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Gunda Yuga Raju, Suprakash Gupta, Lalit Kumar Singh

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Prediction of human performance using EEG data to improve safety and productivity in the mines

Gunda Yuga Raju* and
Suprakash Gupta

Department of Mining Engineering,
Indian Institute of Technology (BHU),
Varanasi, Uttar Pradesh, India
Email: gundayugaraju.rs.min17@iitbhu.ac.in
Email: sgupta.min@iitbhu.ac.in
*Corresponding author

Lalit Kumar Singh

Department of Atomic Energy,
The Nuclear Power Corporation of India Limited (NPCIL),
Mumbai, Maharashtra, India
Email: lksingh@npcil.co.in

Abstract: Dynamic cognitive performance has an impact on the safety and productivity of mine workers. Previous studies show that physiological measures have a good correlation with cognition during task execution. Observing the escalating demand for safe production in mines, it is now a crucial research area to examine the physiological variables that can predict cognitive performance prior to task allocation. In this experimental work, we have tried to predict how well participants will do on upcoming tasks using brain signals captured by electroencephalography. An Electroencephalogram (EEG) was recorded from 40 participants who subsequently took a cognitive test. After data analysis, our results show that EEG features can predict cognitive performance, with $R = 0.48$, $p = 0.002$, for the memory task and $R = 0.546$, $p < 0.001$ for the attention task. This study also discussed the potential area of applicability in mining and some management strategies for dealing with workload and fatigue-related issues.

Keywords: safety; productivity; cognitive performance; data analysis; EEG; electroencephalogram; mining industry.

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Biographical notes: Gunda Yuga Raju is a passionate educator and accomplished mining engineer. He holds a Bachelor's degree in Mining Engineering from Kakatiya University, Telangana, where he achieved a remarkable 76% overall grade. His pursuit of excellence led him to obtain a Master's degree in Technology from IIT BHU, Varanasi, with an impressive Cumulative Performance Index (CPI) of 7.9. Currently, he is a PhD candidate at IIT BHU, focusing on researching human reliability and striving to enhance human performance across different domains.

Suprakash Gupta, with over 25 years of experience, holds a PhD in Mining Engineering from IIT Kharagpur (2004), an MTech in Mining Engineering (1995), and a Bachelor of Engineering degree (1992). He worked as an Assistant Mining Engineer at Hutti Gold Mines (1995–1997) before joining the Mining Engineering Department at IT-BHU in 1998. Throughout his 24+ years of teaching, he has covered subjects like Underground Mine Environment, Reliability Engineering, and Data Analytics. His expertise lies in in-service reliability estimation and equipment maintenance.

Lalit Kumar Singh is a distinguished Scientist in Reactor Safety Analysis with the Department of Atomic Energy, Government of India, specialising in Probabilistic Safety Analysis. With 19 years of experience, he has worked on Pressurized Heavy Water Reactors (PHWR) and Light Water Reactors (LWR). He has successfully completed 33 projects and has expertise in software reliability, system safety, image processing, deep learning, and human reliability analysis. He holds a PhD in ‘Modeling for Early Reliability Prediction of Software Systems’ from IIT (BHU). Additionally, he serves as a faculty member at the Nuclear Training Centre.

1 Introduction

To prevent accidents and reduce their effects, industries around the world have embraced a number of technical breakthroughs like advanced control and automation. Despite the multiple layers of safety, accidents still occur. Considering the mining industry in India, there are numerous accidents throughout the year at various locations. From DGMS Standard Note 2020, the number of mining incidents that were fatal or serious accidents in 2010–2019 varied from 273 to 724 (Government of India, 2020). In the same time period (2010–2019), the number of people who died or were seriously injured ranged from 311 to 788. The main cause of these accidents is mishandling of mining machinery and the fall of people or objects. According to the DGMS, these accidents are caused mostly due to mismanagement by supervisory staff (Annual Report, 2014; Government of India, 2020). Based on these reports, we can conclude that the majority of accidents are the result of a single individual’s decision-making and that the majority of the individuals involved in these accidents are single. From the literature, any incident investigation reveals that human error is a major factor in almost all mishaps and accounts for more than 70% of accidents in mining and manufacturing (Ruckart and Burgess, 2007), chemical facilities (Iqbal et al., 2020), marine and offshore industry (Islam et al., 2017), aviation (Begur and Babu, 2016), nuclear power plants (Choi and Seong, 2020).

