Article

Neurophysiological Evaluation of Students' Experience during Remote and Face-To-Face Lessons. A Case Study at Driving School

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Abstract: Nowadays, fostered by technological progress and contextual circumstances such as economic crisis and pandemic restrictions, remote education is living a growing deployment. However, this growth generated widespread doubts about the actual effectiveness of remote/online compared to face-to-face education.

The present study aimed at comparing face-to-face and remote education through a multimodal neurophysiological approach. It involved forty students at a driving school, during a real classroom, experiencing both the modalities. Wearable devices to measure brain, ocular, heart and sweating activities were employed in order to analyse the students' neurophysiological signals to obtain insights about their cognitive dimension. In particular, four parameters were considered, the Eye Blink Rate, the Heart Rate and its Variability and the Skin Conductance Level. Also, the students filled a questionnaire at the end to obtain an explicit measure of their learning performance.

Data analysis showed a higher cognitive activity, in terms of attention and mental engagement, in presence with respect to remote modality. On the other hand, students by remote felt more stressed, in particular during the first part of the lesson. Analysis of questionnaires demonstrated worst performance by remote, thus suggesting a common “disengaging” behaviour when attending remote courses, thus undermining their effectiveness.

In conclusion, neuroscientific tools could help to obtain insights about mental concerns, often «blind», such as attentional decreasing and stress increasing, as well as their dynamics during the lesson itself, so allowing to define proper countermeasures to emerging issues when introducing new practices into daily life.

Keywords: Neuroscience; education; learning; brain activity; heart activity; skin conductance; neuroimaging; wearable devices

1. Introduction

Fully online or blended education started in the 1990s with the advent of the Internet and World Wide Web, immediately encountering a favourable impact from people in remote locations, or who want to save travel time and costs [1]. With the increasing progress

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of information and communication technologies, online education has become more feasible technologically, economically, and operationally. The possibility of providing educational programmes expanding own catchment area and at the same time saving costs related to physical facilities and personnel has fostered the establishment of companies dedicated exclusively to online education and has also caused institutes and organisations traditionally based on face-to-face education to begin evaluating the possibility of delivering at least hybrid modalities. In the 2016, Dziuban and colleagues [2] described the evolution of online education in four phases using primarily USA context: 1990s (Internet propelled distance education), 2000–2007 (increasing use of Learning Management Systems – LMS), 2008–2012 (growth of Massive Open Online Courses – MOOCs), and beyond with growth of online higher education enrolments outpacing traditional higher education enrolments. Few years ago, a report of the Association to Advance Collegiate Schools of Business (AACSB), based on data collected from 521 accredited schools representing 36 countries, showed an increase in the number of schools offering fully online degree programs at all levels [3]. According to the report, the proportion of schools offering online degrees increased from 25 to 37 percent in the previous five years [4]. However, this growth has been dampened by widespread doubts and misgivings about the actual effectiveness of remote/online compared to face-to-face education. Several reports over the years have shown that for the past decade faculty perceptions towards technology and online education haven't changed much and remained negative [5].

Due to the recent historical scenario, coming out of the Covid-19 pandemic crisis that imposed major restrictions and forced confinement in daily life, alternative solutions to normal activities that required the presence of people were found. One of the sectors most affected by this necessary change has been education and training, which has inevitably forced the use of online remote learning modes.

While dealing with the implementation of online education in the educational programmes, the major challenge has been identified in detaining social contacts and keeping learning going [6]. Online education has become an effective means to provide educational activities and prevent the possible loss of academic sessions because of the prolonged lock down. However, research on online education shows that students displayed a wide range of reactions and behaviours, with most expressing anxiety toward online learning, less motivation and engagement, disappointment regarding graduation ceremony, and a general unsatisfaction because of the perception of the difference between online and standard in-class learning [7].

In this scenario, scientific community started employing new tools and methodologies provided by neuroscientific disciplines to assess the students' experience from a psychological and cognitive point of view, and therefore to investigate which are the differences between the different modalities [8]. The rationale is to employ neuromonitoring devices, i.e. systems for recording students' brain activity (electroencephalography – EEG – or functional NearInfrared spectroscopy – fNIRs –), heart activity (photopletismographic – PPG – or electrocardiographic – ECG – signals), skin sweating (electrodermal activity – EDA –), and to obtain aggregate and synthetic indicators, i.e. the neurometrics [9]–[11], of cognitive phenomena relevant for the field. A lot of works has been published on this topic, but without tackling the matter in a comprehensive way. For example, the majority of works considered only one modality, i.e. in presence [12] or in remote, and in turn with online interactive streaming or pre-recorded no interactive courses [13]–[16]. On the other side, the works usually focussed on one specific cognitive and mental state, mainly attention and/or concentration [17]–[19], cognitive load or workload [20]–[22] and different affective states (frustration, meditation, etc.) [23]–[25]. Finally, each work usually employed just one technology, i.e. EEG or fNIRs or EDA or Eye-Tracking, instead of trying to obtain a multimodal perspective of the user's experience.

