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The Neural Footprint of Play: Classifying Gamer Expertise via Raw EEG and Brain Topography

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Abstract. This study explores the feasibility of classifying videogame expertise using raw electroencephalographic (EEG) signals recorded dur-ing gameplay of *Temple Run*®. EEG data from ten subjects were pro-cessed and analyzed through three complementary approaches. First, a Multilayer Perceptron (MLP) neural network was trained with im-balanced data, followed by a second experiment using Synthetic Mi-nority Oversampling Technique (SMOTE) to correct class imbalance. The models achieved precision above 90%, with the highest accuracy of 92.89% obtained using balanced data and intermediate hidden-layer sizes, demonstrating that raw EEG signals contain discriminative infor-mation without requiring feature extraction. A third experiment involved topographic analysis, revealing distinct spatial activation patterns be-tween video gamers and non-gamers. Novice players exhibited greater parieto-occipital activation, while experienced players showed more fo-cused frontal engagement, reflecting enhanced visuomotor efficiency. To-gether, these results highlight the potential of raw EEG for real-time ex-pertise classification and its broader applications in neurogaming, adap-tive systems, and digital health.

Keywords: EEG, videogames, neurogaming, serious games, neural net-works, expertise classification

1 Introduction

The videogame industry currently stands as one of the most influential sectors within digital entertainment, with global revenues surpassing $180 billion in 2023 (Newzoo, 2023). This rapid growth has driven not only the development of increasingly immersive experiences but also the integration of biomedical technologies. To study the player–game interaction. In this context, electroencephalographic (EEG) signal analysis has gained relevance as a tool for monitoring brain activity in real time during gameplay (Lotte et al., 2018). The use of EEG in gaming has given rise to the field of neurogaming, where brain signals are leveraged to detect variables such as attention, cognitive load, and emotional states (Mühl et al., 2014). This approach has also expanded into the realm of serious games designed for educational or therapeutic purposes, particularly in mental health, rehabilitation, and cognitive training (Pérez Vidal et al., 2024). Recent studies have demonstrated that EEG signals can be used to dynamically adjust game difficulty based on the player's mental state, thereby personalizing the gameplay experience (Anwar et al., 2018). From a neurophysiological perspective, different EEG frequency bands reflect specific cognitive functions. Theta activity (4–7 Hz), especially in frontal regions, has been associated with memory processing and mental effort; the alpha band (8–12 Hz) is linked to relaxation and internal cognitive processing; and beta activity (13–30 Hz) corresponds to sustained attention and active engagement (Berka et al., 2007; Klimesch, 1999). During interaction with videogames, these bands exhibit modulations related to task difficulty, mental workload, and player experience (Antonenko et al., 2022). Notably, it has been reported that expert gamers exhibit distinctive brain activation patterns compared to novice players. For example, Hafeez et al. (2021) found that it is possible to classify expert and non-expert gamers based on EEG features extracted during gameplay. Moreover, other research suggests that gaming experience correlates with greater efficiency in activating fronto-parietal networks, supporting faster motor planning and decision-making processes (Bediou et al., 2018). Despite these advances, most current models rely on sophisticated feature extraction techniques, which may hinder their practical application in real-time environments. In this regard, exploring supervised models capable of operating directly on raw EEG signals offers a promising alternative for practical implementations in both entertainment and health domains (Roy et al., 2019).

The primary aim of this study is to explore the feasibility of identifying video gamers (VG) and non-video gamers (NVG) through raw EEG signals recorded during the execution of the game *Temple Run*®.

2 Methodology

The present work was structured into three experiments aimed at evaluating the ability of EEG signals to distinguish between video gamers (VG) and non-video gamers (NVG) (see Fig. 1).

2.1 Dataset

The data analyzed in this study were compiled from a dataset by Anwar et al. (2018), which is publicly available on the Kaggle platform (https://www. kaggle.com/datasets/enversyed/game-player-expertise-classification).

