Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AF6.20250222
Published: April 8, 2025

A Study of Detecting Human Decision by Interpreting Neural Signal via Electroencephalography (EEG) and Machine Learning in a (Yes/No) Paradigm

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Abstract

In this study, we analyzed the neural phenomenon of decision-making from the perspective of cognitive modes. The main purpose of this study is to investigate the detectability of human decisions from brain signals by a computerized program. We delved into the neural signals to understand the brain functions of the cognitive modes in a binary decision-making context. The decision-making process is based on two different cognitive modes, which are intuitive and analytic. As they are opposite and conflicting by definition and characteristics, we aim to find out whether the mode significantly affects the detectability of the decision. We introduced time limitation vs. adequate time, unclear knowledge vs. clear knowledge, and absence of information during decision-making vs. the availability of information to create an intuitive cognitive mode and analytic mode, respectively. We used a modified Artificial Grammar Learning (AGL) design combined with a Yes/No binary context to create a binary decision-making event. We collected the brain signal during the decision-making using the noninvasive Electroencephalography (EEG) technique. For the investigation of the detectability of the decision, we used the supervised Machine Learning technique for classification analysis. We achieved 95% average accuracy in Analytic mode and 93% accuracy in intuitive mode. With the aim of efficient design, we also identified the top 5 channels for each mode, which can provide up to 80% average accuracy for detecting decisions. This study also suggests that the best Machine Learning algorithms for this purpose are the KNN (K-Nearest Neighbor) and RF (Random Forest) classifiers.

Keywords
Decision-making, Cognitive Mode, Artificial Grammar Learning (AGL), Electroencephalography (EEG), Machine Learning (ML)

1. Introduction
In the world of competition and comparison, success and achievement are quite dependent on proper decision-making and also proper communication of decisions to the executing body. Decision-making is such a domain we cannot define it in a single idea. It can range from moving fingers to grabbing a pen to sign a contract of a million-dollar deal.

As intelligent systems are taking place everywhere in human life to make life easier, the machine's ability to understand the human's decision by directly reading their brain activity would make the decision-execution process swifter. The question is, given the multidimensional and complex characteristics of the decision-making process inside the human brain, can the machine detect the human's decision just by interpreting the neural signals directly fed to the machine? In this study, we looked for the answer to this question. In Figure 1, we have presented the idea behind this study. If a machine (i.e., intelligent computerized programs) can interpret the decision directly from the brain and act accordingly, the human operator will not need to distract from his own responsibility, even if he does not have to look, speak, or use their hands.

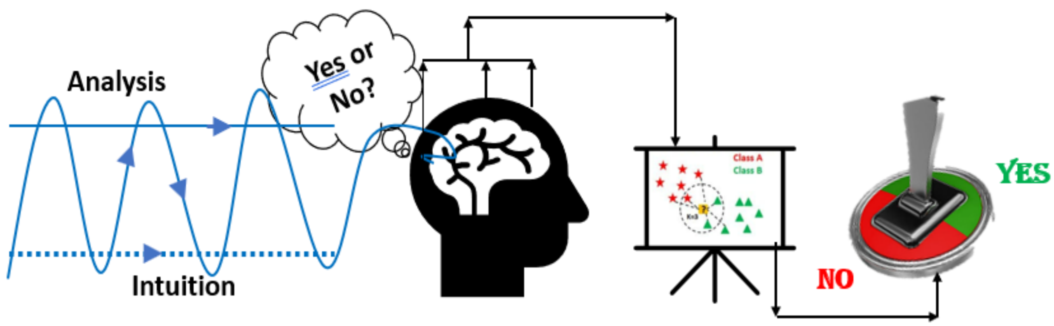


Figure 1. Binary decision processed by analytic and intuitive cognitive modes and transferred to computerized program for execution