If until few years ago this concern was mainly due to the invasiveness of such systems, the restrictions they imposed (for such a reason the majority of the studies was not in realistic settings but in laboratory), and their interference with the natural user's behaviour, the recent technological progress and the establishment of wearable sensing technology [26]–[29] now enables new opportunities for conducting low invasive studies in more ecological settings.

The present study takes advantage from the last considerations. Wearable devices to measure EEG, PPG and EDA signals have been employed on forty students at a driving school, during a real classroom, in order to neurophysiologically evaluate their learning experience in both face-to-face and remote conditions. The use of neuroscientific methodologies should guarantee a deeper and more objective evaluation of students' experience, being based on the direct analysis of mental and physiological reactions [30].

The field of driving training was chosen because it is also living a boom of fully online driving schools providing courses for theory exams, both on the European dimension and worldwide. In the context of driving education, there is the perception that some specific topics, such as for example those ones related to road safety, are particularly relevant, therefore "in-presence" (face-to-face) education should be encouraged in any case.

Anyhow, besides the specific case study, the present work aimed at comparing "in-presence" vs "remote" modalities of teaching, in order to point out the eventual differences in terms of students' cognitive experience and performance. It is important to underline that the overarching purpose of the study is not to determine which modality is the better. On the contrary, considering the current scenario and new lifestyles, there is no doubt that online education is becoming a permanent practice, and therefore we believe that the obvious differences due to the new educational methods should be evaluated in order to understand how to modify and make the most of them without losing efficiency.

2. Materials and Methods

2.1. Participants

Forty (40) participants took part voluntarily to this experiment, receiving a gadget and a free practical driving lesson as compensation. They were all attending the course for obtaining the driving license Class B. They were almost gender balanced (17 males and 23 females) and they were on average 25.9 (± 11.6) years old. All the participants signed the informed consent and the related information sheet, in which the study was explained, before participating in the experiment. The authorization to use the video-graphical material (i.e., photos and videos of the experiment) was also signed. The experiment was conducted following the principles outlined in the Declaration of Helsinki of 1975, as revised in 2008, and it received the approval of Sapienza University of Rome ethical committee (nr. 2507/2020).

2.2.. Experimental protocol

The participants had to follow a normal lesson of their driving license course, lasting 1 hour, and focused on the topic: "Crossroads and related signage". The forty participants were divided into 5 different groups of 8 participants each, due to some logistic concerns, mainly the difficulty of having too many devices streaming the collected data in the same room. Anyhow, the topic of the lesson was the same, it was provided at the same daytime (4 pm) and by the same teacher in order to reproduce as similarly as possible experimental conditions.

During each lesson, the 8 participants have been divided into two subgroups of 4 people: one subgroup attended the lesson in presence (namely, "In-presence condition"), while the other subgroup attended the same lesson by remote (namely, "Remote condition"). In the latter condition, the participants were placed in a separate room in the same driving school, each one of them was seated in a personal workstation with a computer, a webcam and a couple of headphones with microphone, in order to allow interaction with the teacher, and connected by means of a common teleconference software to the same lesson. After half an hour, i.e. after half lesson, the two subgroups switched their position

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thus moving to the other condition. In this way, all the participants experienced both the conditions ("In-presence" and "Remote"), half of them starting with the "In-presence" one and the other half with the "Remote" one.

During the whole lesson, neurophysiological data (please refer to Par.2.3) were recorded from all the participants. Before starting each lesson condition, an individual baseline was recorded for each participant. They were asked to stay relaxed for 1 minute, at their seat in the classroom looking at the teacher desk ("In-presence"), or at their workstation looking at the computer with the teleconference software initialized ("Remote").

At the end of the whole lesson, the participants had to fill a multiple-choices questionnaire of 10 questions, which topics were balanced between the first (5 questions) and the second (5 questions) half of the lesson.

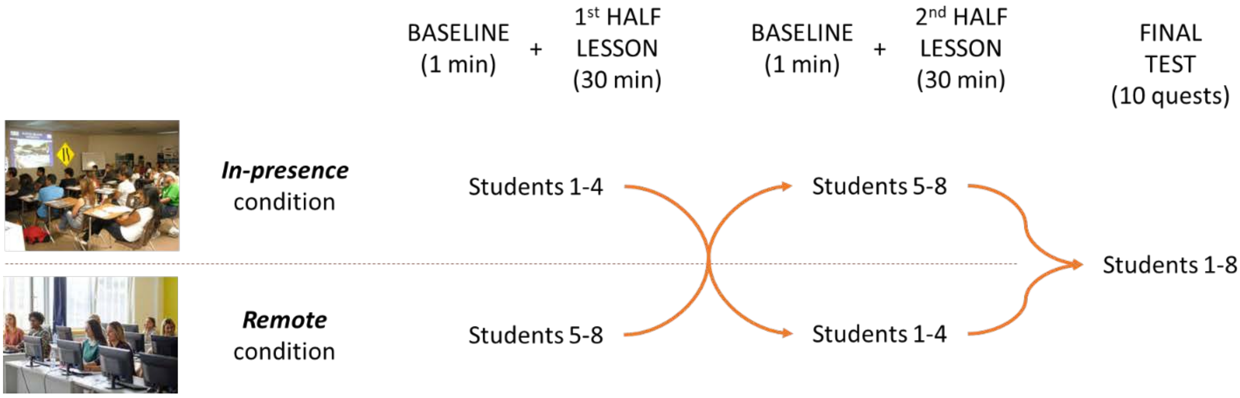

Figure 1. Overview of the experimental protocol for a subgroup of 8 participants.