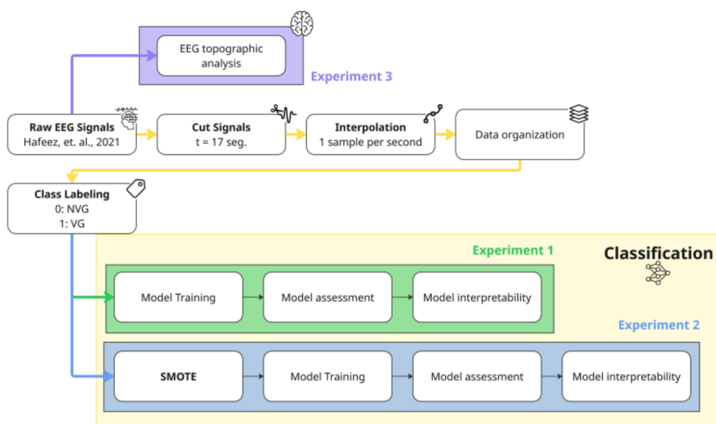

Fig. 1. Methodological framework for gamer classification using raw EEG signals and topographic analysis.

This dataset contains electroencephalographic (EEG) recordings collected dur-ing participants' interaction with the videogame *Temple Run*®. A total of 10 subjects participated, each completing five gameplay sessions. It is worth noting that in this study, informed consent was obtained from all participants prior to data collection. During each session, EEG signals were recorded using an Emotiv Epoc+ device, with a sampling rate of f_s = 128 Hz and 14 channels (electrodes) arranged according to the 10–20 international system. The specific electrode positions used are shown in

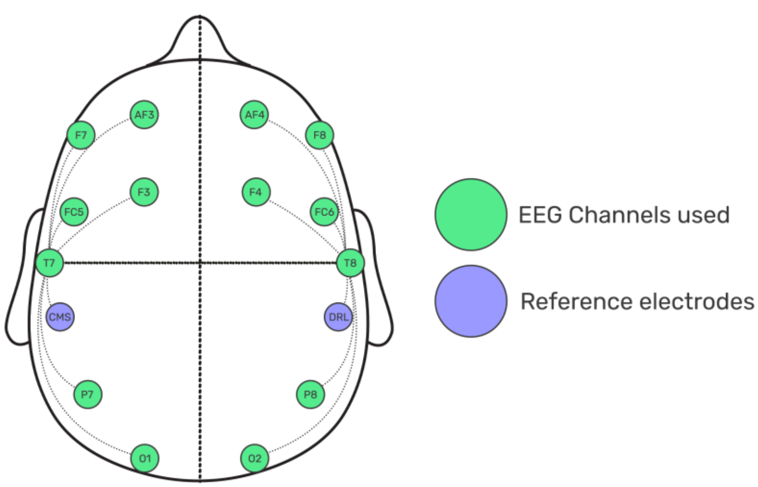

Fig. 2 and include: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4.

Fig. 2. Electrode layout used for EEG acquisition based on the Emotiv EPOC system. Green circles represent active channels; purple nodes indicate CMS (Common Mode Sense) and DRL (Driven Right Leg) references. The original purpose of the dataset was to develop a framework for classifying user expertise during gameplay, enabling the distinction between novice and expert players based on their EEG activity. This classification was based on features extracted from the temporal, frequency, and spatio-temporal domains of the signals. However, it is essential to note that due to data availability in the original source, the present study only used the EEG recordings corresponding to gameplay sessions 1 through 4, excluding the fifth session. This decision was made to ensure consistency and integrity across all analyzed subjects.

2.2 Cut signals and downsampling

According to the information available in the dataset, all 10 participants played for at least 17 seconds in at least one of the four gameplay sessions considered. Therefore, all EEG signals were trimmed to a uniform duration of 17 seconds, en-suring comparability across subjects and sessions. Subsequently, temporal down-sampling was applied to the trimmed signals to reduce data density without compromising the essential information required for classification. A new sam-pling rate of one sample per second was established, representing a substantial reduction from the original rate (f_s = 128 Hz). While this transformation implies the loss of high-frequency information, the present study focuses on identifying general brain activation patterns between video gamers and non-gamers, rather than detailed analyses of fine oscillations or specific frequency bands. Moreover, using raw EEG signals with high temporal resolution can increase the risk of overfitting, especially when working with a limited number of subjects. By re-ducing the number of samples per second, the input structure of the classifier is simplified, the dimensionality of the dataset is decreased, and the risk of the model learning irrelevant noise or subject-specific fluctuations is minimized. Fi-nally, all data were normalized to a scale between 0 and 1.