Mining is a complex industry with a dynamically changing, risky workplace environment. Although the mine workers are physically trained and able to perform the task, their dynamic cognitive ability may be inadequate for completing it correctly or without error (Allahyari et al., 2008). Here, ‘human cognitive ability’ refers to a person’s capacity to complete a task using their innate knowledge within the required time, accurately and with due attention. Statutory bodies like DGMS have stipulated various standards for organisational and environmental factors to avoid accidents. But it is just a prerequisite for the weakest link ‘human’, highly prone to errors, to be attentive to the surroundings and do productive work. This motivates our study to help mine

management by giving a methodology to quantify cognitive capability that can set some human standards to accomplish the allotted task safely and effectively. The takeaway from this study is also significant for the policy-making, mining practice and the mining society as a whole.

This study aims to match the human cognitive capability with the allocated task, even before their allocation. The primary objectives of this research are as follows:

- Developing a suitable method for assessing cognitive capability and human performance.
- Exploring the correlation between cognitive capability metrics and the performance in the impending task.
- Building a model for predicting human performance in the impending task.

The rest of the article is organised as follows. Section 2 presents the literature on the interconnection between cognitive phenomena and popular physiological indicators. Section 3 describes the experimental study and the detailed experimental procedure. Section 4 presents the results of the experiment along with the discussion. Potential applications of the study in mines' safety are enumerated in Section 5. Finally, in Section 6, we have discussed some of the limitations and concluded the findings.

2 Background of research

When an individual is physically fit for a job, human performance mainly depends on certain cognitive phenomena (Wickens et al., 2021). Cognitive phenomena like workload and fatigue are found and well-researched to improve safety and productivity (Islam et al., 2018). There are many research studies that have tried to evaluate cognitive capability (Comberti et al., 2019; Leva and Builes, 2017). Laux and Plott (2007) attempted to incorporate the cognitive aspect of human error into risk assessment methodologies. However, research into human cognitive ability to improve safety and productivity is still in its infancy.

Evaluating workload and fatigue has been done using questionnaires for a long time. Real-time workload and fatigue measurement, which previously relied primarily on behavioural measures such as eye activity and speech, has received little attention (Chen et al., 2016; Kodappully et al., 2016). Recent research studies found that physiological measures unintentionally reveal an individual's internal status. Andreassi (2010) established ways for objectively and quantitatively measuring performance using several physiological indicators. Some of the frequently employed physiological indicators include Electroencephalogram (EEG), Electrocardiogram (ECG), Electrooculogram (EOG), and Electrodermal Activity (EDA). The use of these indicators has also significantly improved our understanding of cognition (Argyle et al., 2021). A more widely used and reliable method for assessing workload and fatigue is the quantitative analysis of EEG (the brain's electrical activity) signals.

The EEG power in frequency bands, like theta (4–8 Hz), alpha (8–12 Hz) and beta (12–30 Hz) can accurately indicate cognitive ability (Simpson and Rafferty, 2022). EEG power bands, along with behavioural indicators such as blink rate and length, are used to examine the cognitive correlates of fatigue and attention (Ko et al., 2020). According to widespread consensus, increased workload and fatigue are associated with higher beta

wave power and reduced alpha and theta wave power in the frontal lobe (Borghini et al., 2014). Additionally, eye-blink activity has been studied as a performance indicator in choice-response tasks to determine the central nervous system's capacity for cognitive processing (Paprocki and Lenskiy, 2017). Eye blinks indicate the level of attention paid to specific tasks (Maffei and Angrilli, 2018), the reallocation of mental resources (Benedetto et al., 2011), changes in cognitive states or transitions in information processing (Bafna and Hansen, 2021).

In all the above studies, recordings are made when the subjects are performing certain tasks. And these methodologies will be of use only for evaluating human performance in parallel with the task activity. The practical adaptability of such technologies in industries is questionable with respect to their compatibility with ergonomic standards and resource availability. But there is another way of dealing with the issue: progressing the research toward devising a methodology for evaluating human cognitive capability prior to task allocation.

After the first few hours of work, overall cognitive performance decreases throughout the day as fatigue and workload increase (Chtourou et al., 2013; Grech et al., 2009; Thomas et al., 2012). So, if we can predict the human cognitive capability prior to the task allotment, then it is possible to reduce the risk of mishaps. So, in this research, we tried to predict human cognitive performance using the features extracted from EEG recordings prior to the task. And our primary focus will be on the characteristics that have been linked to workload and fatigue in earlier studies.