2.3. Data collection

Neurophysiological data, in particular ocular blinking (electrooculography, EOG), heart activity (photoplethysmography, PPG) and skin sweating (electrodermal activity, EDA) were recorded from all the participants during both the lesson conditions. At the end of the whole lesson, the participants had to fill a questionnaire about the topics of the lesson. Here below, data acquisition and analysis are described for each data type.

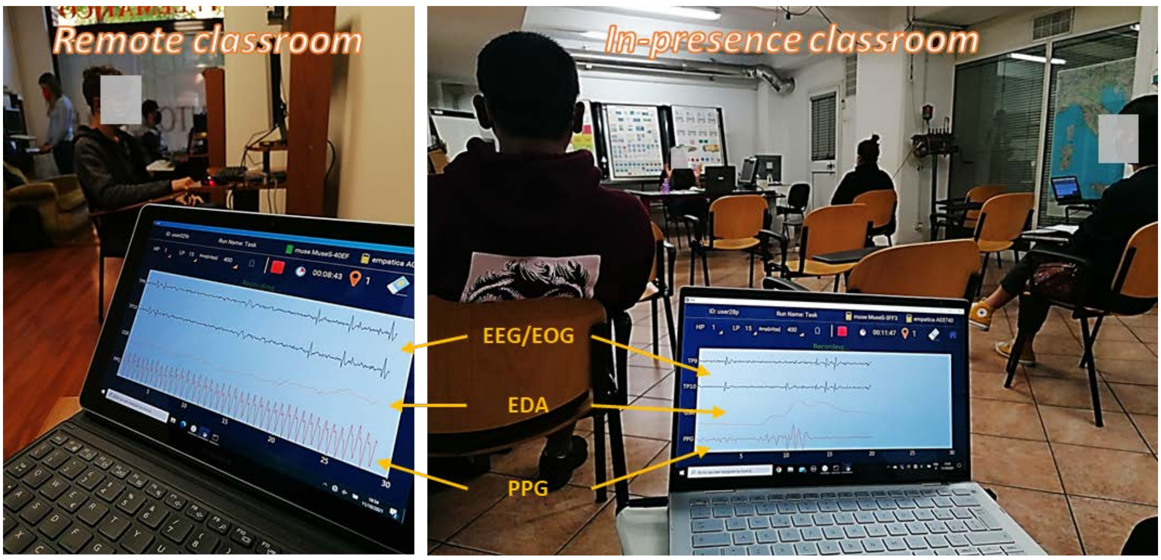

Figure 2. Two pictures of the signal recording during the experimental task in both the conditions (IN-PRESENCE and REMOTE). In particular, the first two blue channels are related to the EEG data gathered

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from the Muse S, from which the EOG pattern has been obtained (the blinks shapes are visible). The last two orange channels are respectively the EDA and the PPG data gathered from the Empatica.

2.3.1. EOG signals acquisition and analysis

The EOG signal were recorded by a commercial wearable device aimed to record Electroencephalographic (EEG) signals, i.e. the Muse S (InteraXon Inc., Toronto, Canada). It consists of a headband including four EEG channels placed over prefrontal and temporal regions, namely TP9, TP10, AF7 and AF8 of the 10-10 International System. The signals recorded from the four channels are collected with a sampling frequency of 256 Hz and they are referred to AFz. Due to the debated quality of EEG data collected by such a device [31], [32], it has been used only to estimate ocular blinking activity, having the blinks an intrinsically higher signal to noise ratio.

The whole data analysis was offline performed by means of Matlab (Mathworks Inc., USA). Raw EEG data were digitally filtered by a 5th order Butterworth band-pass filter (high-pass cut-off frequency = 1 Hz, low-pass cut-off frequency = 12 Hz). Such frequencies have been chosen in order to consider the power spectrum range containing almost the entire spectral content of ocular blinks [33], [34]. At this point, the channel (among the 4 available ones) with the most visible EOG pattern was selected by the same expert, in particular a biomedical engineer with more than 4 years of experience. Then, the Reblinca algorithm [35] was used to detected eye-blinks. In particular, the algorithm has been optimized, by including three specific criteria based on signal amplitude, shape and distribution, in order to discriminate true (real blinks) from false (noise) positives. So, for each participant and for each condition, the Eye Blink Rate (EBR) was estimated as "Blinks per minute". In particular, the inverse EBR has been computed, since the EBR has been found to be inversely correlated with vigilance [36], as described also along the discussions. Then, the inverse EBR values of each subject were normalized by subtracting the individual EBR baseline mean value and by dividing them per the EBR individual standard deviation.

