Identification of Mechanisms and Biomarkers of Learning Efficiency Based on Multimodal Data

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***Abstract*—In today's rapidly evolving world, the ability to efficiently learn and process new information is increasingly crucial. This study aims to identify mechanisms and biomarkers of learning efficiency using multimodal data. We designed and conducted a neurophysiological experiment simulating educational activities over two days with 26 participants aged 18 to 30. Behavioral data such as *memory time*—the interval from stimulus presentation to participant response—were analyzed to understand cognitive processes during learning. Participants underwent the Multidimensional Fatigue Inventory (MFI-20) test to assess their psychophysiological state before and after the experiment. Our findings reveal a statistically significant decrease in performance 50–60 minutes after presenting new information, aligning with Ebbinghaus's forgetting curve. This suggests that unfamiliar information not properly assimilated within this time frame does not enter long-term memory. The results underscore the importance of reviewing new information shortly after learning to enhance retention. By identifying key behavioral markers and understanding their impact on learning efficiency, this study contributes to the development of intelligent expert systems that optimize educational activities based on individual psychophysiological characteristics.**

***Index Terms*—biomarkers, learning, quality of learning, multimodal data, behavioral data**

I. Introduction

In today's world, the amount of information is always increasing. The need to process it quickly and efficiently is also growing. Therefore, the ability to learn and analyze new data effectively is becoming very important [1]. This trend means we need new approaches in education and learning. These approaches should be based on understanding the biological foundations of how we learn and absorb new information [2].

This scientific research is relevant because we need to improve the effectiveness of the educational process [3]–[5]. We can achieve this by using intelligent expert systems to optimize educational activities. These systems should consider each person's unique psychophysiological traits and cognitive state [6]. This is due to the fact that, for example, fatigue negatively affects the efficiency of information assimilation [7], [8].

This field is actively studied worldwide [9]–[11]. However, most research does not discuss the specific physical mechanisms that create patterns of neural activity. As a result, the methods developed often depend heavily on individual characteristics.

Considering this, the scientific significance of this study lies in identifying the mechanisms that form patterns of neural activity in the brain during learning. The scientific novelty is in discovering characteristics related to the biophysical mechanisms by which the brain processes educational information of different types (visual, auditory, combined) using multimodal neurophysiological data.

II. Methods

To study this problem, we designed and conducted a neurophysiological experiment. The experiment simulated educational activities and was carried out in two stages over two days. Twenty-six students aged 18 to 30 took part in the experiment.

On the first day, participants went through a learning phase where they were presented with 180 facts from different areas of scientific knowledge (physics, chemistry, computer science, pedagogy, art, history). After the learning phase, they took a test to check their knowledge of the facts.

On the second day, participants only went through the testing phase. To assess their prior knowledge of the facts, each participant completed an additional questionnaire at the end of the experiment.

To evaluate the psychophysiological state of the participants before and after the experimental study, various additional tests are often conducted. One of the best methods for monitoring the current level of fatigue is the Multidimensional Fatigue Inventory (MFI-20) [12]. It consists of 20 items and allows for assessing fatigue on five scales: general asthenia, physical asthenia, reduced motivation, decreased activity, and mental asthenia. The MFI-20 provides a comprehensive assessment of participant fatigue.

One of the key elements in solving such tasks is the analysis of behavioral data during information assimilation. Behavioral data, such as memory time (Figure 1), defined as the interval from the moment a stimulus is presented to the moment the participant responds, provide valuable information about the cognitive processes occurring during learning.

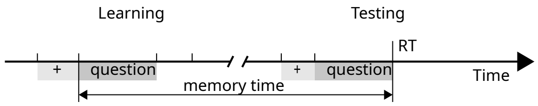

Fig. 1. Definition of memory time characterization where: learning - learning stage, testing - testing stage, RT - reaction time, question - presented fact.

Analyzing changes in memory time helps us assess how effectively new information is learned. It also allows us to understand how different factors affect the speed and quality of responses. We use repeated measures analysis of variance (RM ANOVA) for statistical processing of these data. We chose RM ANOVA because it accounts for differences within the same individuals. This method lets us analyze changes in measurements under different conditions or over time for the same subjects. This is especially important when studying cognitive processes, where individual characteristics can significantly influence the results.