2.3 Data organization and labeling

The interpolated data were structured by subject, session, and channel, gen-erating a 10×4 cell array, where each row corresponds to a subject and each column to a session. Each subject was assigned a binary label: 0 for non-video gamers (NVG) and 1 for video gamers (VG), forming the dataset used for binary classification.

2.4 Experiment 1: Classification with imbalanced data

In the first experiment, the original dataset was used without any adjustments to the class distribution. For the classification task, a Multilayer Perceptron (MLP) model was trained and evaluated using multiple configurations. Specifically, the 14 channels of raw EEG signals were used as input features. Various numbers of neurons in the hidden layer were tested (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 30, 40, 50, and 100 neurons). The output layer consisted of a single neuron respon-sible for binary classification between video gamers (VG) and non-video gamers (NVG). A sigmoid activation function was used in all layers of the model. This activation function was chosen for several reasons: First, its nonlinear nature allows the network to learn complex relationships between inputs and outputs, even with a limited number of neurons. Second, its output range, bounded be-tween 0 and 1, is particularly suitable for normalized data in the same range, ensuring consistency between the input scale and the internal response of the neurons. Finally, when using raw EEG signals, the sigmoid function enables smooth transitions between input values, which can contribute to better con-vergence during the training process—especially in configurations with a small number of hidden neurons.

2.5 Experiment 2: Classification with balanced data (SMOTE)

The second experiment replicated the procedure described above but used a balanced version of the training dataset. Since the original dataset contained information from 4 video gamers (VG) and six non-video gamers (NVG), the SMOTE (Synthetic Minority Oversampling Technique) algorithm was applied to correct the class imbalance. This technique generated synthetic samples for the minority class (VG) by creating linear combinations of its nearest neighbors, thereby achieving a more balanced distribution (see Equation 1).

$$\bar{x} = x_i + \lambda * (x_{zi} - x_i) \qquad (1)$$

where:

– $\bar{x}$ is the newly generated synthethic sample.
– x_i is an original sample from the minority class.
– x_{zi} is one of the k nearest neighbors of xi, also from the minority class.
–$\lambda \in [0,1]$is a randomly generated value for each sample, controlling the position between x_iy x_{zi}.

This procedure is repeated as many times as necessary to achieve the desired class balance. Unlike traditional oversampling techniques that replicate exist-ing instances, SMOTE generates new samples that are distributed consistently within the feature space, thereby reducing the risk of overfitting and enhancing the generalization capability of the classification model. The purpose of this ex-periment was to assess whether class balancing improves the model's ability to identify subjects belonging to the minority class correctly. The same MLP pa-rameters and configurations were maintained, and the training, validation, and interpretive analysis procedures were repeated to compare classifier performance with that of the first experiment in terms of precision.

2.6 Experiment 3: EEG topographic analysis

In parallel with the classification experiments, a topographic analysis of brain activity was conducted using the original EEG data, without applying temporal downsampling. The objective of this analysis was to visually compare the clas-sification model's results with the actual spatial patterns of cortical activation and to explore potential functional differences between the video gamer (VG) and non-video gamer (NVG) groups. To do so, the average activity per chan-nel was computed for each subject during each of the four gameplay sessions. These channel-wise averages were then grouped by class, allowing for the visual-ization of the overall brain activity distribution for each group. Based on these averaged values, topographic maps were generated using two-dimensional spatial interpolation with cubic splines, aiming to produce a continuous and smoothed representation of scalp-level EEG activity. The visualization was constructed us-ing the standard layout of the 14 electrodes, by the international 10–20 system, projected onto a circular mesh in Cartesian coordinates. Individual topographic maps were created for each group (VG and NVG), enabling the visual identifi-cation of differentiated activation patterns between the two user profiles. This topographic analysis complemented the quantitative classification results by pro-viding a spatial representation of brain activity, facilitating the interpretation of the cortical regions potentially involved in distinguishing between groups.