2.3.2. PPG signals acquisition and analysis

The PPG signal was collected by means of a wearable bracelet, i.e. the Empatica E4 (Empatica Inc., Boston, USA), worn at the wrist of the non-dominant hand. The signal was acquired with a sampling frequency of 64 Hz.

The whole data analysis was offline performed by means of Matlab (Mathworks Inc., USA). Raw PPG data were digitally filtered by using a 5th order Butterworth band-pass filter ([1 – 5] Hz) in order to reject the continuous component as well as the slow signal drifting, and to emphasize the PPG signal patterns related to the pulse. At this point, the Pan-Tompkins algorithm [37] was employed to detect the pulse-related peaks, so to calculate the Inter-Beat-Intervals (IBI signal). The so obtained IBI signal has been processed in order to remove any type of artefacts (such as the spurious oscillations visible in the Figure 2, right side, on the PPG data) by means of the HRVAS Matlab suite [38]. At this point, the clean IBI signal has been processed to estimate the Heart Rate (HR) as "Beats per minute". Then, the HR values of each subject were normalized by subtracting the individual HR baseline mean value and by dividing them per the HR individual standard deviation.

The IBI signal has been also analysed for estimating the Heart Rate Variability (HRV). In particular, the HRV was analysed in the frequency domain by computing the Lomb-Scargle periodogram [39] of the IBI signal. Analysis has shown that the Lomb-Scargle periodogram can produce a more accurate estimate of the Power Spectrum Density (PSD) than Fast Fourier Transform methods for typical HR data. Since the HR data is an unevenly sampled data, another advantage of the Lomb-Scargle method is that in contrast to Fast Fourier Transform-based methods it is able to be used without the need to resample and de-trend the RR data [40]. According to the scientific literature, the PSD of the HRV signal has been computed over the Low (LF: 0.04 ÷ 0.15 Hz) and the High Frequencies (HF: 0.15 ÷ 0.4 Hz), and then the LF/HF ratio has been computed as a relevant indicator of HRV [41]. The LF/HF values of each subject were normalized by subtracting the individual LF/HF baseline mean value and by dividing them per the HR individual standard deviation.

2.3.3. EDA signals acquisition and analysis

The EDA signal was collected by means of the previously mentioned wearable bracelet, i.e. the Empatica E4 (Empatica Inc., Boston, USA), worn at the wrist of the non-dominant hand. The signal was acquired with a sampling frequency of 4 Hz.

The EDA was firstly low-pass filtered with a cut-off frequency of 1 Hz and then a correction artefacts Matlab tool was applied in order to clean the signal from the discontinuities and the spurious peaks. Lastly, the signal was processed by using the Ledalab suite [R], a specific open-source toolbox implemented within the Matlab (MathWorks, Natik, Massachussets) environment for EDA processing. The continuous decomposition analysis [50] was applied in order to estimate. the tonic (SCL) and the phasic (SCR) components. The SCL is the slow-changing component of the EDA signal, mostly related to the global arousal of the participant. On the contrary, the SCR is the fast-changing component of the EDA signal usually related to single stimuli reactions. In this study the SCR component estimation was affected by the low sampling frequency of the device (i.e. the Empatica E4), therefore only the slow-varying SCL component has been considered for the analysis. Also in this case, the SCL values of each subject were normalized by subtracting the individual SCL baseline mean value and by dividing them per the SCL individual standard deviation.

2.3.4. Questionnaire

At the end of the whole lesson, the participants had to individually fill a multiple-choices questionnaire of 10 questions, which topics were balanced between the first (5 questions) and the second (5 questions) half of the lesson. The questions were the same between all the participants, and taken by the official quiz used for the final exam.

2.3.5. Statistical data analysis

All the normalized neurophysiological parameters, i.e. the EBR, the HR, the HRV in terms of LF/HF and the SCL, were estimated by using the same 60-seconds-long time resolution, i.e. one value each minute. Such a time window length was chosen because it is the minimum requirement allowing to obtain an adequately resolved power spectrum of the IBI signal in order to obtain a reliable HRV estimation. The other neuro-parameters have been averaged coherently. Then, each condition (lasting 30 minutes) has been divided into ten 3-minutes-long time windows. For each condition, all the neuro- parameters have been averaged across subjects for each time window, therefore the result was a 10-points-long time series for each neuro-parameter for both the conditions (In-presence vs. Remote). The two conditions have been so compared by means of paired statistical tests. In particular, statistical non-parametric paired t-test, i.e. Wilcoxon signed rank test, has been employed to compare the two conditions since the data sample size was low ($n = 10$) and it was not possible to demonstrate Gaussianity of data distributions. Coherently, the effect size has been estimated by calculating the matched-pairs rank biserial correlation coefficient (analogous of the Cohen's d coefficient for non-parametric tests) [42].

Results from questionnaires have been only qualitatively analysed.

