

# Influence of Dominant Electrical Brainwaves on Learning Performance

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**Abstract:** In this work, we developed a new approach to predict learning performance regarding a group, by analyzing his brain activity during a two-day experiment. In fact, we recruited 21 participants and asked them to read multiple texts in the first day and to answer questions about these texts on the second day. In our experiment we recorded for every learner the amplitude of the six main frequency bands and we computed the rate of the dominant brainwave vector per second. The other factor that we register is the variation of this rate during the two days of the experiment. The combination of these factors was used to predict the learner performance of the 21 participants and permitted us to predict the learning performance with 76% of accuracy.

## Introduction

In the learning process, there are two important stages: acquiring knowledge and restoring it later. If knowledge is well restored, that means that it was well assimilated. The marks that learners obtain at the end of a test inform about their learning performance. We want to investigate in this paper the impact that the electrical brain activity can have on this performance. We choose to focus on that specific activity because of the importance in finding a specific pattern that could distinguish a good performance from a bad one.

Most researches in the field of Artificial Intelligence (AI), Human-Computer Interactions (HCI) and Intelligent Tutoring Systems (ITS) defined emotional, cultural and psychological optimal conditions for learning [4, 5, 10]. Kort, Reilly and Picard [10] proposed a comprehensive four-quadrant model that explicitly links learning and affective states. They explain the positive and negative emotions that influence learning. This model however has not yet been supported by empirical data from human learners. D’Mello [6] study reports data to integrate affect-sensing capabilities into an intelligent tutoring system with tutorial dialogue, namely AutoTutor. They identified affective states that occur frequently during learning. They applied various classification algorithms towards the automatic detection of the learners affect from the dialogue patterns manifested in AutoTutor’s log files.

As a complement to these studies, this paper aims to explore the influence that electrical brain activity can have on learning performance. We record brainwaves with a non-invasive brain-computer interface that reads brain signals using an electroencephalogram (EEG) called Pendant EEG [12]. EEG-based brain-computer interfaces use sensors placed on the head to detect brainwaves and transmit them to a computer for further processing and analysis [13]. We collected data from 24 participants. We used machine learning techniques to predict the learner’s mark according to the group mark average (learner’s mark can be either higher and equal or lower than the group average). At the end of this paper, we engage in a discussion regarding a future work about implementing a classifier within an agent which will communicate with an Intelligent Tutoring system. This agent will automatically be able to predict the learner’s performance and eventually better adapt the tutor’s intervention by selecting the best pedagogical strategy to suit the present learner.

## Brain Behavior Assesment

In the brain, six basic types of waves can be distinguished. Each of these waves can be the dominant one over a period of time. When a brainwave is the dominant wave, it gives information about the learner state. Each wave is identified by amplitude and an interval of frequencies. The brainwaves that we measured were categorized into 6 different frequency bands, or types, known as delta, theta, alpha, beta1, beta2 and beta3. Each of these wave

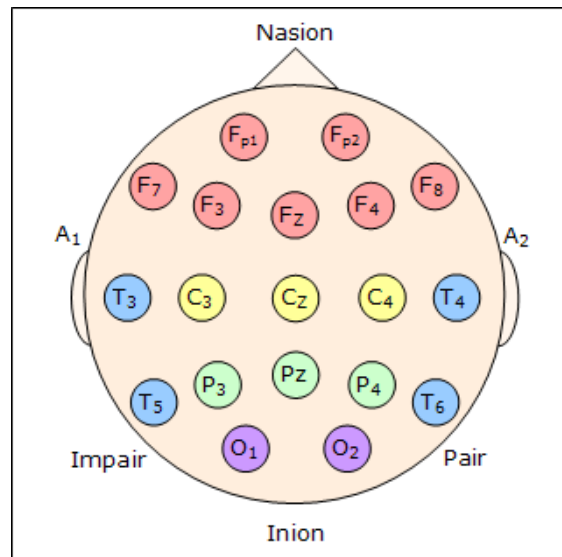
type correlates with a particular mental state [1, 3]. Table 1 lists the different frequency bands and their associated mental states.