3 Methodology

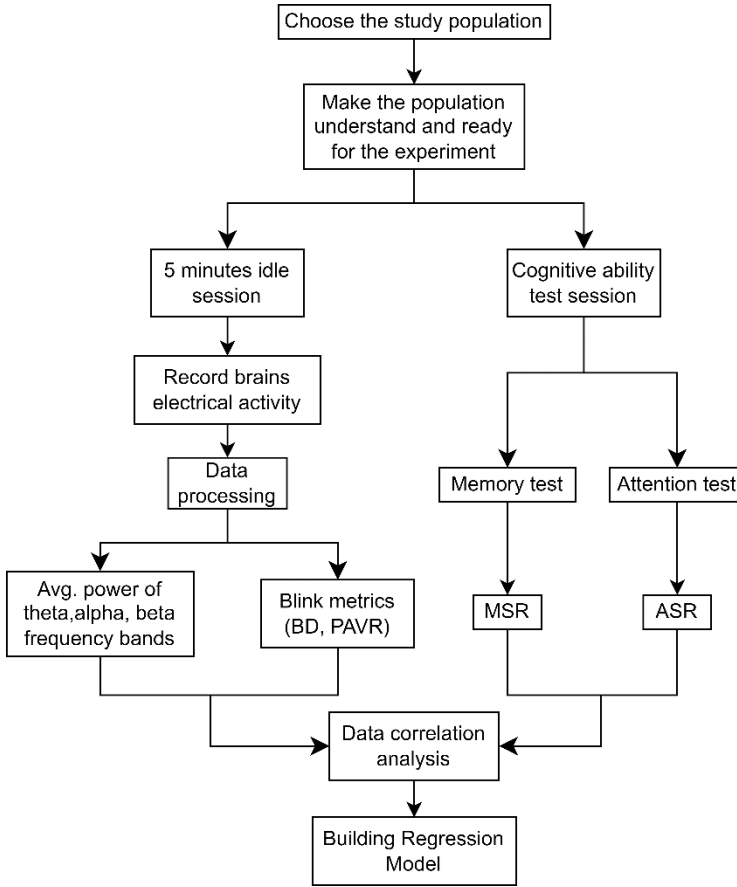
In this research, we tried to achieve our objective by building a model based on the EEG features as input variables and cognitive performance as the output variable. For this, our experiments started with a 5-minute idle session where we recorded brainwaves from the participants, and later we made them attend a cognitive ability test session. We evaluated working memory and attention in this cognitive ability test, which are the key components in the information processing theory (Awh et al., 2006). The sequence of methodology steps is shown in Figure 1.

All the participants are trained with cognitive tests by making them attend the tests once a day for a week prior to the actual experiment. This will make sure that the participants have reached their in-built capability level for that specific test. On the day of the experiment, it is easy to judge whether the participant is up to his capability level on that specific day or not.

3.1 Ethics statement

The procedure and the purpose of conducting the study were explained to the participants a week before commencing the experiment. This ensures that the participants are well accustomed to the test and have reached their inbuilt capability level by attending the test at least once a day. The participants were assured that the final experiment would not cause any harm, nor it would have any negative consequences. Written consent to participate in the experiment was obtained from all the interested participants. The study received approval from the Institutional Evaluation Committee, where the work is carried out.

Figure 1 The sequence of methodology steps



3.2 Experimental Setup

The experiment was carried out in a controlled environment to avoid sudden changes in temperature, noise or illumination levels. The preparedness of the participants was judged by their confirmation that they were capable of completing the task and self-motivated (without any incentive for their participation). It was ascertained that the participants didn't have any caffeine or nicotine in their systems. The participants were tested individually using a cellular phone. Figure 2 shows a pictorial representation of the experimental setup.

The experiment consists of two sessions: session A is a 5-minute idle period, and Session B is a 5-minute test of cognitive ability. In session A, Ultracortex Mark IV EEG headset was used to record the subjects' brains' electrical activity. In Session B, the participants took a cognitive ability test in Lumosity software. This software is a cognitive training application marketed to enhance working memory, divided attention and other cognitive processes (Hardy et al., 2015).