3. Results

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In the following, results from 35 out of the 40 participants are presented, since 1 participant left the experiment before its conclusion, while 4 participants had at least one corrupted data so only participants having a fully sound dataset have been included into the analysis.

3.1. Neurophysiological parameters

The analysis of the inverse Eye Blink Rate parameter (Figure 3) showed that the EBR was almost significantly higher (lower values when considering the inverse) during the *Remote* than the *In presence* condition (Wilcoxon signed rank test: z = 1.886; p = 0.064; effect size = 0.673).

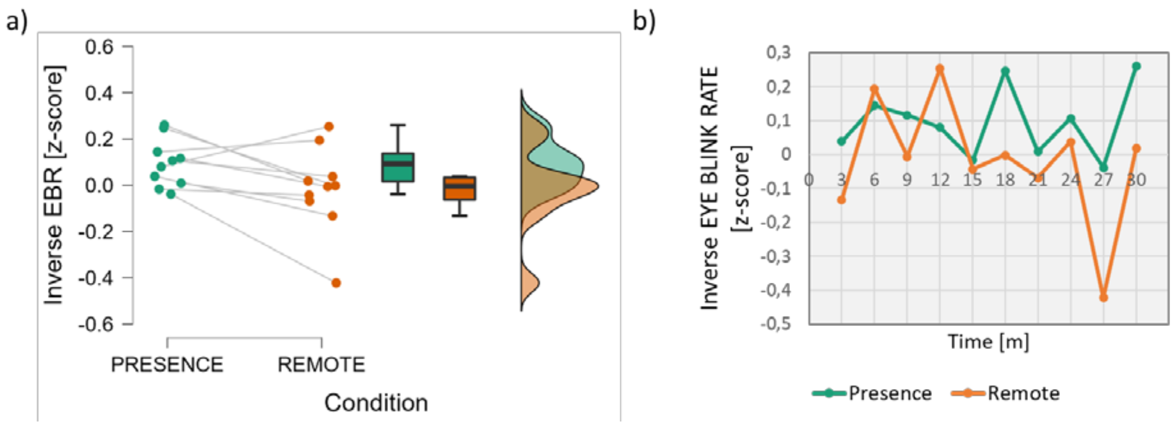

Figure 3. Analysis of the inverse Eye Blink Rate parameter. On the left (a), mean and confidence interval (95 %) of the distributions related to the two conditions (In presence and Remote). On the right (b), the dynamics of the inverse EBR averaged across students along the time span of the lesson.

In particular, the difference was more evident after the first 15 minutes, where the inverse Eye Blink Rate of the *Remote* condition remained always lower than the *In presence* one, and even lower than the '0' level (Figure 3.b). Being the scores normalized with respect to the Baseline, it means that in the second part of the lesson by remote the students experienced a blink frequency even higher (so lower inverse values) than during the initial resting condition, i.e. the baseline.

In terms of heart activity, a significant effect has been found both in terms of heart rate and its variability. In particular, the analysis of the Heart Rate parameter (Figure 4) showed significantly higher values during the *In Presence* than the *Remote* condition (Wilcoxon signed rank test: z = 2.497; p = 0.016; effect size = 0.891).

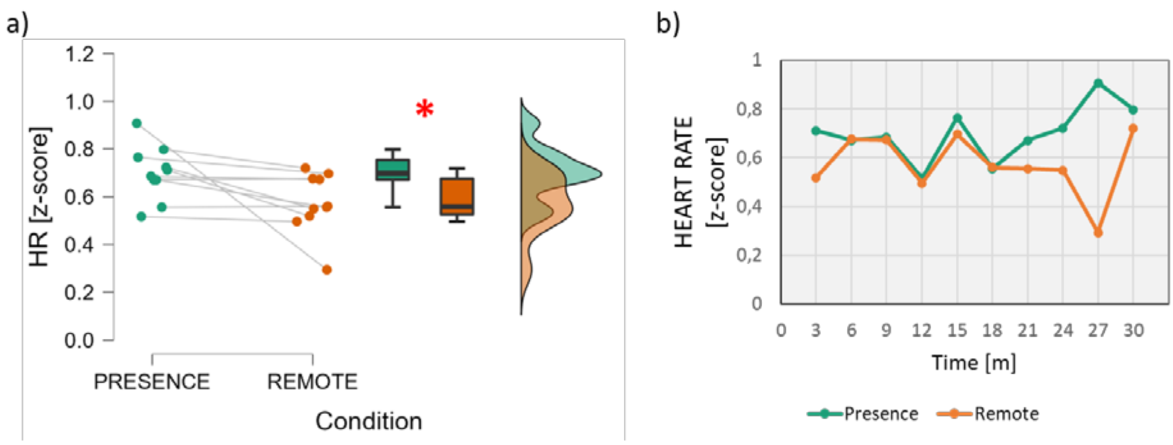

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Figure 4. Analysis of the Heart Rate parameter. On the left (a), mean and confidence interval (95 %) of the distributions related to the two conditions (In presence and Remote). The red asterisk indicates the presence of a statistically significant effect. On the right (b), the dynamics of the HR averaged across students along the time span of the lesson.