**Table 1:** Brainwaves Types and their associated Mental States

Brainwave	Frequency	Mental State
Delta ( $\delta$ )	0-4 Hz	Deep sleep
Theta ( $\theta$ )	4-8 Hz	Creativity, dream sleep, drifting thoughts
Alpha ( $\alpha$ )	8-12 Hz	Relaxation, calmness, abstract thinking
Beta1 ( $\beta_1$ )	12-15 Hz	Relaxed focus
Beta2 ( $\beta_2$ )	15-20 Hz	High alertness
Beta3 ( $\beta_3$ )	+20 Hz	Agitation

## The Two Day Study Description

To measure the learners' brainwaves, we use Pendant EEG, a portable wireless EEG. Electrode placement was determined according to the 10-20 International System of Electrode Placement [13]. This system is based on the location of the cerebral cortical regions. In our case, three electrodes were sufficient [11]. Furthermore, they were placed on  $PC_z$ ,  $A_1$  and  $A_2$  as shown in Figure 1. Pendant EEG sends the electrical signals to the computer via an infrared connection. Light and easy to carry, it is not cumbersome and can easily be forgotten within a few minutes. The learner wearing Pendant EEG is completely free of his movements.



**Figure 1.** The 10-20 International System of Electrode Placement

The experiment includes 24 participants. They were selected from the Computer Science Department of Université de Montréal. Each participant, while connected to Pendant EEG, was asked to read 7 texts on the first day and to answer 35 questions related to the text they read on the second day. The duration of the experiment on each day for each participant varies between 30 and 40 minutes. It is important to note that brainwave activity was recorded during the two days: that is during text reading (day 1) and test answering (day 2).

## Brain Behavior Analysis and its Impact on Learning Performance

The purpose of this work is to examine how brain profile can affect learning performance. Indeed, our system can determine whether an individual in a group has successfully learned a lesson or passed an exam by analyzing his brain behaviour with regards to the other learners in the group. The first challenge we set forth was to identify learning performance indicators. The other challenge we wanted to address was the variables that could play a crucial role in representing and modeling the learner's brain profile.

For the first challenge, we evaluated the quality of learning by considering the marks obtained by the learners in the activity of the second day which consists of answering questions from a test. A total number of 23 learners took part in our experiment. Nevertheless, two have been discarded from the analysis because of their major lack in understanding and reading French, the language used in this experiment.

The second challenge was answered by measuring the brain activity, and building for each learner, a set of wave dominance vectors. Indeed, these vectors represent, in an ordered manner according to the dominance wave, the values of the six possible wave bands, namely alpha, beta1, beta2, beta3, delta and theta. Thus, the first element of the vector is the most dominant band measured. For example, at one moment, a learner may have the following vector V1: {delta, beta2, alpha, beta1, theta, beta3}. We recall that during the experiment a new vector for a learner, was recorded, following a change in one of the six values of the vector. For example, beta2's value in V1 exceeds that of delta and all other four values remain constant. In that case, we would have a new vector V2: {beta2, delta, alpha, beta1, theta, beta3} attributed to the learner.

We therefore got at the end of this activity, a number of vectors for each learner. This number can obviously differ from a learner to another and depends on the time spent in the learning activity. Since that duration differs from one student to another, we weighted therefore the number of wave vectors emitted by the duration (measured in seconds). We obtain, for each learner, a rate of vectors per second. This rate serves as a measure that reveals the brain intensity and will be used as a characteristic when modeling the learner's brain profile. Table 2 shows a sample from the 21 learners' marks as well as the rates of emitted brain waves during the second learning activity.

**Table 2.** Learner's marks and brain waves data relative the second learning activity

<b>Learner_id</b>	<b>Learner_mark</b>	<b>Dominance vector rate per second</b>
1	74	4.53
2	20	3.50
3	34	5.15
...	...	...
13	54	0.51
...	...	...
21	34	5.06
<b>Average</b>	39	2.65
<b>Standard deviation</b>	11.88	2.22

By analyzing Table 2, we can see that the first learner who incidentally happened to have the best mark, which varies from 0 to 100, has one of the highest rates of dominance vector emission. On the other hand, learner 3 also has a high wave emission rate, but his mark is below the average. In the same way, learner 13 having an emission rate low compared to the average, have had a mark higher than the group average.