Figure 2 Experimental setup (Session A and Session B)

Extra precautions were taken during the test to ensure that EEG records were unaffected by any external noise. As head and body movements can cause noise in the EEG during session A, participants were encouraged to sit comfortably, remain as motionless as possible and make as few head movements as possible. In order to limit background electrical noise, the EEG headset was placed on each subject's head, and the amplifier was located one metre from the computer and other electronic devices in the room. The participants were under observation to ensure that they weren't falling asleep or closing their eyes throughout the entire session.

3.3 EEG recording

EEG was recorded using the OpenBCI helmet and stored on the computer using OpenBCI GUI software. The placement of three electrodes on the frontal lobe (Fp1, Fpz and Fp2) followed the 10–20 system. Each channel of the EEG headset was recorded at a sampling rate of 250 Hz. Using RFDuino radio modules, the helmet communicates wirelessly with a computer using the OpenBCI USB dongle. Being the electrodes nearest the eyes, they record Electromyographic (EMG) signals along with EEG. These recordings are then stored as a CSV file on the computer's local drive.

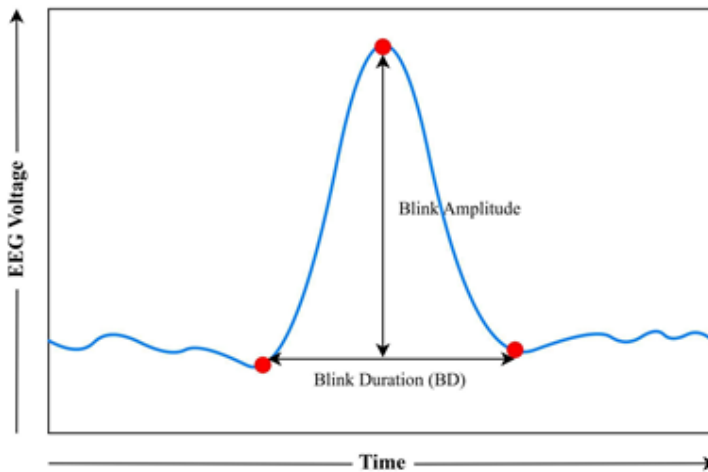
3.4 Data preparation

Recordings from 40 dumper operators, with an average age of 27 ± 5 years, were collected once. Close observation of the data revealed that two of the 40 participants were nodding off during Session A and had to be excluded. As a result, information from 38 of 40 subjects was available for analysis.

EEG Signal Processing: EEG recordings are first band-passed from 4 Hz to 30 Hz to remove unnecessary frequency bands. Then, we cleaned the signal of artifacts (i.e., eye-blinks) and effects of external noise sources (i.e., electromagnetic fields from electrical devices) by applying signal-space projection. Signal space projection helps to transform a large collection of signals into a smaller collection of signals with the primary goal of denoising or reducing the dimensionality of the original signals. Later, we used the power spectral density function to determine the power distribution within a signal across a range of frequency bands (theta, alpha, beta). Finally, we evaluated the average power of various frequency bands (AvgTheta, AvgAlpha and AvgBeta) and also averaged these power values of different frequency bands across different electrodes. For the above computation, we used a popular application called ‘Brainstorm’ (Tadel et al., 2011).

From the raw EEG recordings, we additionally captured two blink metrics: Blink Duration (BD) and the Positive Amplitude Velocity Ratio (PAVR). Blink duration is the amount of time an eyelid takes from the beginning of its closure and subsequently to its full opening, and PAVR is the proportion of the blink’s maximum signal amplitude to its maximum signal velocity. We chose these variables because earlier studies reported that BD, and BD along with mean PAVR manifest significant relations with the individual’s performance and the subject’s alertness, respectively (Johns, 2003; McIntire et al., 2014). Also, there are studies that show a correlation between performance lapses and eye-blink measures like BD and PAVR (Ftouni et al., 2013). For eye-blink metrics extraction, we first summed up the brain impulses across the three electrodes, and then we used the MATLAB toolbox BLINKER (Kleifges et al., 2017). BLINKER is an application that is used to automatically analyse eye blinks from EEG data using machine learning techniques. Finally, we averaged BD (AvgBD) and PAVR (AvgPAVR) for the subjects’ eye blinks across the entire session A. A typical eye-blink waveform is shown in Figure 3.