On the other hand, the analysis of the Heart Rate Variability (Figure 5) showed significantly higher LF/HF values during the *In Presence* than the *Remote* condition (Wilcoxon signed rank test: z = 2.396; p = 0.014; effect size = 0.855).

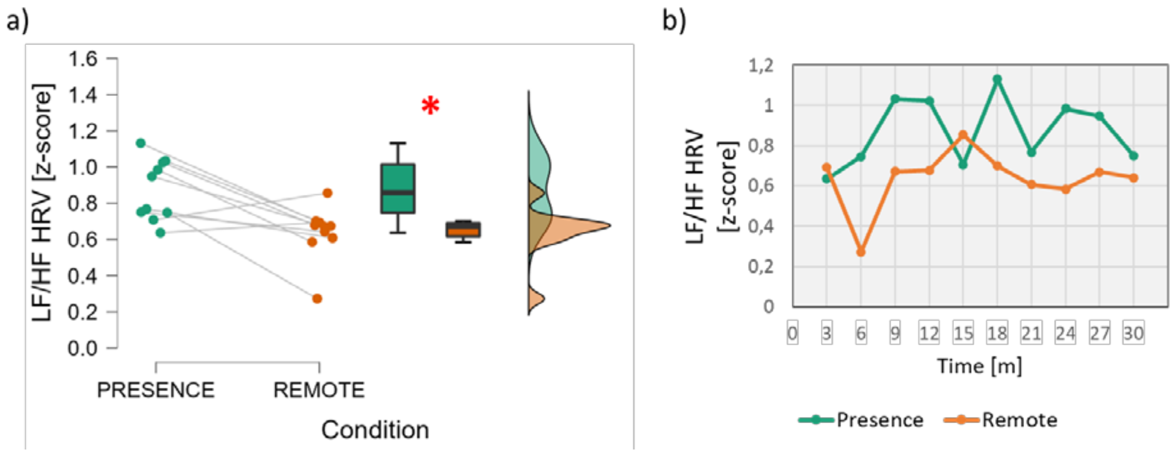

Figure 5. Analysis of the Heart Rate Variability, and in particular of the ratio between Low and High Frequencies. On the left (a), mean and confidence interval (95 %) of the distributions related to the two conditions (In presence and Remote). The red asterisk indicates the presence of a statistically significant effect. On the right (b), the dynamics of the HRV parameter averaged across students along the time span of the lesson.

With regards to skin sweating, the analysis of the Skin Conductance Level (Figure 6) showed significantly higher values during the *Remote* than the *In presence* condition (Wilcoxon signed rank test: z = - 2.599; p = 0.006; effect size = - 0.927).

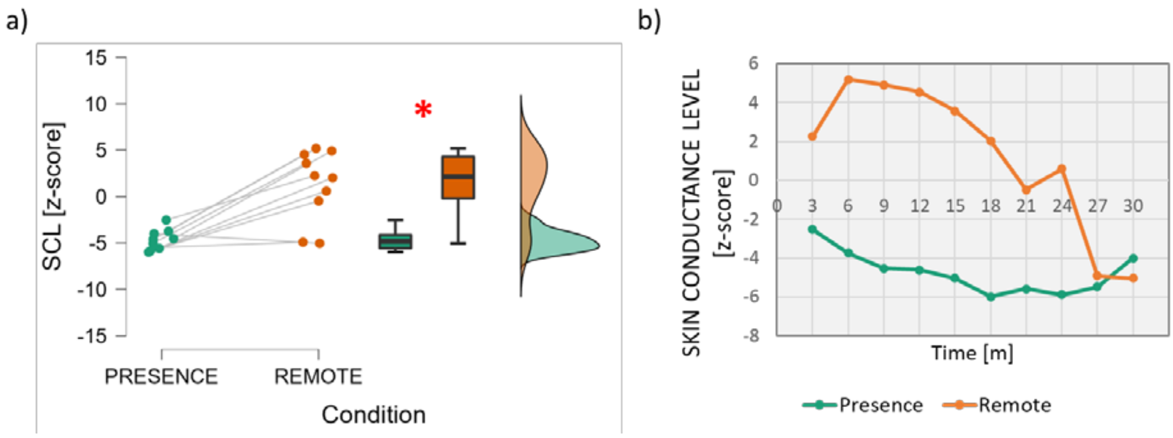

Figure 6. Analysis of the electrodermal activity, and in particular of the Skin Conductance Level. On the left (a), mean and confidence interval (95 %) of the distributions related to the two conditions (In presence and Remote). The red asterisk indicates the presence of a statistically significant effect. On the right (b), the dynamics of the SCL parameter averaged across students along the time span of the lesson.

3.2. Questionnaires

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Results of questionnaires have been analysed from a qualitative point of view. First of all, for each participant the questions have been categorized into subjects covered during the *In presence* and the *Remote* condition. Then, it has been calculated the percentage of right and wrong answers for each condition (Figure 7). The results showed an increase in errors in the *Remote* condition, where subjects gave 3.5 % more wrong answers (15.2 % vs 11.7 % of wrong answers in the *In presence* condition).

