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Preparations for Multimodal Analytics of an Enactive Critical Thinking Episode

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Abstract: Multimodal analytics provides a different perspective to understand and characterise learning tasks and potentially model the process. However, the logistics and the analysis process are often cumbersome to easily adopt the approach. We had earlier developed a platform that enables us to synchronise learning environment interaction data and signal streams from various physiological sensors. Also a framework was proposed that looked at critical thinking as a constituent of its interactions and developed an embodied cognition narrative. In this study we used ENaCT, the online critical thinking task environment and studied an episode of critical thinking that a participant attempted in it. We collected physiological data, specifically signals from EEG and GSR sensors along with the interaction logs within the ENaCT environment. We present an initial analysis of the multimodal data.

Keywords: Multimodal analytics, thinking task, GOAL system, ENaCT framework.

1. Background

Multimodal data is often collected in the context of analysis of learning tasks. However, the set of data collected, the purpose of its analysis and the method of processing the data vary for different contexts. For instance, Andrade, A. (2017) collected multimodal data in the context of mathematics learning trajectories. To explain the embodied actions, fine-grained logs of hands and gaze data, depicting motion, were mapped against the levels of student performance. In another recent study, also in the domain of mathematics in motion-based learning environment (Lee-Cultura, Sharma & Giannakos 2021), explorations were made with video-based data encoding and involve eye-tracking and physiological sensors to analyse play and problem-solving behaviours of kids. Overall such approaches focused on the learning episodes and aimed to investigate the patterns and the predictive capabilities of the signals gathered during the learning tasks. Other research focused on development of tools for analysis of multimodal data in educational context (Di Mitri et al.,2019) or application of specific analysis methods in the context of learning. For instance, earlier using EEG sensors and applying wavelet decomposition methods researchers analysed challenge level, need of skill level, engagement, stress and focus (Miyauchi & Kawasaki, 2018; Conrad & Bliemel, 2016). More recently event-related potentials (ERP) of a sensory stimulus was used to analyse attention, sense of task complexity and language-related cues (Huang et al., 2020).

1.1 Research Objectives

To our knowledge limited work focused on specifically characterizing episodes of critical thinking with multimodal data. In this study we utilize ENaCT as a theoretical framework to investigate the interactions and signals captured during the critical thinking task. In this pilot, we aimed to establish a data collection and analysis pipeline of physiological signals to be integrated into the ENaCT framework. In the current article, we present the visualisations of that data to answer the research question: *What are the interactions and corresponding changes in the physiological attributes and behaviours during an interaction enabled thinking episode?*

1.2 Embodied Narrative of Critical Thinking (ENaCT) Framework

The ENaCT framework (Figure.1) is an integrated framework for aligning learning design and learning analytics of critical thinking (Mishra et al. 2020). It adopts an embodied and enactive cognition perspective, explicitly considering that the affordances of (technology-enhanced) environments and the actions that a person performs on these affordances, are integral to a person's thinking. Specifically, it does not consider actions in the task environment and generated artefacts as products of critical thinking, rather that the generated artefacts also generate new affordances (and hence thinking possibilities) for the problem solver. The ENaCT framework uses Paul & Elder's (2008) "Elements of Thought" to build the task model for design and analytics. As seen in Figure 1, the framework has two parts; the conceptual part models how one's actions with the artefacts in the environment relate to the execution and learning of critical thinking, and an analytics part which models how these actions and artefacts relate to the assessments and models of performance and learning. Connecting these two parts is the task model that describes how different actions constitute the execution or application of the elements of thought. In this work we explore how the physiological signals can be used to characterise the levels of behaviors observed during the task.