A priori, this initial analysis shows that learning performance is not directly correlated with the rate of wave emissions recorded in the testing phase during the second day. In fact, in this experiment, marks obtained during the second day question answering session, are closely related to the reading activity of the first day since there is memorization involved. It then seemed more intuitive to take into account the rate of waves emitted during the first day. These data are presented in Table 3.

**Table 3.** Learner's brainwaves data corresponding to the first learning activity

<b>Learner_id</b>	<b>Dominance vector rate per second</b>
1	0.40
2	3.36
3	3.48
...	...
13	0.50
...	...
21	1.12
<b>Average</b>	2.27
<b>Standard deviation</b>	2.06

Table 3 shows that the first learner, who had the highest mark and had a high emission rate of emitted dominances during the second day, has the lowest rate in the first learning activity. For learner 13, the emission rate characteristic remains nearly constant between the two days. Therefore, it would be interesting to include this

variation in the analysis of the learner's brain behaviour. Figure 2 illustrates the change in the dominance vector rate per second for day two when compared to day one. More than half of the participants had a higher dominance vector rate on the second day.

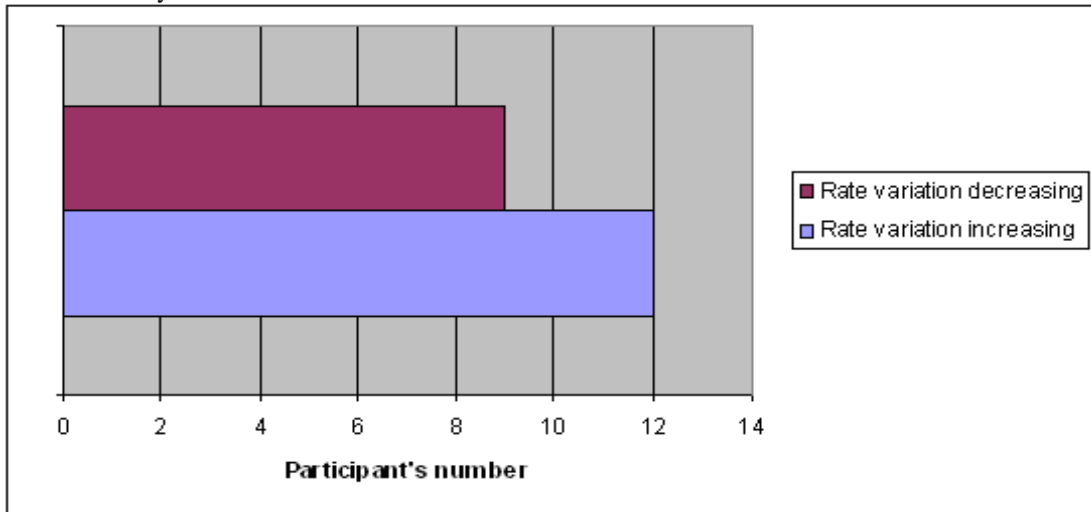


Figure 2. Change in the dominant vector rate per second for day two.

In this case, we were interested in comparing learners between themselves. In other words, the rate of emitted brain waves is compared to the average of the whole group. Each learner has then a rate either lower or higher (and equal) than the group average on the second day. By the same way, learner's marks will be computed with regards to the average of the group. Thus, a learner can obtain a mark that is either lower (<) or higher and equal (>=) than the group average as depicted in Figure 3.