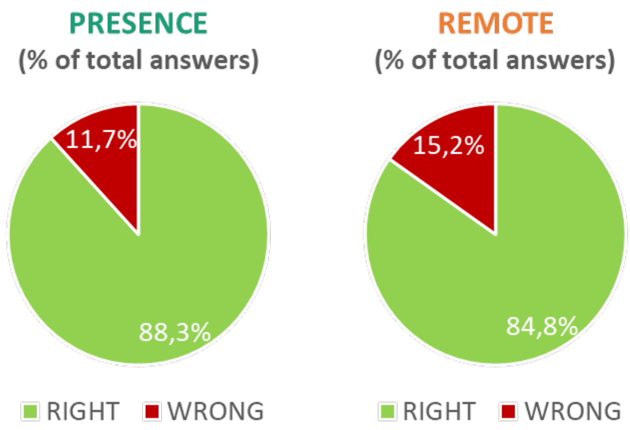

Figure 7. Percentage of right and wrong answers provided by the participants to the subjects covered during the In presence (left) and Remote (right) condition.

Since these results could have been biased by only few students having provided a relevant number of wrong answers in the *Remote* condition, for each student it has been compared the number of wrong answers in both the conditions, and the student performance have been assessed accordingly as follows (Figure 8):

- Worst by PRESENCE, if the participant gave more wrong answer with respect to subjects covered during the *In presence* condition;
- Worst by REMOTE, if the participant gave more wrong answer with respect to subjects covered during the *Remote* condition;
- EQUAL, if the number of wrong answers was the same with respect to the two conditions.

Half of the sample (55.17 %) did not show any difference, almost one third of them (31.03 %) had worst performance with respect to the *Remote* condition, while only the 13.79 % had worst performance with respect to the *Presence* condition.

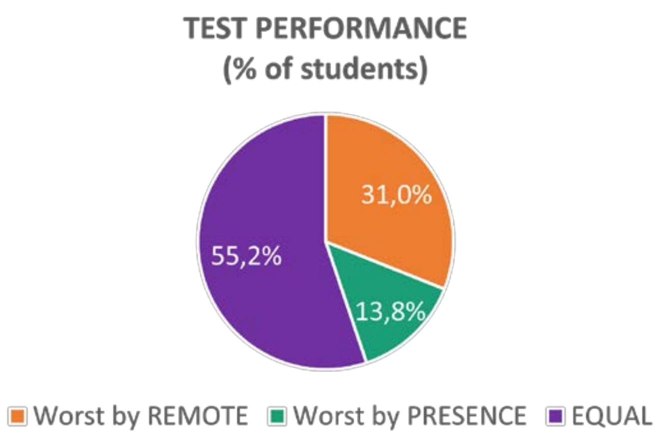

Figure 8. Percentage of students divided according to their test performance: in orange, students that gave more wrong answers with respect to the Remote condition, in green, students that gave more wrong answers with respect to the Presence condition, in violet, students who did the same number of errors.

4. Discussion

The present study involved forty students at a driving school, during a real classroom, in order to evaluate and compare their experience in face-to-face and remote learning conditions. Wearable devices to measure EEG, PPG and EDA signals have been employed in order to analyse the neurophysiological activities of the students during both the modalities and therefore to obtain insights about the cognitive dimension. In particular, four different neuroindicators have been considered, the Eye Blink Rate (estimated from the EOG component of the EEG data), the Heart Rate and its Variability (estimated from the PPG data) and the Skin Conductance Level (estimated from the EDA data). Also, the students filled a questionnaire at the end in order to obtain an explicit measure of their learning performance.

The Eye Blink Rate (EBR) has been investigated as a prompt of attention. In fact, the EBR has been demonstrated to be inversely correlated to attention and vigilance, i.e. increasing EBR is a biomarker of attention decreasing, loss of situation awareness and even drowsiness [36], [43], [44]. Such findings have been demonstrated also in scientific literature related to education and learning [45], [46]. In the present work, for convenience, the inverse of the EBR was considered in order to have a direct correlation with attention. An almost significant effect has been found (Figure 3), since the EBR tended to be lower (and so the attention higher) during the *In Presence* condition. Actually, the statistical significance was not achieved ($p = 0.064$) but the effect size (= 0.673) was between medium (Cohen's $d = 0.5$) and large (Cohen's $d \geq 0.8$) [47]. The difference was more evident after the first 15 minutes, where the inverse Eye Blink Rate of the *Remote* condition, i.e. the attentional level, remained always lower than the *In presence* one, and even lower than the '0' level (Figure 3.b), i.e. the baseline.