III. Results

Based on the design of the experimental study, participants underwent MFI testing before and after the experiment, on the first and second day respectively. Figure 2 shows the results of this testing for each day of the experiment.

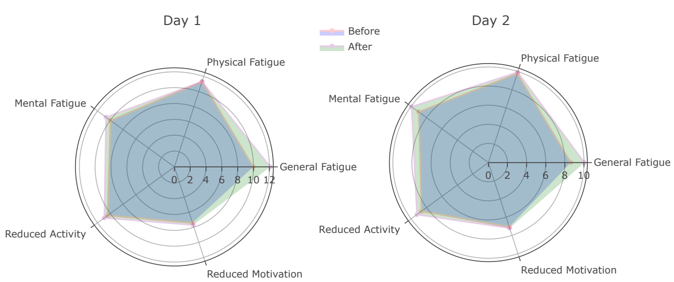

Fig. 2. Mean scores of different types of fatigue from the MFI-20 test for the first and second days of the experiment.

Based on the results of the MFI test, it can be observed that during the experiment, participants primarily suffered from general fatigue and decreased motivation caused by the duration of the experiment. The results also indicate that all participants had the same level of asthenia, suggesting uniform conditions of subjective fatigue.

To evaluate the performance of information assimilation, we used the proportion of correct answers. Figure 3 shows the dependence of success rate on memory time and prior knowledge of the fact. To conduct statistical analysis and incorporate time as a factor, we categorized memory time into the following ranges: 6–22, 22–38, 38–55, and 55–71. These ranges were determined based on the minimum and maximum memory times recorded for the entire group of subjects.

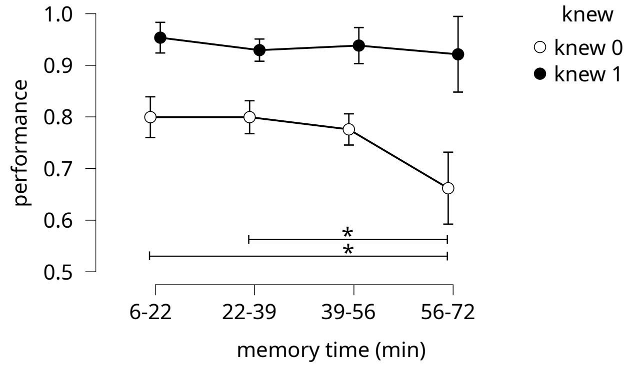

Fig. 3. Dependence of performance on the time elapsed since the presentation of the fact and prior knowledge. The symbol * denotes statistical significance in post hoc analysis using t-test with Holm's correction for multiple comparisons.

The results show that performance depends on prior knowledge of the fact and the time elapsed since its presentation. It can also be said that performance decreases significantly 50–60 minutes after the presentation of the fact. The obtained result is consistent with Hermann Ebbinghaus's classic forgetting curve experiment [13]. The findings show that memory retention decreases sharply within the first hour after learning new information. This indicates that after the specified time interval, information that has not been properly assimilated does not enter long-term memory. RM ANOVA test showed statistically significant results shown in Table I, there MTime is *memory time*.

TABLE I
Correlation table

Factor	Sphericity Correction	df	F	p
MTime	None	3.000	6.038	$< .001$
	Greenhouse-Geisser	1.783	6.038	0.006
Knew	None	1.000	141.80	$< .001$
	Greenhouse-Geisser	44.563		
MTime * Knew	None	3.000	3.276	0.026
	Greenhouse-Geisser	1.561	3.276	0.060

Conclusion

As a result of our study, we compared the overall level of asthenia and subjective fatigue indicators for the group of subjects in an experiment simulating educational activities. Additionally, we demonstrated a statistically significant difference in performance based on the time elapsed since the presentation of the fact and prior knowledge. The results indicate that after 50–60 minutes, unfamiliar information, if not well assimilated, does not enter long-term memory. This suggests that reviewing new information within this time frame can significantly increase the chances of better assimilation.

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