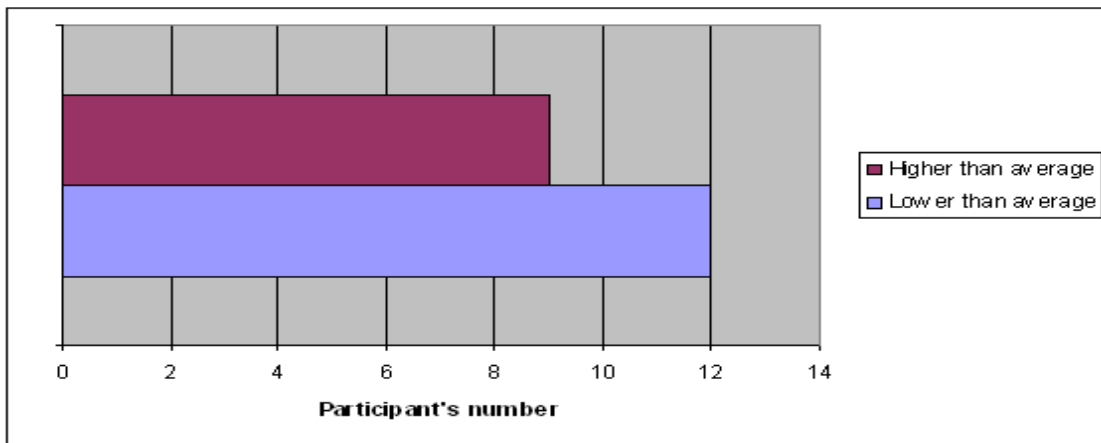


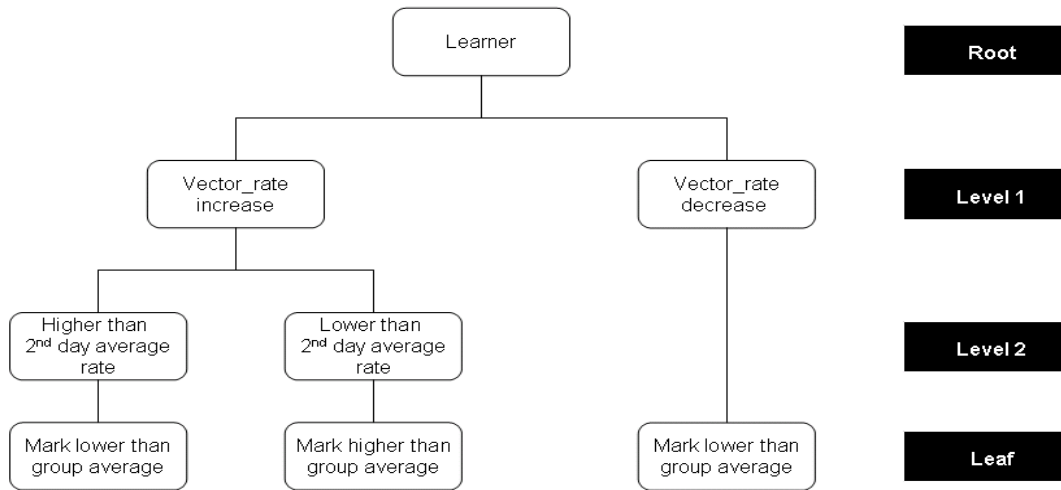
Figure 3. Learner's marks proportions

We created a group profile, computed from the combination of these factors. This profile allows the prediction of the learning performance of an individual regarding to a group. This profile is mainly based on the variation of the learner brain behavior between the two learning activities and the wave vector rate intensity emitted during the second day. The details about the model are presented in the next section.

## Results and Discussion

To build the model associated to the prediction of the learning mark class (higher or lower than the group average), we used the ID3 algorithm [9] with a ten fold cross validation. This algorithm produced a decision tree by computing the information gained for each attribute and selecting the greatest one. This tree is shown in Figure 4.

This model involves two levels corresponding to the brain characteristics between the root and the leaves of the tree. The root represents the learner: it is the starting point for the prediction of the class mark that can be either higher (and equal) or lower than the group average. This class is represented by the leaves of the tree. The first level is the direction of the emitted wave variations (vector rate/s) between the two days. This variation can obviously either increase or decrease. The second level of the tree is the second day dominance vector rate/s: it may be either lower or higher (and equal) than the average dominance brainwaves emitted during the second day. For example a learner whose variation vector rate decreases between the two days is classified as “Mark lower than group average”.



**Figure 4.** Decision tree associated to the learning mark class prediction

According to the built prediction model, a learner with a vector-decreasing rate between the two days will tend to have a mark lower than the group average. On the other hand, a learner having an increasing vector rate between the two days and a wave rate higher than the average during the second day would also have a mark lower than the average. Also according to this tree, in order to have a mark higher than the average, the learner vector rate computed between the two days should increase. Furthermore, that rate should be lower than the group average rate on the second day. This situation reflects a more intense brain activity during the second day and therefore more "productive" since the second day is a question answering-based without exceeding the average of the group activity.