Figure 3 A typical eye-blink waveform



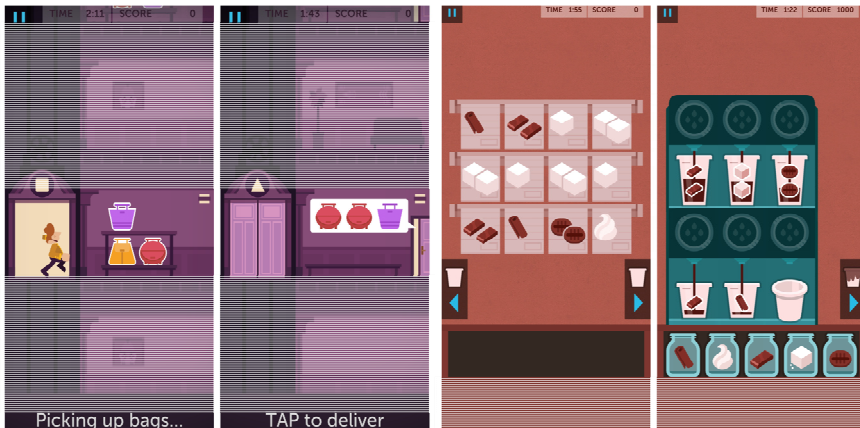
In Session B, participants played two games that tested memory capacity and attention capacity. As shown in Figure 4, the first two images are different stages of the memory game, and the latter two are the two views of the task in the attention game. In the

memory game, a bellboy picks up different kinds of bags on different floors in the hotel. The participant’s task is to remember the number of different bags the bellboy picks. Later, on some of the floors, the guest will request a certain bag or bags. Then the participant should recall whether he has such a bag or bags and immediately tap the mobile screen to deliver them. If the player taps the screen to deliver, and the guest requirement matches exactly what the player previously picked from other floors, then it is a success. It is a failure if the player taps to deliver and does not have what the guest requested. The game duration is nearly 150 seconds, and the complexities like the number of bags picked and the lift’s speed increase with the increasing level of the game.

In the attention game, there will be different screens or focus points for orders received and a coffee vending machine. The participant will receive orders for coffee with different flavours, and he should prepare them on the given machine. If he delivers the ordered coffee, then it is a success. It is a failure if he makes coffee with a flavour that does not match the ordered flavour or if the coffee overflows from the cup. The game duration is 120 seconds, and the complexity like the number of coffee flavours and coffee vending points increases with the increasing level of the game. Finally, we found the success rate for each participant in both games (Memory Success Rate (MSR) and Attention Success Rate (ASR)).

$$\text{Success Rate} = (\text{number of successes}) / (\text{number of successes} + \text{number of failures})$$

Figure 4 Working memory and attention tests in Session B.



Note: The first two images indicate the stages in the memory game. The last two images indicate two views of the tasks in the attention game.

3.5 Data analysis

As mentioned above, we have estimated five predictor variables (AvgBD, AvgPAVR, AvgTheta, AvgAlpha and AvgBeta) and two response variables (MSR, ASR). For further analysis, outliers were identified and replaced with linear interpolation of neighbouring, non-outlier values. Later, we normalised the data or rescaled the range of data to [0, 1]. Finally, we performed a correlation analysis and investigated the effect of AvgBD, AvgPAVR, AvgTheta, AvgAlpha and AvgBeta on cognitive performance (MSR and ASR).

4 Results and discussion

A Pearson correlation coefficient was computed to determine the relationship among all the variables and is given in Table 1. Here, the p-value is the probability that the null hypothesis is true, which states that there is no relationship between the two compared groups. With a *p*-value less than the significance level ($\alpha = 0.05$), we successfully reject this null hypothesis, and there may be a statistically significant relationship between the two groups.