In terms of heart activity, a significant effect has been found in terms of both Heart Rate ($p = 0.016$) and Heart Rate Variability ($p = 0.014$), in both the cases with a large effect size (> 0.8). HR has been demonstrated to be positively correlated to Mental Workload, i.e. the increasing of this indicator should suggest a higher mental effort [48], [49]. The HRV indicator, computed as the ratio between Low and High frequencies, is considered a biomarker of Attention and Mental Effort. This indicator has been demonstrated to increase when the user is cognitively involved in the task [43], [50]. In other words, both the parameters are positively correlated with cognitive engagement and mental resources allocation, as demonstrated also by previous works [51]–[53]. In the present work, both the parameters were greater for the *In presence* condition, therefore suggesting a higher cognitive engagement with respect to the *Remote* condition. Anyhow, it is important to point out that in both the conditions the values were positive, i.e., higher than baseline, thus the students were less but still mentally engaged also during the *Remote* lesson. It is also interesting to note that, in terms of HR, the difference between the two conditions appears after 18 minutes (Figure 4.b).

Last but not least from a neurophysiological point of view, also the analysis of skin sweating pointed out a significant effect. In fact, the Skin Conductance Level was significantly higher during the *Remote* condition, and only after 24 minutes converged to values similar to those measured *In presence*. The SCL is usually considered a biomarker of physiological arousal and even stress [54]–[56], Previous works in the educational field demonstrated a positive correlation between skin conductance, in particular when it increases over baseline values, and students' stress and aggressive behaviours [57], [58]. In the present works, while no evident SCL fluctuations have been found *In presence*, a large increasing has been measured at the beginning of the *Remote* condition. This cue of stress could be explained by the specific "remote modality" considered in this study, i.e. an interactive

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remote modality during a hybrid classroom with people also in presence. In this way, such physiological effect could be due to a certain discomfort, and even stress, experienced because of the less immediate interaction with the teacher by remote. Technical or functional issues, such as speaking with the microphone still muted, the difficulty to participate to the discussion because the teacher is distracted by people in presence, could cause stress and so lead to loss of interest and attention. Interestingly, this effect tends to disappear at the end, when the other indicators suggested a decreasing of attention and mental engagement. In other words, it seems that during a hybrid classroom, sustaining attention for a prolonged time and remaining mentally engaged is more demanding and stressing.

Not surprisingly, analysis of questionnaires, intended as a measure of "learning performance", showed an increase in errors on topics attended by remote, with performance deteriorating in about one third of the students.

In any case, as introduced, the overarching aim of the study was not to determine which modality is the better. On the contrary, considering the current scenario and new lifestyles, the rationale was to deploy innovative methodologies for investigating and pointing out the differences, in terms of students' experience, between different educational modalities, in order to define strategies and countermeasures to deal with the arisen concerns. As a practical example, from this study it could be concluded that during hybrid modalities interaction of people by remote should be facilitated and encouraged, and the lesson should be organized in more and shorter modules, for instance four 15-minutes-long instead of two 30-minutes-long modules, in order to avoid attentional and engagement dropping.

At the best of our knowledge, this is the first study employing simultaneously different neuro-devices investigating both the Central (brain activity) and Autonomic (heart and sweating activities) Nervous Systems, on a not negligible sample size (i.e. 40 participants), in real settings and considering both the educational modalities, i.e. *In presence* and by *Remote*. The study is however to be intended as preliminary, due to the novelty and complexity of the experimental approach. In future studies, a similar approach should be enriched by a more deep analysis of students' brain activity, it should involve a larger sample size, and it should be applied in different contexts (besides the driving training) in order to demonstrate the cross-domain validity of the obtained outcomes. Also, on a more applied level, it would be interesting to compare different alternatives of remote modalities, for example a full remote classroom (instead of a hybrid situation as that investigated), or remote modalities without interaction with the teacher (i.e., pre-recorded courses). Anyhow, beyond the results obtained and discussed, it suggests how the use of these new wearable technologies opens new scenarios on the study of students' experience to improve the effectiveness of teaching and optimise the use of new educational modalities that are becoming widespread.

5. Conclusions

Analysis of neurophysiological indicators highlights a higher «cognitive activity», in terms of attention and mental engagement, during the *In presence* lesson with respect to *Remote* modality. On the other hand, analysis of skin sweating seems to suggest a higher stress, in particular during the first part of the lesson, in students by *Remote*. This could be due to the less smoothness in interacting with the teacher. Analysis of questionnaires demonstrated worst performance on the questions related to the subjects taught by remote. Therefore, there is evidence of a common "disengaging" behaviour when attending remote courses, that could undermine the teaching effectiveness.

In general, the use of physiological indicators could help to obtain insights about possible mental causes, that are often «blind» to an external supervisor, such as attentional decreasing and stress increasing, as well as their dynamics during the lesson itself. Neuroscientific tools become so a powerful mean that could add value to traditional assessing methods and could allow to define proper countermeasures to emerging issues when living through periods of transition to new tools, practices and protocols.

Supplementary Materials: The following supporting information can be downloaded at: www.mdpi.com/xxx/s1, Figure S1: title; Table S1: title; Video S1: title.

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Data Availability Statement: The aggregated data analysed in this study might be available on request from the corresponding author.
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