validation of algorithms able to associate features on a wider scale. These results suggest that patients with a high level of pain are indicative of ineffective treatment and that intra-patient variation can indicate the need for a more adjusted treatment regime, for example, to contrast the effect of the medication gradually fading during the day. This exemplifies the potential usefulness of telemonitoring systems in clinical practice for NP.

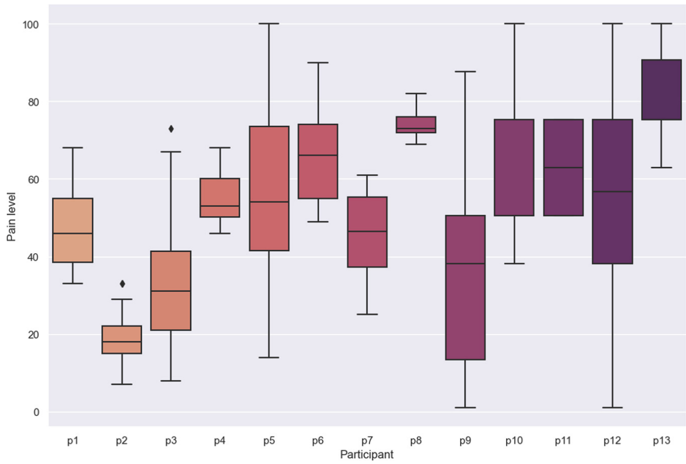

Fig. 2. Distribution (box plots) of the pain levels as reported on the mobile phone app for each patient.

The distribution of HRV measurements is shown in Fig. 3 for those 8 patients who have provided the data so far. Here, the main observation is that most values are within reasonable limits (between 20 and 80 ms) and both inter and intra-patients variability are present. No clear relationship can be derived from the charts between HRV and pain levels, therefore a more detailed analysis will be required in the future, for example by extracting low and high-frequency components of the HRV signals [13,31].

In terms of EEG sessions, we found that maintaining the connection between the tablet, the portable EEG device and the Mobistudy server was not sufficiently reliable. For this reason, we decided to avoid sending the data to the server when patients were recruited and opted to extract the EEG files from the tablet when returned.

Aside from some technical issues such as this, most patients have been able to record their EEG using this new technology. However, patients with a higher degree of motor impairment required assistance in the use of the system. Thus

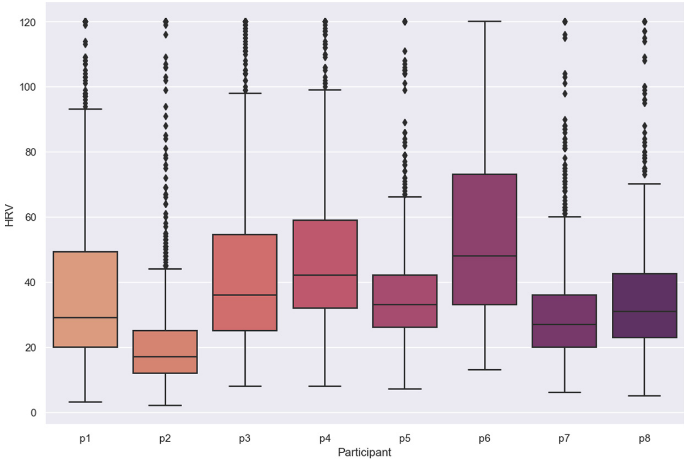

Fig. 3. Distribution (box plots) of the heart rate variability (in ms) measured by the wearable device, per patient.

far, four patients have brought the tablet and the EEG device at home while others were in-patients and therefore helped by a lab technician during the recordings if needed.

EEG sessions are currently being analysed in greater depth by discarding sections of the signal corrupted by noise and by computing spectral density characteristics that will be fed into machine learning algorithms. This is done as we are noticing that several sections of the collected EEG signals have spurious frequencies which we believe are due to poor cabling. This is supported by having used both models of the Hero device with USB and Bluetooth connections, and noticing that the wireless model produces cleaner recordings. Of the 198 sessions from 9 patients analysed so far, 91 sessions (46%) have been discarded because of bad signal quality.

Results from the usability and technology acceptance questionnaires are provided in Tables 1 and 2 respectively. Descriptive statistics about the answers provided to each section show that the app was well received among patients. In terms of quality (uMARS questionnaire [15]), the app was considered engaging, and functional, with a good degree of information, appealing aesthetics and of good quality. Even if positive, engagement scored the lowest among the categories, which shows that filling in the VAS scale 3 times per day may be perceived as tedious.

In terms of long-term acceptance (MOHTAM questionnaire [17]), both usability and perceived usefulness were evaluated high, which indicates that, notwithstanding the repetitiveness of the task, patients find it useful and would be happy to perform it in the long term. This is also confirmed by the answers related to the perceived impact of the uMARS questionnaire, as patients perceive that the app facilitates both the reporting of their pain levels and the participation in clinical studies.

Table 1. Mean and standard deviation of the answers provided to the uMARS questionnaire, by category, on a Likert scale from 1 (negative evaluation) to 5 (positive evaluation). N of patients = 7.