1.1 Decision-making and cognitive mode

When it comes to understanding the mechanism and underlying process of decision-making, there can be so many variables that can affect it (Paulus, 2005). In our study, as we are in the very first stage of investigating the detectability of decisions through neural signals, we narrowed down our scope to binary decision-making, that is, in a two-option context. Among all other factors and parameters that can affect decision-making, we considered looking at the cognitive modes- intuitive mode and analytic mode. We chose to look at the cognitive modes because they are constantly affecting the thought processes parallelly and alternatively. We wanted to look at whether the modes of cognition significantly affect the decision's detectability (by machine). Both of the cognitive modes have their individual characteristics (Laureys et al. 2009; Román et al. 2019), and thus may work differently inside the brain during decision-making. Intuitive decision-making, in which the underlying process and calculations are not very clear to the conscious mind, is fast, automatic, and can be a result of an evolutionary process or experience. On the other hand, analytic decision-making can be explained in terms of process and calculations; it can be slow and may need adequate resources to make the information available for the analysis process. Both of the modes have their own benefit when it comes to decision-making. Intuitive decision-making can be beneficial when there are limitations of resources, unavailability of the full picture, and a fast response is needed. Analytic decision-making has its own diverse domain in terms of the different levels and kinds of analysis that can be needed when resources like information are available and enough time is provided. Hence, we come to investigate these two modes of decision-making from the perspective of neural signals in order to discover the usability of brain signals and functions in the improvement of human-machine teaming.

1.2 Decision-making and BCI

Nowadays, Brain-Computer Interface (BCI) is not a novel technology anymore. The basic definition of BCI depicts the technology that enables communication between the human brain and computers, bypassing peripheral limbs and nerves (Nicolas-Alonso and Gomez-Gil 2012). It is already considered a practical technology in the rehabilitation domain, where people cannot use their external limb due to some nerve damage, but so far, in most successful cases, the invasive technique provides proper performance (Müller-Putz et al. 2016). Though the understanding and practical usability of the brain signal is currently in an embryonic state (especially with noninvasive techniques), it offers great potential with BCI technology. Especially with numerous technologies for decision-aid being invented, BCI has strong potential to work as a bridge between those advanced intelligent technologies and human "thoughts." Hence, our study is based on the idea that human can communicate their decision directly to the machine without the involvement of an external limb. Not only will it provide a direct communication means for rehabilitation purposes, but it will also offer the technology where humans will not need to distract from their current focus to send commands to a machine rather, the machine can interpret the humans' thoughts by interpreting live-transmitting brain signals and can act accordingly. Understanding the detectability of decisions in different cognitive modes will help us to design systems so that humans can benefit as per situational needs.

1.3 Human "Brain" Factor of Decision-making

In this study, we have investigated the neural signals in the binary decision context, which means the human would make a decision among binary options, like "yes" or "no," "go" or "no-go," etc. Previously, numerous studies have discussed that the decision-making process happens in the frontal lobe of the human brain (Román et al. 2019). But Wang et al. (2006) showed that in practical scenarios, it can be so complex and entangled with other processes, that knowing this much might not be enough to communicate with the brain. We will look into neural signals regarding electrodes (which represent the scalp area) and observe which electrodes provide better detectability, and whether the electrodes (and thus the scalp area) differ as with cognitive mode. We will also observe if the two modes are mixed up; the neural signal can still be interpreted to detect the decision made in the brain.

1.4 Problem Statement

Currently, researchers are delving into understanding human brain functions of different cognitive and affective processes so that technology can be designed in a human-centric way. Still, the human brain is quite enigmatic to be interpreted in a scientific way. Especially, "reading" the human brain signal by machine can be too complex in the context of decision-making. Also, to use the BCI technology in a practical manner, the design has to be user-friendly. So far, the practical BCI technology is centered around rehabilitation purposes, which includes mostly invasive technologies. Noninvasive findings of BCI technology are still in a developing state to be implemented in a practical scenario. With this background, in our study, we addressed the issues to investigate as outlined below.