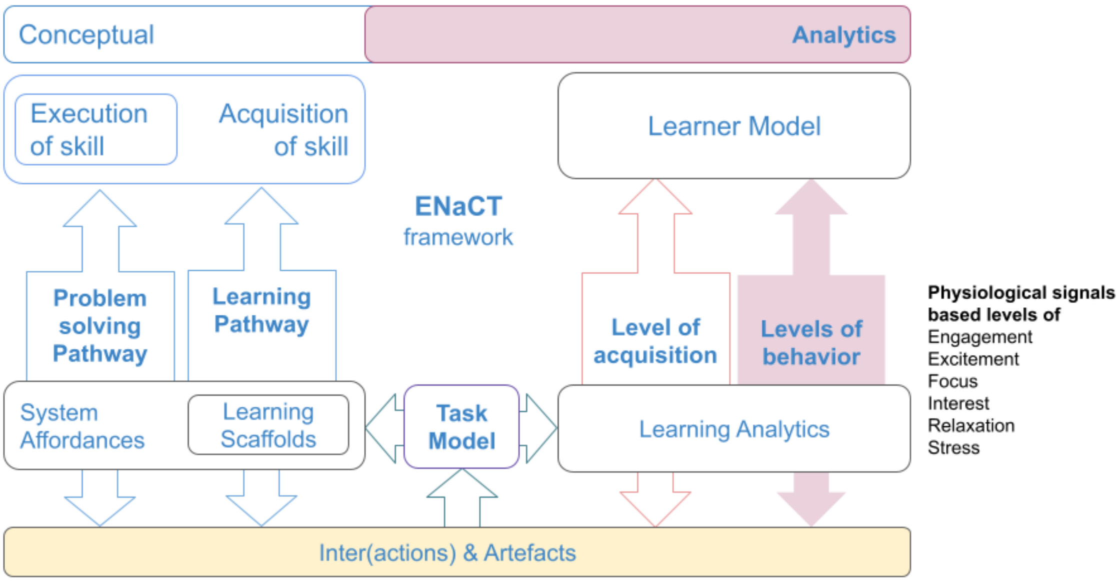

Figure 1. ENaCT framework and the system architecture

2. Materials and Methods

2.1 ENaCT Interface and Critical Thinking Task

In the ENaCT environment the participants are given a specific critical thinking task which involves responding to a focus issue while integrating information from multiple representations. The responses were scaffolded according to the Paul and Elders (2008) elements of thoughts. Figure 2 provides the different elements that were present and its corresponding use during the task.

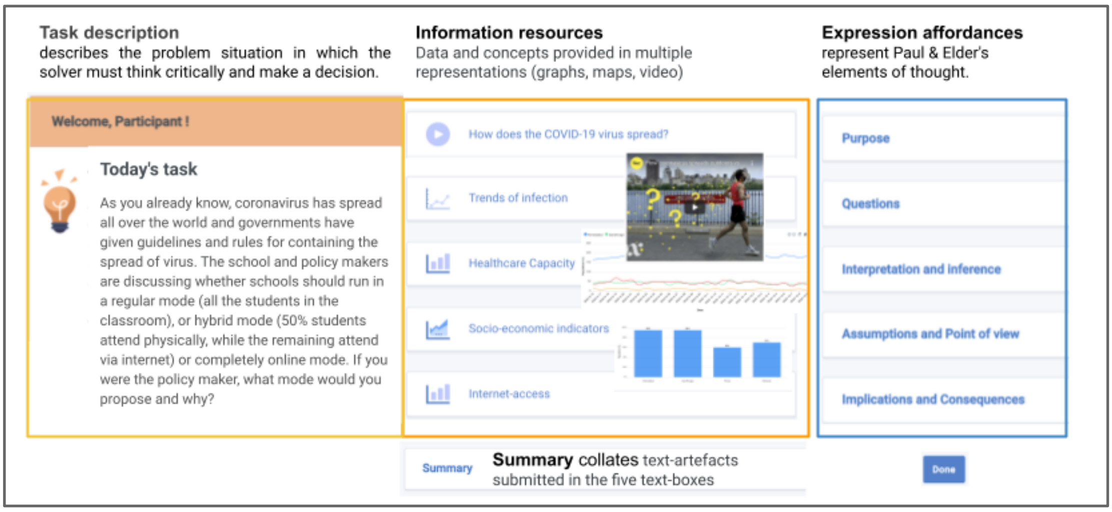

Figure 2. Critical thinking task environment (Majumdar et al. 2021)

2.2 Data Collection and Technology Architecture

2.2.1 Interactions form the online task environment

The technology is based on the Learning Evidence and Analytics Framework (Ogata et al. 2018) where the learning tools are integrated into a central learning management system with LTI protocol, and learner interactions and created artefacts are logged in a learning record store. The interaction logs enable tracing problem-solving narratives in the ENaCT environment. Figure 3 highlights the system connections.

2.2.2 Sensor data

It is possible to collect high resolution physiological data related to the variation of the electrical properties of the skin by electrodermal activity (EDA) sensors and the electrical activity of the brain by electroencephalography (EEG) sensors. The data pipeline captures heart rate, EDA and temperature data from Empatica E4 devices and EEG data from Emotiv insight devices.