3 Results and discussions

This section presents the main findings of the study, organized into two com-plementary approaches: on one hand, the automated classification of gameplay experience using raw EEG signals; and on the other, the topographic analysis of electrical brain activity during the gaming sessions. Together, these approaches provide a comprehensive understanding of the functional differences between video gamers (VGs) and non-video gamers (NVGs).

3.1 EEG-Based Classification of Gamer Expertise

The performance of the Multilayer Perceptron (MLP) model was evaluated across two experiments: the first using the original (imbalanced) dataset, and the second using a balanced version generated through the SMOTE algorithm. Table 1 presents the precision scores obtained for each configuration of hidden layer neuron count.

In Experiment 1, which incorporated synthetic samples for the minority class, precision improved across most configurations, reaching a maximum of 92.89% (20 neurons) and an overall average of 76.67%. These results suggest that the use of SMOTE enhances the model's ability to correctly classify video gamer subjects, particularly in intermediate MLP configurations (e.g., 15 and 20 hidden neurons). However, it is worth noting that the highest performance in both experiments was achieved with more complex architectures (100 neurons in Exp. 1; 20 neurons in Exp. 2), which could imply an increased risk of overfitting if not correctly managed. On the other hand, Table 2 presents a comparison between the methodology and results of the present study and those reported by Hafeez et al. (2021). Although both studies use the same dataset, there are substantial methodological differences that help explain the variation in classifier performance.

One of the most relevant differences lies in the sampling rate used. While Hafeez et al. preserved the original rate of 128 Hz, this study applied temporal downsampling to reduce it to 1 Hz, aiming to decrease the data dimensionality and prevent overfitting issues—particularly given the limited number of avail-able subjects.

Neurons	Precision (Exp. 1)	Precision (Exp. 2 - SMOTE)
1	65.00 %	66.91 %
2	66.03 %	64.09 %
3	68.68 %	70.34 %
4	71.91 %	74.02 %
5	75.88 %	73.41 %
6	68.97 %	67.28 %
7	75.44 %	60.66 %
8	76.91 %	85.75 %
9	78.68 %	78.06 %
10	76.47 %	74.51 %

15	79.56 %	87.13 %
20	83.82 %	92.89 %
30	81.91 %	76.47 %
40	78.97 %	81.25 %
50	66.91 %	75.74 %
100	91.18 %	91.54 %
Average	75.48 %	76.67 %

Table 1. Comparison of MLP precision across different hidden layer sizes for both experiments.

Aspect	This study (Exp. 1 and 2)	Hafeez et al. (2021)
Sampling rate	1 Hz	128 Hz
Relevant channels	All 14 channels used (no selection)	AF3 and P7 (selected by correlation)
Feature type	Raw EEG	Power spectral density (band-based)
Classifier	Multilayer Perceptron (MLP)	K-nearest Neighbors (KNN)
Highest precision	92.89 % (MLP, with SMOTE, 20 neurons)	98.33% (KNN, with SMOTE, 2 channels)

Table 2. Comparative analysis between this study and Hafeez et al. (2021).

Although this reduction entails a loss of temporal resolution, it simplifies the signal representation and focuses the analysis on general activation trends. Another key distinction concerns the type of input data used in the mod-els. Hafeez et al. employed features derived from power spectral density (specific frequency bands), following a correlation-based channel selection process (AF3 and P7). In contrast, the present study utilized raw EEG signals directly, with-out any feature extraction or channel reduction. Regarding the classification algorithm, Hafeez et al. reported that a K-Nearest Neighbors (KNN) classifier achieved a precision of 98.33% using balanced data and only two selected chan-nels. Conversely, this work implemented a Multilayer Perceptron (MLP) model, reaching a maximum precision of 92.89% using balanced data via SMOTE and a hidden layer with 20 neurons. Although the performance is slightly lower, it is worth noting that it was achieved without any feature engineering or prior chan-nel selection. Overall, the results suggest that while more optimized approaches, such as those of Hafeez et al., can yield higher precision through dimensionality reduction and feature extraction, it is possible to achieve competitive perfor-mance using raw EEG signals and robust supervised models, such as MLP. This opens the door to developing more generalizable systems that are less dependent on preprocessing stages, which is especially valuable for real-time applications or environments with uncontrolled conditions.