First, whether the brain signal of a binary decision-making task can be interpreted by machines; in numerous researches, binary decisions (e.g., go/no-go) have been investigated, but in most cases, those findings are focused on performance and speed (of decision making). None of the research, as per the knowledge of the authors, has investigated the detectability of the decision by ML in a comprehensive manner. This is the primary purpose of our study. Second, whether the cognitive mode would affect the detectability of the decision through neural signals. Third, to improve the efficiency of the design from an engineering perspective, we sought reduced numbers of electrodes that could provide reasonable accuracy. Fourth, using brain signals to communicate with computers comes with the challenge that it normally is contaminated with lots of artifacts and noise, which needs cleansing to get a "clean" brain signal, which is quite an elaborate process. In our study, keeping the efficiency of the system in mind, we investigated raw signal, which means we performed classification analysis directly collected neural signal without any cleansing and pre-processing and wanted to see whether the signal is still interpretable by the machine.

2. Literature Review

Understanding the architecture of the decision-making process from different perspectives has been a topic of research for a long time (Román et al. 2019). The neural knowledge of decision-making has revealed important information that offers the means of designing medical tools (Mason and Birch 2003), better technology, and so on (Yang et al. 2020). Researchers are working on using these neural signals to directly communicate with the system, which is called the Brain Computer Interface (BCI) (Nicolas-Alonso and Gomez-Gil 2012). Technologies like BCI-controlled wheelchairs or robots to move in left/right direction using noninvasive technology (Galán et al. 2008) and BCI-controlled robot arms for disabled people with invasive technology have been able to materialize (Müller-Putz et al. 2016), though with a number of challenges and difficulties (Maiseli et al. 2016). Therefore, researchers are continuously studying how to improve brain-machine communication by investigating neural signals.

For this purpose, the detectability of the brain signals in different contexts, such as workload (Aricò et al. 2016), and trust/distrust (Firoz et al. 2022) are being focus of the research. These kinds of detection by machine learning (ML) models are being considered to be implemented in different Brain-computer communication, such as a safety measure in human-autonomy teaming (Firoz et al. 2023).

3. Methods

3.1 Artificial Grammer Learning (AGL)

In our study, we conducted a decision-making study using the Artificial Grammar Learning paradigm (AGL) (Reber 1967). This design has been previously used in numerous studies to understand implicit learning (Dienes et al. 1991) and to investigate the brain function of intuitive decision-making (Firoz and Seong 2023a, 2023b). In this study, we have expanded the investigation of the previous study(Firoz and Seong 2023a), which used the AGL paradigm to understand the brain function of intuitive cognitive mode. Briefly, we can state that, in AGL, there is a ruleset (which is the Artificial Grammar), and some strings of letters (which are the artificial "words" s) are shown to the participants, whence the participants are to tell whether the "word" follows the rules or not. We modified the AGL design to evoke different cognitive modes. For the intuitive mode, we designed it with time limitations and unavailability of information, and participant have to answer from their "experience." For analytic mode, we provided enough time and made the information available so the participant could follow logic and make deliberate decisions. In both cases, the participants have to decide whether the word follows the rules "Yes" or not "No." That is how our binary (Yes/No) decision-making experimental setup is designed.

3.2 Electroencephalography (EEG)

Electroencephalography is a popular technique, especially for noninvasive brain study. In this study, we used the Emotiv EpocFlex device, which consists of a head cap that is to be fitted to the participant's head. We used 30 channels that follow 10-20 systems of electrode management and used saline solution to maintain conductivity between the scalp and the electrode. The data sampling rate was 128 Hz.

3.3 Machine Learning

This study is about improving human-computer interaction in practical applications, and thus appropriately considered using Machine Learning (ML) techniques to analyse and construct models that will be able to handle the complexity of neural signals and also can be embedded in a computerized system

4. Data Collection

4.1 Participants

The participants took part in the study in a voluntary manner. Informed consent was taken from them, explaining the study, which was approved through IRB. The participants had normal or corrected to normal vision, were free of current or past neurological and psychiatric disorders, and were in a stable mental state during the study. The 5 participants' age ranges are 18 years to 35 years. Among them, three are male, and two are female by their self-identification.