2.2.3 Architecture to synchronize data streams

We use the GOAL architecture to synchronize the data from the online learning environment and the physiological sensors (Majumdar et al. 2020). A data upload option caters to any sensors that provide CSV files with time information. All the data (interactions and sensor generated) is linked to only a machine readable id of the user and synchronized on a common timeline to be uploaded on the activity record store. Figure 3 provides the overview of the technology architecture and the set of data collected.

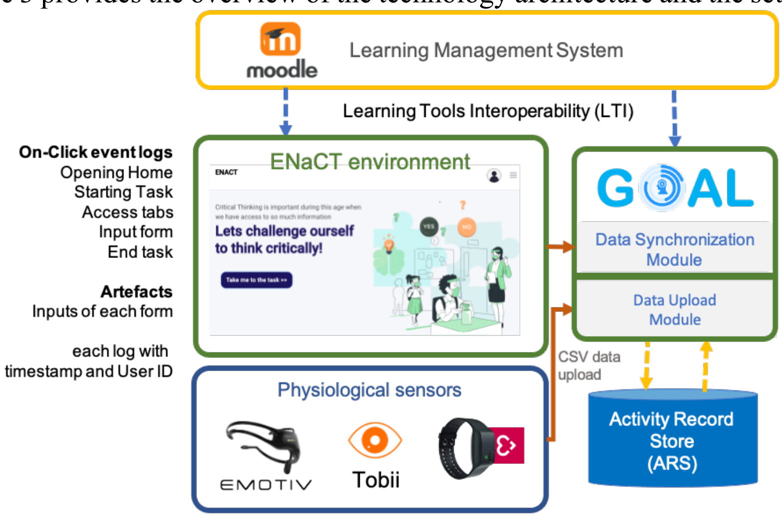

Figure 3. System architecture for data collection during the study

2.3 Research Methods and Participants

A phenomenographic research approach was chosen for the study (Marton 1981, Jan Larsson & Inger Holmström, 2007). Only one episode of thinking was observed in detail with the above mentioned multiple data sources. There were 5 participants (2F) who participated independently in the session. Four of them were graduate students and one was a postdoc researcher. For the current analysis we selected the data of only the postdoc researcher (Par-2). Par-2 was selected based on the level of engagement in the activity, the notion of being an expert amongst the selected participants for a thinking task and lastly the level of detailed reflections drawn at the end of the session. Further the physiological signals for that participant were also of high quality (EEG signals average quality above 85%).

3. Visualised Data of the Critical Thinking Episode

3.1 Interactions During the Activity

Figure 4 presents the interactions of the participant within the ENaCT environment during the CT episode. The interaction logs extracted from the database were grouped into the following task-relevant action categories: OpenHome (landing on ENaCT platform), OpenTask (opening the task page), information-interaction (Info_Int), and artefact creation (Art_Cre). Info_Int are the actions users performed with the information affordances, while Art_Cre are the actions that users performed within the expression affordances. Art_Cre logs were further separated into two types: Art_Cre_acc, when the user simply accessed the panel to create or modify their text-response, and Art_Cre_sub when the text-response was submitted. Summary is when the user opens the summary panel and OpenSurvey (opening post survey after task). The data is plotted using Tableau (v.2021.2.1) on a timeline which is represented as the horizontal axis. The value is the local time.
The participant spent 15 minutes 19 seconds in the ENaCT environment. In total there were 39 interactions. From figure 4 it is seen that the participant had the 15 information interaction in two grouped periods of time. 5 interactions were related to accessing the answering panels and 14 submissions were made. However, regarding the excessive submission clicks for the 5 fields, we verified with the screen capture video. It was found that due to a server error to send the log the participant repeatedly clicked the submit button in a quick succession generating extra 9 interaction logs for one of the submission fields. In the Figure 4 plot those successive clicks were removed.