3.2 Topographic analysis of brain activity during gameplay

As a complement to the quantitative analysis, a topographic visualization of average brain activity was conducted for each of the four gameplay sessions, with subjects divided into two groups: non-video gamers (NVG; subjects 5 to 10) and video gamers (VG; subjects 1 to 4).

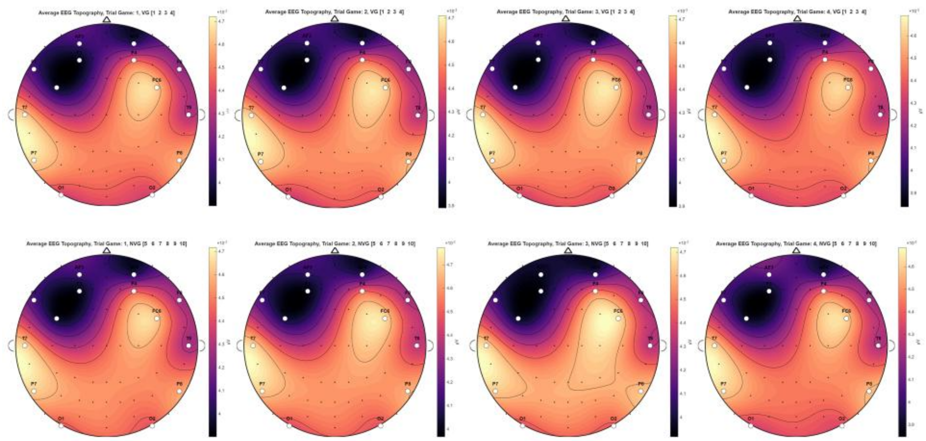

Fig. 3. Topographic EEG comparison across four gameplay sessions between video gamers (VG) and non-video gamers (NVG). Each column corresponds to one gameplay session (1 to 4), with VG group averages displayed in the top row and NVG in the bottom row.

Figure 3 displays the spatial evolution of electrical brain activity across the four gameplay sessions, distinguishing between video gamers (VG) and non-video gamers (NVG). In the maps corresponding to the NVG group (bottom row), a consistent pattern of lower activation is observed in the left frontal regions (F3, FC5, and F7), and increased activity is noted in the right parieto-occipital areas (P8, O2), particularly during sessions 1 and 2.
This pattern can be interpreted through the Parieto-Frontal Integration The-ory (P-FIT), which posits that the interaction between frontal and parietal brain regions forms a critical network for complex visual processing, attention, and fluid reasoning [12]. In NVG subjects, heightened activation in posterior areas may reflect greater cognitive effort required to decode novel visual stimuli, in the absence of automated strategies typically developed by experienced players.
Moreover, studies on cognitive load indicate that theta-band activity in the frontal cortex is associated with executive control. At the same time, increased alpha and beta power in parietal and occipital regions corresponds to elevated perceptual processing demands [7, 8]. The reduced frontal activation observed in NVG participants may signal lower executive efficiency, whereas posterior hyperactivation could represent a compensatory neural mechanism.
In contrast, video gamers (VG, top row) exhibit a more symmetrical and stable pattern across sessions, with a progressive increase in right frontal activity (FC6 and F4) and a relative reduction in posterior regions. This configuration suggests enhanced visuomotor and executive efficiency, likely stemming from familiarity with the game's dynamics.
The more focused and homogeneous activation distribution observed in VG supports the idea of a more automated processing strategy, one that is less reliant on basic sensory resources. This aligns with prior research demonstrating that gaming experience improves sustained attention, decision-making, and the func-tional efficiency of frontoparietal networks [10, 13]. Collectively, these findings support the hypothesis that gaming experience alters brain activation patterns, optimizing the deployment of cognitive resources during complex tasks.

4 Conclusions

The results of this study demonstrate that it is possible to distinguish between video gamers (VG) and non-video gamers (NVG) through the analysis of raw EEG signals, without the need for complex feature extraction techniques. The Multilayer Perceptron (MLP) neural network, trained on simplified and normal-ized temporal signals, achieved precision levels exceeding 90% under balanced conditions, validating this approach as a robust and accessible tool for neurocog-nitive classification tasks.