4.2 Procedure

The whole study was conducted in two steps for each participant. The first step is for intuitive decision-making. We followed the process as conducted in a previous study [17]. For the next step, that is analytic decision-making. The process is the same for both steps, except for a few differences introduced to invoked different cognitive modes. Firstly, for intuition, the participants did not learn the rules beforehand; they just saw some example words for a limited time to gain "experience." for the analytical part, the participants learned about the rules in a well-explained manner, and it made sure they understand how the rules work. Secondly, for intuition, the rules were not presented when the participants made decisions about test items. For the analytical part, the rules were written as text and presented on the screen along with the test times. Thirdly, for intuition, there were time limitations to making decisions; for the analytic part, there were no time limitations, and participants could ponder the rules as long as they wanted. Participants pressed "1" if the answer was yes and "0" if the answer was no. After making the decision about the test items, the participants shared their strategy, whether they followed intuition, analytics, or just wild guesses. We considered only the mode of cognition as they self-reported.

4.3 Dataset

From the two steps of the whole experiment, we achieved two separate datasets. As we only considered their self-reported mode, we did not consider the response if the participant shared their strategy as "wild-guess" or "analytic" for the intuitive part, and vice versa. We considered the 1.5-second time window before pressing the button to observe the brain function of decision-making. As we collected the signal as 128Hz, for each response, we got 1.5x128=192 datapoints. For both of the datasets, we considered the response decision as classes- Yes/No (pressed "1" or "0" respectively). We analyzed the classification on both datasets separately and also accumulated them to observe the performance in a mixed-mode situation.

4.4 Data Analysis

For data analysis, we used the Machine Learning technique for classification purposes. Ours is a binary class problem, where we are investigating whether the machine can detect the response as "Yes" or "No." For this purpose, we used seven widely used classification algorithms, those are:, K Nearest Neighbour (KNN), Random Forest (RF) classifier, Decision Tree (DT), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Logistic Regression (LR), Naïve Bayes (NB) to find the best suitable algorithm for this instance. We used a 10-fold cross-validation technique to obtain average accuracy over all folds to observe as a performance parameter. We used 80% of the data to train the algorithm for the 10-fold cross-validation. To choose the best features, we used the Univariate Feature Selection technique to obtain the variance of the channels and considered the highest variance channel as the best, and so on.

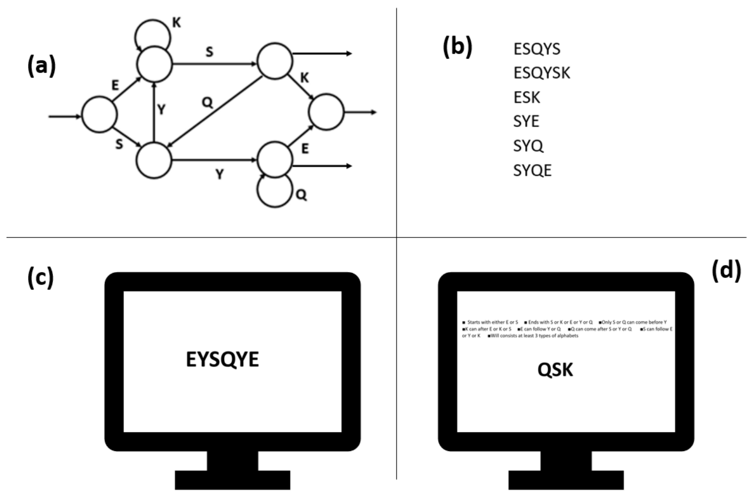


Figure 2. (a) example of Artificial Grammar Rule, (b) example of artificial "words" following the Artificial Grammar Rules, (c) example screen as presented for the intuitive session, (d) example screen as presented for the analytic session**.**

5. Results and Discussion

5.1 Numerical Results

As per our first question, we observed the average accuracy of classification as presented in Table 1.