**Table 4.** Summary of the evaluation on test split

Correctly Classified Instances	Incorrectly Classified Instances	Kappa statistic
76.19 %	23.81 %	0.4186

A summary of overall results as well as the details of accuracy are given in Table 4 and 5. It is shown that we could predict with more than 70% whether the learner would have a mark higher or lower than the group average mark. Indeed, we reached a rate of 76.2 % while trying to correctly classified instances. The precision is 0.706 for the «Mark lower than group average» class and 1 for the « Mark higher than group average » class.

**Table 5.** Detailed accuracy per class

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
1	0.556	0.706	1	0.828	Mark lower than group average
0.444	0	1	0.444	0.615	Mark higher than group average

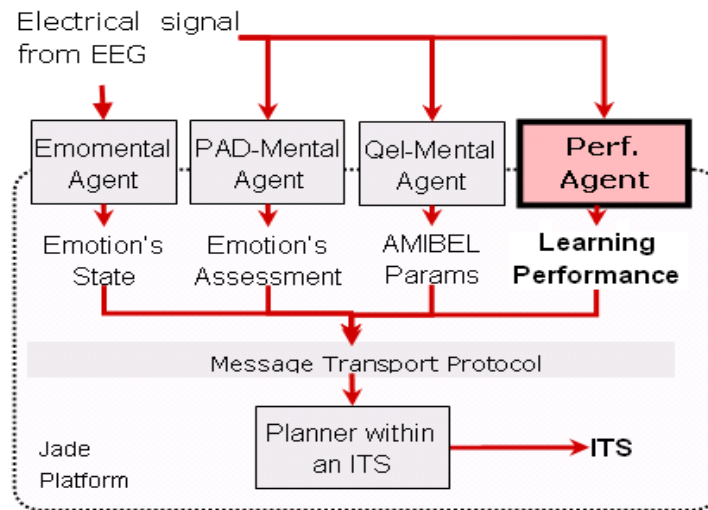
Besides, from the confusion matrix described in Table 5, we can see errors in assigning classes to instances. In fact, all learners of the « lower than group average mark» class were correctly predicted and that 4 over 9 students have been correctly assigned to the « Higher than group average mark» class.

**Table 6.** Confusion matrix

S	H	← classified as
12	0	Lower than group average mark [S]
5	4	Higher than group average mark [H]

## Implementing the Agent and Integrating it to an ITS

The agent in this paper, called the Perf. Agent for Performance Agent, is destined to integrate a brain interaction framework that communicated with an ITS. Through our system, learner brainwaves will be analyzed and results provided to the Planner Agent of the ITS. Figure 5 shows an excerpt of that framework with a focus on the currently developed agent in this paper called the Performance Agent. It will represent the continuity of our previous work [6, 7]



**Figure 5.** Architecture of the future integration

We are currently implementing the integration up on JADE platform [2] (Java Agent Development Framework). Communication between the agents is realized through the use of the FIPA Agent Communication specification that deals with Agent Communication Language (ACL) messages. The new agent receives the electrical signal from the EEG and some other calculated attributes related to the learner group. It transmits the prediction result to the planner (a central agent that coordinate tasks within the ITS) and the ITS is able to generate appropriate responses to assist the learner and adapt the content and the pedagogical strategies.

## Conclusion

We have investigated in this paper the impact of the brain's electrical behavior on the learner's performance. The study conducted enabled us to record the learner's brainwave activity between a two-day period. Brainwave activity was filtered in the form of dominant wave types and computed in our system. Our statistical analysis enabled us to predict, with a very encouraging accuracy of 76%, the probability of the learner's performance based on dominant vector rates changes. Indeed, the obtained decision tree utilizes the increase or decrease in the vector rate, along with the group average mark, to predict the learner's expected average mark with regards to the group's mark. This paper's contribution is two-fold: first, we established a link between brainwave emissions and the expected mark with regards to a group. Second, our Performance Agent, once implemented, can seamlessly integrate with an intelligent tutoring system, thus augmenting not only its efficiency but its intervention quality as well. It is in fact one of our future goals. We intend in the near future to combine this agent in our Multi-Agent Platform and validate its efficiency in a future experiment.

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