Category	Mean	Standard deviation
Engagement (q1–q5)	3.33	1.22
Functionality (q6–q9)	4.56	0.58
Aesthetics (q10–q12)	4.33	0.58
Information (q13–q16)	4.40	0.71
Subjective quality (q17–q20)	3.39	1.42
Perceived impact in monitoring pain levels (q21–q26)	3.37	1.33
Perceived impact in participating in clinical studies (q27–q32)	4.07	1.45

Table 2. Mean and standard deviation of the answers provided to the technology acceptance questionnaire, by category, on a Likert scale from 1 (negative evaluation) to 5 (positive evaluation). N of patients = 7.

Category	Mean	Standard deviation
Perceived ease of use (q1–q7)	3.55	0.98
Perceived usefulness (q8–q12)	3.31	0.79

5 Conclusions and Future Work

This work presents an IoT-based system for recording EEG and HRV as biomarkers for pain levels in spinal cord injury, used as part of a clinical study. The system uses a complex setup consisting of a portable EEG device, a smartwatch, a tablet application and a mobile phone application. So far, fifteen patients have been using the system successfully, showing that data can be collected and that the app is usable. While collection and analysis of the data is ongoing work, our preliminary results show that the data can be used to profile patients in a clinically meaningful way.

Nonetheless, the complexity of setting up the devices, connections, and overall usability of this novel technology is still a challenge that needs to be addressed. Over time, such work needs to ensure ease of use for the intended patient group as well as to improve and validate the reliability of devices included in the system to minimize the risk of corrupted signals.

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References

1. Abrecht, C.R., Nedeljkovic, S.S.: Neuropathic pain. In: Yong, R., Nguyen, M., Nelson, E., Urman, R. (eds.) Pain Medicine, pp. 541–543. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-43133-8_145
2. Anwar, D., Garg, P., Naik, V., Gupta, A., Kumar, A.: Use of portable EEG sensors to detect meditation. In: 2018 10th International Conference on Communication Systems & Networks (COMSNETS), pp. 705–710. IEEE (2018)
3. Attal, N., Bouhassira, D., Baron, R.: Diagnosis and assessment of neuropathic pain through questionnaires. Lancet Neurol. **17**(5), 456–466 (2018)
4. van den Berg-Emons, R.J., Schasfoort, F.C., de Vos, L.A., Bussmann, J.B., Stam, H.J.: Impact of chronic pain on everyday physical activity. Eur. J. Pain **11**(5), 587–593 (2007)
5. Crichton, N.: Visual analogue scale (VAS). J. Clin. Nurs. **10**(5), 706–6 (2001)
6. Cruccu, G., et al.: EFNS guidelines on neuropathic pain assessment. Eur. J. Neurol. **11**(3), 153–162 (2004)
7. De Pascalis, V., Vecchio, A.: The influence of EEG oscillations, heart rate variability changes, and personality on self-pain and empathy for pain under placebo analgesia. Sci. Rep. **12**(1), 1–18 (2022)
8. Finnerup, N.B., et al.: Pharmacotherapy for neuropathic pain in adults: a systematic review and meta-analysis. Lancet Neurol. **14**(2), 162–173 (2015)
9. Forte, G., Troisi, G., Pazzaglia, M., Pascalis, V.D., Casagrande, M.: Heart rate variability and pain: a systematic review. Brain Sci. **12**(2), 153 (2022)
10. Haanpää, M., et al.: Neupsig guidelines on neuropathic pain assessment. PAIN® **152**(1), 14–27 (2011)
11. Kächele, M., Werner, P., Al-Hamadi, A., Palm, G., Walter, S., Schwenker, F.: Bio-visual fusion for person-independent recognition of pain intensity. In: Schwenker, F., Roli, F., Kittler, J. (eds.) MCS 2015. LNCS, vol. 9132, pp. 220–230. Springer, Cham (2015). https://doi.org/10.1007/978-3-319-20248-8_19
12. Karri, J., Zhang, L., Li, S., Chen, Y.T., Stampas, A., Li, S.: Heart rate variability: a novel modality for diagnosing neuropathic pain after spinal cord injury. Front. Physiol. **8**, 495 (2017)
13. Koenig, J., Jarczok, M., Ellis, R., Hillecke, T., Thayer, J.F.: Heart rate variability and experimentally induced pain in healthy adults: a systematic review. Eur. J. Pain **18**(3), 301–314 (2014)
14. Loggia, M.L., Juneau, M., Bushnell, M.C.: Autonomic responses to heat pain: heart rate, skin conductance, and their relation to verbal ratings and stimulus intensity. PAIN® **152**(3), 592–598 (2011)
15. Martin-Payo, R., Carrasco-Santos, S., Cuesta, M., Stoyan, S., Gonzalez-Mendez, X., Fernandez-Alvarez, M.D.M.: Spanish adaptation and validation of the user version of the mobile application rating scale (uMARS). J. Am. Med. Inform. Assoc. **28**(12), 2681–2686 (2021)
16. McGeary, D.D., McGeary, C.A., Gatchel, R.J.: A comprehensive review of telehealth for pain management: where we are and the way ahead. Pain Pract. **12**(7), 570–577 (2012)