Table 1. 30 channel performance results at different cognitive modes

	Analytic		Intuitive		Mixed	
Algorithms	Avg Acc	Std	Avg Acc	Std	Avg Acc	Std
KNN:	95.80%	0.003	93.90%	0.008	95.2%	0.005
RF:	94.60%	0.005	92.00%	0.014	93.7%	0.006
DT:	90.50%	0.007	84.40%	0.017	86.2%	0.005
SVM:	83.50%	0.009	83.50%	0.013	75.4%	0.008
LR:	68.20%	0.016	45.30%	0.022	62.5%	0.009
LDA:	68.00%	0.019	45.30%	0.022	62.8%	0.009
NB:	61.00%	0.013	57.00%	0.026	56.6%	0.015

As we observed, the performance is best with KNN and RF; we have considered these two algorithms for further analysis. We have checked the performance of the model with the reduced number of channels, with 15 channels, 10 channels, and 5 channels. The results are presented in Table 2. The reduced number of channels has been chosen by the Univariate Feature Selection method, where the channels' variance is ranked and the most variance channel is considered as best and ranked accordingly. The best 5 channels are also listed for different modes of cognition in Table 2.

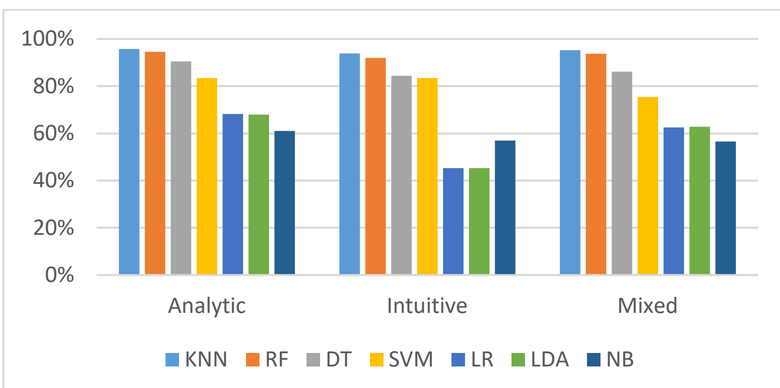
5.2 Graphical Results

For better perception, Table 1 result is presented as graphical view in Figure 3(a), where we can clearly see the performance of different algorithms for different cognitive modes in binary decision making. We can observe here, that the algorithms' performance have different trend for Intuitive vs. Analytic mode.

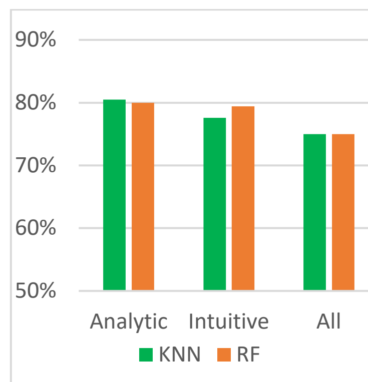
Table 2. Reduced Channel models' performance with different cognitive modes

	Analytic		Intuitive		All	
	KNN	RF	KNN	RF	KNN	RF
30-channel	95.8%	94.6%	93.9%	92.0%	95.2%	93.7%
15-channel	95.0%	93.5%	89.8%	88.8%	92.1%	90.6%
10-channel	91.4%	89.4%	84.1%	85.1%	88.2%	86.3%
5-channel	80.5%	80.0%	77.6%	79.4%	75.0%	75.0%
Top 5 channels	P8, FC1, PO10, FC2, CP6		CP1, FC5, Cz, F3, F7		P8, PO10, FC1, CP6, FC2	

In Figure 3(b), we wanted to highlight the difference in performance in different cognitive modes. From Table 2, we can understand, which is also aligned with the general sense, that reducing channels reduces performance (along with how much the reduction is). From Figure 3(b), we observe that the Random Forest classifier gives better accuracy in the 5-channel model for Intuitive mode, which is contradictory to other scenarios.