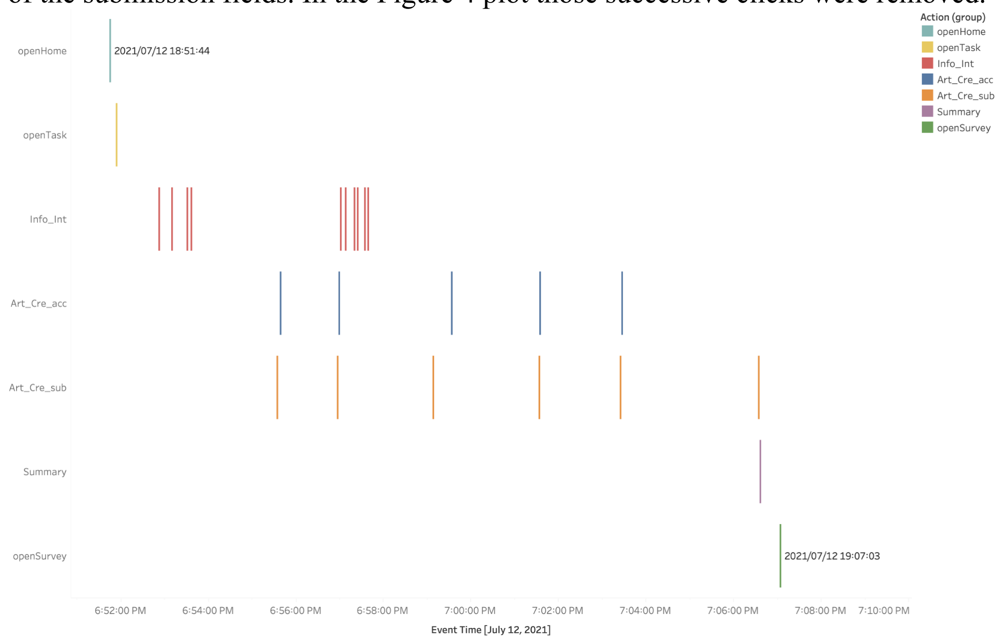

Figure 4. Interactions in the ENaCT environment

3.2 EEG Data Processing

The EEG signals were processed to extract the emotional aspects. Currently we utilized the EmotivPro (v2.7.2) software's algorithm for extracting the emotion levels and select the scaled normalised values. The data from the EMOTIV Insights sensor was collected and the software extracted bandpowers and computed engagement, excitement, interest, relaxation and stress levels. The data is then masked with the task cues from the ENaCT environment. While the sensor sampled at a higher frequency, the emotion levels were computed each second and visualised in Figure 5 as the normalized and scaled value. The average value of each of the emotions across the activity are denoted by the reference line in each pane.