Table 1 Correlation between the variables

		<i>AvgBD</i>	<i>AvgPAVR</i>	<i>AvgTheta</i>	<i>AvgAlpha</i>	<i>AvgBeta</i>	<i>MSR</i>	<i>ASR</i>
<i>AvgBD</i>	Pearson Correlation	1	.318	-.195	-.230	-.360*	-.361*	-.253
	Sig. (2-tailed)		.051	.240	.164	.026	.026	.125
	N	38	38	38	38	38	38	38
<i>AvgPAVR</i>	Pearson Correlation	.318	1	.120	.098	-.072	-.239	-.210
	Sig. (2-tailed)	.051		.475	.557	.666	.148	.206
	N	38	38	38	38	38	38	38
<i>AvgTheta</i>	Pearson Correlation	-.195	.120	1	.997**	.940**	.370*	.458**
	Sig. (2-tailed)	.240	.475		<.001	<.001	.022	.004
	N	38	38	38	38	38	38	38
<i>AvgAlpha</i>	Pearson Correlation	-.230	.098	.997**	1	.949**	.388*	.494**
	Sig. (2-tailed)	.164	.557	<.001		<.001	.016	.002
	N	38	38	38	38	38	38	38
<i>AvgBeta</i>	Pearson Correlation	-.360*	-.072	.940**	.949**	1	.480**	.546**
	Sig. (2-tailed)	.026	.666	<.001	<.001		.002	<.001
	N	38	38	38	38	38	38	38
<i>MSR</i>	Pearson Correlation	-.361*	-.239	.370*	.388*	.480**	1	.259
	Sig. (2-tailed)	.026	.148	.022	.016	.002		.117
	N	38	38	38	38	38	38	38
<i>ASR</i>	Pearson Correlation	-.253	-.210	.458**	.494**	.546**	.259	1
	Sig. (2-tailed)	.125	.206	.004	.002	<.001	.117	
	N	38	38	38	38	38	38	38

Notes: * Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

The analysis finds a significant negative and weak relationship between MSR and AvgBD level. There is also a significant positive relationship between MSR and the levels of AvgTheta, AvgAlpha and AvgBeta. All these predictors have a weak relationship with MSR, except AvgBeta, which has a moderate relationship [$r(38) = 0.48, p = 0.002$]. As the level of AvgBeta increases, the level of MSR increases.

On the other hand, ASR also had a significant positive moderate relationship with AvgTheta, AvgAlpha and AvgBeta levels. As the level of AvgTheta, AvgAlpha and AvgBeta increases, the level of ASR increases.

4.1 Regression Model 1 summary

In a sample of 38 EEG records of dumper operators ($N = 38$), as there is a moderate relationship between the level of AvgBeta and MSR, we performed a regression analysis with the level of AvgBeta to predict MSR as given in the equation (1)

Equation (1): MSR Regression Line

$$MSR = 0.4 + 0.65 * AvgBeta \quad (1)$$

The ANOVA results are statistically significant with $F(1, 36) = 10.777, p = .002$. As $R^2 = .23$ in this case, only 23% of the variance in the level of MSR is explained by the levels of AvgBeta.

4.2 Regression Model 2 summary

In a second regression study, even though there is a similar relationship between AvgTheta, AvgAlpha and AvgBeta with ASR, but due to interrelation between the predictor variables, we performed a regression analysis with only the level of AvgBeta to predict ASR and found the equation (2).

Equation (2): ASR Regression Line

$$ASR = 0.438 + 0.586 * AvgBeta \quad (2)$$

Here, $R^2 = .298$ shows that the levels of AvgBeta only account for 29.8% of the variance in the level of ASR. The ANOVA results were significant, $F(1, 36) = 15.258, p < .001$.

4.3 Discussion

The present study investigated eye blink metrics and brain wave activity during idle conditions to find their relationship with cognitive performance in the upcoming task. Here, the mental workload was administered by activating cognitive functions through cognitive tests (memory and attention). The memory test mainly focused on the recognition of objects, the level of short-term memory and mathematical problem-solving capability, which were tested along with the capability to respond timely and accurately. In the attention test, the main focus is on the recognition of objects and levels of attention, which are tested along with the capability to respond promptly and accurately. Hence, the designed experiment measures cognitive performance through the assessment of memory and attention capabilities.

To be cognitively capable, a person must maintain focus and effectively employ working memory, which is stimulated by dopamine (Castner and Williams, 2007). On the other hand, evidence suggests that dopamine controls blinking (Jongkees and Colzato, 2016). The release of dopamine in the striatum is modulated by the basal ganglia, which are related to the cerebral cortex and important for memory, attention, and consciousness (Bostan et al., 2013; Joansson et al., 2015; Schroll and Hamker, 2013). This experimental study finds that eye-blink activity (AvgBD) derived from EEG can be used as a metric for assessing the changes in task performance, which is in agreement with the earlier

studies done by Rac-Lubashevsky et al. (017). Also, studies have shown that brain frontal lobe related processes are in charge of upholding a high degree of attention and thus can assess fatigue (Chermahini and Hommel, 2010; Duncan et al., 2015). The same is reflected in our study with a significant relation of AvgTheta, AvgBeta and AvgAlpha with task performance. Overall, this experimental study investigated and established that the dynamics of eye-blink measures (BD) and brain waves (Theta, Alpha, Beta) are reliable predictors of individual cognitive ability in the upcoming task performance (success rate).