(a)



(b)

Figure 3. (a)Performance as average accuracy from different algorithms for Different modes of cognition, (b) Best five channels' performance with KNN and RF

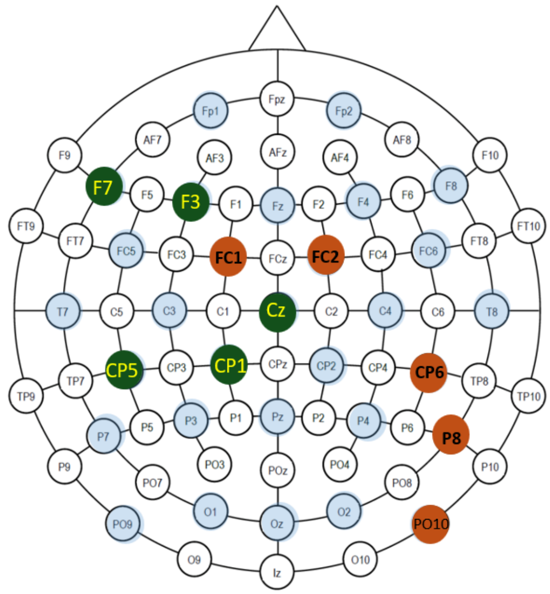


Figure 4. Five best channels' location on scalp for analytical and intuitive mode (Red colored for Intuitive and Green color for Analytic)

While we can see that the detectability of the decision- Yes or No- is possible with 75%-80% average accuracy even with 5 channels, we can also observe that the most variance is coming from different locations for analytical and intuitive cognitive modes. These channel locations of the scalp are indicated in Figure 4., we can see that for different modes, the channels are quite clustered- intuitive at the left-front area and analytic at the right-hand area, having an overlapping at the mid-central zone.

5.3 Proposed Improvements

This research undertook a novel approach to connect the human brain and advanced computerized systems. Whence, the above observations and findings from the study shade light in so many angles, it still has some limitations, and hence further improvement can be done in future studies. Firstly, this study is a preliminary approach, and therefore further refining and polishing can be done in future studies in designing the experiment. Secondly, which we will accept as the most critical drawback, is- the limited number of participants; to come to a conclusion scientifically, much more observation on a more diverse population is needed. Thirdly, to address the efficiency factor, we totally bypassed the pre-processing steps; in several previous studies, it has been established that normalization can improve the performance of the machine learning models (Firoz et al. 2022, 2023, 2024); in future studies, different levels of cleansing and pre-processing can be done to understand their effect on the model performance. Fourth, this study was designed with one kind of decision-making, based on AGL; to conclude or understand overall cognitive mode aspects, different kinds of study can be conducted and compared. Fifth, as a preliminary study, this study addressed a binary decision-making process, where, decision-making is such a complex process that in most cases it has more outcomes/choices rather than just two. Despite these limitations, this preliminary study offers a new look to improve human-machine teaming using human's own assets (i.e. neural signals) and technological advancement of computers, and future studies.

5.4 Validation

From the above observations, we can see that our four research questions have been addressed adequately at the preliminary level and further studies can be conducted based on these findings to learn more about these matters. The first research question, where we wanted to understand whether the yes/no decision can be detected by a machine learning model, is answered as 94%-96% accuracy can be achieved with 30 channels. We can also see that the model's performance is being affected at least at some level, by the mode of cognition. From the perspective of design efficiency, we presented the trend of decreasing performance when the number of channels is decreased. Also, this performance is achieved with completely raw data.

Alongside the aimed research questions, this study also presents an observation regarding different cognitive modes. It is also observed that the best channels for intuitive and analytic decisions are totally different. This observation can draw a question toward neuroscience direction- whether those areas are associated with analytic and intuitive cognitive processing. However, we can state that the design can be customized based on the situation, considering the demand for cognitive mode in that situation. We can also state that, even with a mixed-mode scenario, reasonable accuracy can be achieved with proper channel selection.

6. Conclusion

This study suggests a hypothesis that the cognitive mode of decision-making can affect the design of the brain-machine interface. Also, the computational cost and discomfort can be reduced significantly (30 channels to 10 or 5 channels) by choosing the proper channels. Further studies with more participants will be able to draw conclusions about these hypotheses.

Acknowledgements

This study is funded by NSF Engineering Research Center for Hybrid a new domain Autonomous Manufacturing Moving from Evolution to Revolution (ERCHAMMER) under Award Number EEC-2133630

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