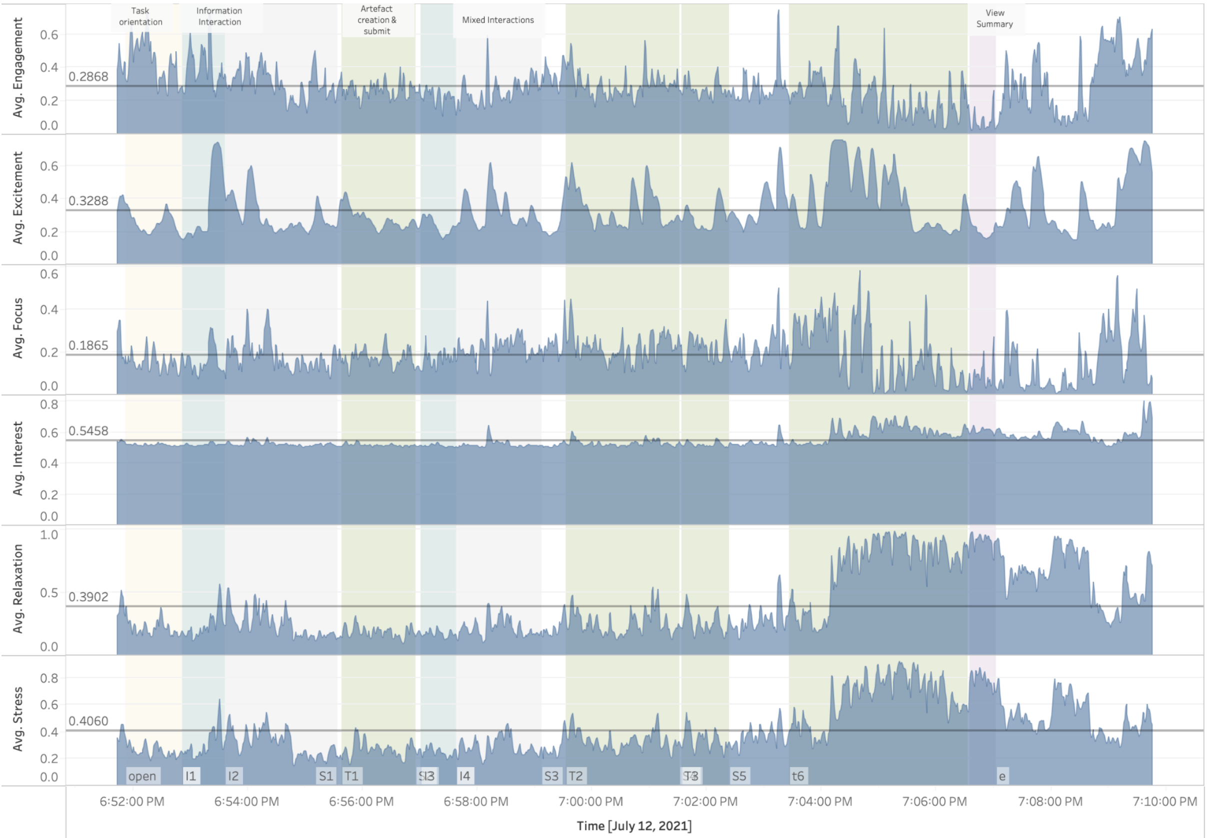

Figure 5. The analysis of the EEG data

3.3 EDA data processing

The EDA data provides information regarding the intensity of the emotional state or response as emotional arousal cues. In order to preprocess the signal and get components with their peak information, we used a Python toolbox called Neurokit2 by Makowski et al. (2021).

The EDA signal basically consists of two additive processes namely tonic and phasic signals. Tonic signals are the ones fluctuating very slowly and depicting the general trend whereas the phasic signals are varying very fast and representing the skin conductance responses. In figure 6A, the first window shows the cleaned EDA signal whereas the second window depicts the phasic component with all the related peak information and the third window shows the tonic component. In figure 6B, the tonic and phasic signals are marked by the intervals gathered from the ENaCT environment.
In a minute the average number of peaks for the intervals in order are 5, 4, 14, 16 and 4.