The regression models created with AvgBeta in our study revealed basal ganglia circuit activity. Therefore, a change in these predictor variables might indicate a change in dopamine levels, though further study is needed to investigate this idea.

5 Application of this study in mine safety

Presently, this study can be implemented in parallel to the mine HEMM operator training in the simulators. When they are getting trained, there is a chance to record their EEG, which can be correlated with their performance. Using this information, a regression model can be created to predict performance in simulator settings. Later, the model can be used to predict the operator's performance in industrial settings before allotting any work. Following this study and using some of the below-mentioned managerial strategies to deal with workload and fatigue, it is possible to improve safety and productivity in mines.

5.1 Some of the strategies to deal with workload and fatigue

Working with heavy workloads is a perennial issue in all industries since their inception. If this occurs, it can lead to inefficiency in workplace activities as well as decreased job satisfaction and stress. To avoid negative consequences, it is critical to recognise when the workload is excessive and learn how to manage it effectively (*A Guide to Managing a Heavy Workload (With Advice and Tips)*, 2021). Some of the effective strategies to manage a heavy workload are:

- 1) Taking frequent breaks.
- 2) Breaking down tasks into sub-tasks.
- 3) Avoiding multitasking.
- 4) Understanding one's own limitations.
- 5) Planning one's tasks and setting realistic deadlines.
- 6) Prioritising important responsibilities.
- 7) Collaborating and communicating with team members.

Fatigue is defined as a state of being overly tired with low energy and a strong desire to sleep that interferes with normal daily activities. Many cases of exhaustion are caused by stress, insufficient sleep, poor diet, and other lifestyle factors (Choices, 2023; Yazdi and Sadeghniaat-Haghighi, 2015). Some of the strategies to combat fatigue include:

- 1) Eat often to beat tiredness.
- 2) Regular exercise.
- 3) Sleep well or minimise sleep loss.
- 4) Cut out caffeine.
- 5) Naps during night shifts
- 6) Drink more water.
- 7) Circadian adaptation (Appropriate timed exposure to bright light helps produce circadian adaptation to night work).

6 Limitations and conclusions

This study has three main limitations, and they provide potential avenues for further investigation. First, the cognitive tests are simple and small. When training the workforce, EEG tests should be performed in simulators to increase the adaptability of the designed method in the industry. Second, there might be individual differences that affect the generalisation of results. To deal with these individual differences, it is necessary to study each participant separately. Third, as we previously explained, eye-blink metrics are a measure of the dopamine level in the body, and dopamine is a hormone believed to be linked to happiness (Sharot et al., 2009). For instance, a study by Chermahini and Hommel (2010) showed that a good mood increases cognitive flexibility, or the capacity to modify one's cognitive processing techniques in order to complete new tasks. Therefore, it is necessary to include the subjects' emotional states in subsequent research. Finally, a bigger sample size would have given our analyses more statistical power, even though the sample size we utilised in this experimental work is consistent with that usually employed in this domain of research. Therefore, in order to better interpret the data, we advise future studies to employ larger sample sizes.

In order to test whether the levels of AvgBD, AvgPAVR, AvgTheta, AvgAlpha and AvgBeta predict the levels of MSR and ASR in a sample of 38 dumper operators, this study created statistically significant regression models. We postulate that the predictor variables can be employed as a diagnostic of dopamine and basal ganglia functioning since eye blinks are linked to cognitive activities like attention and frontal lobe brain electric potentials are linked to memory. Additionally, we found a strong relationship between cognitive performance and the AvgBeta power of the operator's brain waves during a resting period. Based on this result, it is possible to compare the cognitive abilities of participants without engaging in any tasks.

Our findings are significant in showing how experimental modelling can be used in a variety of cognitive trials. Such models can be adopted by industries to increase workers' productivity and safety. Understanding the function of dynamic cognitive functioning might be useful in further research as well. To sum up, the results of this study showed that using the brain potentials at rest, the regression model created can be utilised to assess cognitive performance in the forthcoming activity. Finally, by implementing some of the previously mentioned managerial strategies for dealing with workload and fatigue, it is possible to improve safety and productivity not only in mines but in any safety-critical industry.

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