17. Mohamed, A.H.H., Tawfik, H., Al-Jumeily, D., Norton, L.: MoHTAM: a technology acceptance model for mobile health applications. In: 2011 Developments in E-systems Engineering, pp. 13–18. IEEE (2011)
18. Möltner, A., Hölzl, R., Strian, F.: Heart rate changes as an autonomic component of the pain response. Pain **43**(1), 81–89 (1990)
19. Mussigmann, T., Bardel, B., Lefaucheur, J.P.: Resting-state electroencephalography (EEG) biomarkers of chronic neuropathic pain. a systematic review. NeuroImage 119351 (2022)
20. Natarajan, A., Pantelopoulos, A., Emir-Farinas, H., Natarajan, P.: Heart rate variability with photoplethysmography in 8 million individuals: a cross-sectional study. Lancet Digit. Health **2**(12), e650–e657 (2020)
21. Prada, E.J.A.: The internet of things (IoT) in pain assessment and management: an overview. Inform. Med. Unlock. **18**, 100298 (2020)
22. Rajesh, M., Muthu, J.S., Suseela, G.: iPainRelief-a pain assessment and management app for a smart phone implementing sensors and soft computing tools. In: 2013 International Conference on Information Communication and Embedded Systems (ICICES), pp. 434–441. IEEE (2013)
23. Rost, S., Van Ryckeghem, D.M., Koval, P., Sütterlin, S., Vögele, C., Crombez, G.: Affective instability in patients with chronic pain: a diary approach. Pain **157**(8), 1783–1790 (2016)
24. Salvi, D., Lee, J., Velardo, C., Goburdhun, R.A., Tarassenko, L.: Mobistudy: an open mobile-health platform for clinical research. In: 2019 IEEE 19th International Conference on Bioinformatics and Bioengineering (BIBE), pp. 918–921. IEEE (2019)
25. Salvi, D., Olsson, C.M., Ymeri, G., Carrasco-Lopez, C., Tsang, K.C., Shah, S.A.: Mobistudy: mobile-based, platform-independent, multi-dimensional data collection for clinical studies. In: 11th International Conference on the Internet of Things, pp. 219–222 (2021)
26. Samandari, R.: Integration of bluetooth sensors in a windows-based research platform. Bachelor's thesis, Malmö University (2021)
27. Siddall, P.J., McClelland, J.M., Rutkowski, S.B., Cousins, M.J.: A longitudinal study of the prevalence and characteristics of pain in the first 5 years following spinal cord injury. Pain **103**(3), 249–257 (2003)
28. Spenkelink, C., Hutten, M.M., Hermens, H., Greitemann, B.O.: Assessment of activities of daily living with an ambulatory monitoring system: a comparative study in patients with chronic low back pain and nonsymptomatic controls. Clin. Rehabil. **16**(1), 16–26 (2002)
29. Sundararaman, L.V., Edwards, R.R., Ross, E.L., Jamison, R.N.: Integration of mobile health technology in the treatment of chronic pain: a critical review. Regional Anesth. Pain Med. **42**(4), 488–498 (2017)
30. Thurnheer, S.E., Gravestock, I., Pichierri, G., Steurer, J., Burgstaller, J.M.: Benefits of mobile apps in pain management: systematic review. JMIR Mhealth Uhealth **6**(10), e11231 (2018)
31. Tracy, L.M., Ioannou, L., Baker, K.S., Gibson, S.J., Georgiou-Karistianis, N., Giummarra, M.J.: Meta-analytic evidence for decreased heart rate variability in chronic pain implicating parasympathetic nervous system dysregulation. Pain **157**(1), 7–29 (2016)
32. Van Gorp, S., Kessels, A., Joosten, E., Van Kleef, M., Patijn, J.: Pain prevalence and its determinants after spinal cord injury: a systematic review. Eur. J. Pain **19**(1), 5–14 (2015)

33. Van Weering, M., Vollenbroek-Hutten, M., Tönis, T., Hermens, H.: Daily physical activities in chronic lower back pain patients assessed with accelerometry. Eur. J. Pain **13**(6), 649–654 (2009)
34. Vanneste, S., De Ridder, D.: Chronic pain as a brain imbalance between pain input and pain suppression. Brain Commun. **3**(1), fcab014 (2021)
35. Vuckovic, A., Gallardo, V.J.F., Jarjees, M., Fraser, M., Purcell, M.: Prediction of central neuropathic pain in spinal cord injury based on EEG classifier. Clin. Neurophysiol. **129**(8), 1605–1617 (2018)
36. Xhyheri, B., Manfrini, O., Mazzolini, M., Pizzi, C., Bugiardini, R.: Heart rate variability today. Prog. Cardiovasc. Dis. **55**(3), 321–331 (2012)
37. Xu, J., Zhong, B.: Review on portable EEG technology in educational research. Comput. Hum. Behav. **81**, 340–349 (2018)
38. Yang, G., et al.: IoT-based remote pain monitoring system: from device to cloud platform. IEEE J. Biomed. Health Inform. **22**(6), 1711–1719 (2017)