Additionally, the topographic analysis of brain activity revealed consistent spatial differences between the two groups. NVG participants exhibited greater activation in parieto-occipital regions. In contrast, VG participants exhibited more focused activation in the right frontal areas, a pattern consistent with previous findings on functional efficiency and visuomotor control. This dual ap-proach (quantitative and spatial) not only validates the model's performance but also provides insight into the neural mechanisms underlying gameplay ex-perience.

Together, these findings reinforce the feasibility of using EEG as a tool to study user experience in gaming, with potential future applications in neurogam-ing, adaptive difficulty personalization, cognitive state detection, and the devel-opment of tools in the field of serious games for health and education.

References

Anwar, S. M., Saeed, S. M. U., Majid, M., Usman, S., Mehmood, C. A., y Liu, W. (2018). A game player expertise level classification system using electroencephalography (EEG). *Applied Sciences, 8*(1), 18. https://doi.org/10.3390/app8010018

Antonenko, P., Paas, F., Grabner, R., y van Gog, T. (2022). Assessment of instantaneous cognitive load imposed by educational videos: An EEG study. *Frontiers in Neuroscience, 16*, 744737. https://doi.org/10.3389/fnins.2022.744737

Bediou, B., Adams, D. M., Mayer, R. E., Tipton, E., Green, C. S., y Bavelier, D. (2018). Meta-analysis of action video game impact on cognitive function: A meta-analytic investigation. *Psychological Bulletin, 144*(1), 77–110. https://doi.org/10.1037/bul0000130

Berka, C., Levendowski, D. J., Lumicao, M. N., Yau, A., Davis, G., Zivkovic, V. T., Olmstead, R. E., Tremoulet, P. D., y Craven, P. L. (2007). EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. *Aviation, Space, and Environmental Medicine, 78*(5 Suppl.), B231–B244.

Hafeez, T., Ahmed, A., Ali, M., y Syed, E. (2021). EEG in game user analysis: A framework for expertise classification during gameplay. *PLOS ONE, 16*(6), e0246913. https://doi.org/10.1371/journal.pone.0246913

Jung, R. E., y Haier, R. J. (2007). The parieto-frontal integration theory (P-FIT) of intelligence: Converging neuroimaging evidence. *Behavioral and Brain Sciences, 30*(2), 135–187. https://doi.org/10.1017/S0140525X07001185

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Research Reviews, 29*(2–3), 169–195. https://doi.org/10.1016/S0165-0173(98)00056-3

Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., y Yger, F. (2018). A review of classification algorithms for EEG-based brain–computer interfaces: A 10 year update. *Journal of Neural Engineering, 15*(3), 031005. https://doi.org/10.1088/1741-2552/aab2f2

Mishra, J., Zinni, M., Bavelier, D., y Hillyard, S. A. (2011). Neural basis of superior performance of action videogame players in an attention-demanding task. *Journal of Neuroscience, 31*(3), 992–998. https://doi.org/10.1523/JNEUROSCI.4834-10.2011

Mühl, C., Allison, B. Z., Nijholt, A., y Chanel, G. (2014). Review of affective brain-computer interfaces: Principles, state-of-the-art, and challenges. *Brain-Computer Interfaces, 1*(2), 66–84. https://doi.org/10.1080/2326263X.2014.912881

Newzoo. (2023). *Newzoo Global Games Market Report 2023—Free version*. https://newzoo.com/resources/trend-reports/newzoo-global-games-market-report-2023-free-version

Pérez Vidal, A. F., Cervantes, J.-A., Rumbo-Morales, J. Y., Sorcia-Vázquez, F. D. J., Ortiz-Torres, G., Moncada, C. A. C., y de la Torre Arias, I. (2024). Development of RelaxQuest: A serious EEG-controlled game designed to promote relaxation and self-regulation with a potential focus on ADHD intervention. *Applied Sciences, 14*(23), 11173. https://doi.org/10.3390/app142311173

Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T. H., y Faubert, J. (2019). Deep learning-based electroencephalography analysis: A systematic review. *Journal of Neural Engineering, 16*(5), 051001. https://doi.org/10.1088/1741-2552/ab260c