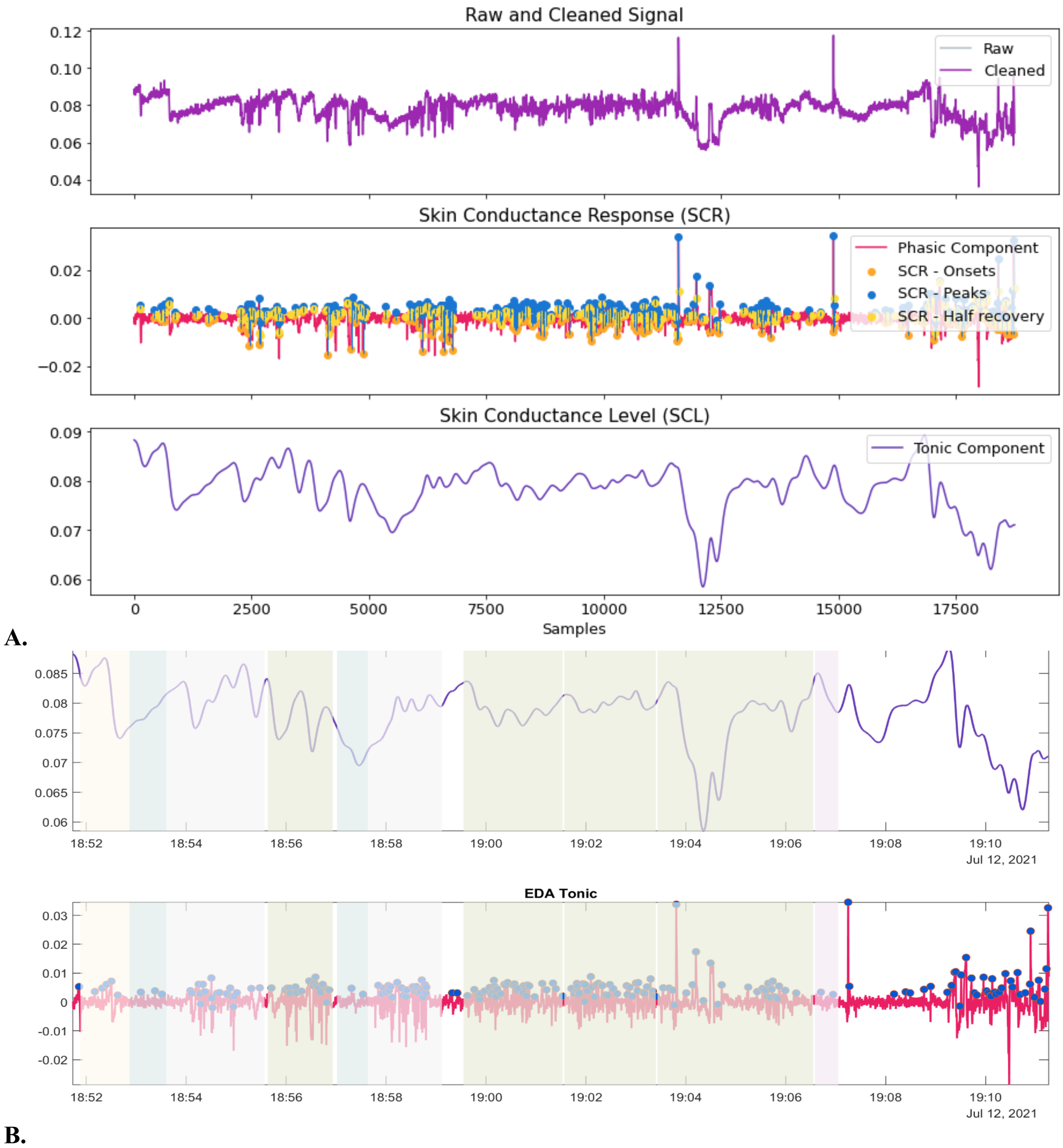

Figure 6. The analysis of the EDA

3.4 *Eye Tracking of The Participant*

Eye tracking gaze data was directly visualized as heatmap using the eye tracker software and overlaid on the screen capture. As the task involved multiple interfaces and scrolling the analysis of the eye tracking data would require further pre-processing in the future. Currently, it provides an indication of the focus in the different areas of interactions and is used for visual exploratory data analysis. The snapshot of the heatmap in different sections of the interface is presented in Figure 7.

Figure 7. Screenshot of heatmap of fixation of eye gaze

4. Discussion and Future Work

4.1 Thinking Episode of Participant 2 (Par-2)

The interactions of the participant (Par-2) as seen in Figure 4 highlighted that there was an interface exploration phase in the beginning. The main sets of interactions were in the information panels area to check what kind of information was presented. The questions given as prompts were already seen as labels so there were no click interactions required there. This was also confirmed from the eye tracking video and in the post task reflections during the interview with the participant.

Further from the interaction data, Par-2 did not go back and forth with the information panels and the artefact creation panels. To respond and note *What are the interpretations of the data?,* the revisit to the information panel was seen. Par-2 mentioned the intention was to only get the trend of the relative values presented in the different information panels to answer that and hence back and forth details were not considered. However, we have seen different behaviors in our previous novice studies (Mishra et al. 2021, Majumdar et al. 2021) where participants who had more frequent back and forth actions also tended to respond with relatively better insights about the interpretations of the data they observed.

Par-2 also had a distinct viewing summary panel action at the end. While one of our design conjectures was participants would access the summary panel to take the affordance of their own input to further think (Majumdar et al. 2021), however as observed in this case too, the summary was accessed at the end of the task attempt to kind of verify the artefacts created.

For the analysis of the EEG and EDA data, an essential step is to create temporal masks for tagging specific activity periods. In figure 5 we have labelled the 5 masks as follows: *task orientation* - where the participant reads the requirements of the task; *information interactions* - interactions with the given information panel; *Artefact creation and submit* - accessing the artefact panel, typing and submitting response; *View summary* - viewing summary panel; *Mixed interaction* - having multiple panels open on screen and the interval where we can not indicate distinctly whether it is a information interaction or artefact creation action. The following mixed interaction phase was identified while the data was being tagged after synchronising. Currently it required further manual identification from the screen recording to distinct the phases. However, that would limit the scaling of the analysis process and hence we created the distinct state to label such a situation.

4.2 Analysis Approaches to Thinking Episodes with Physiological Data

While preparing to analyse the collected data, we also reviewed some of the multiple ways to analyse the physiological signals in previous studies (See Table 1). Conventionally, EEG data is analysed through either event related potentials (ERP) or frequency bands. ERP is mainly reflecting the average response to a task with a certain duration of 1,5 - 2 seconds. Through this component it is possible to assess the attention and learning levels, the complexity of tasks as well as language related processes such as semantics (Huang et al., 2020). The frequency band approach involves time-frequency decomposition. The resultant bands on theta, alpha, beta and gamma ranges can be further processed for their power, ratio, entropy, topography and pattern change to get cues about challenge levels of tasks, need of skill, the levels of attention, engagement and focus as well as stress (Miyauchi & Kawasaki, 2018; Conrad & Bliemel, 2016).

As for the EDA data, a common approach involves the raw signals to be segregated in phasic and tonic components. From the phasic components, it is possible to relate the emotional arousal with the stimulus and gather information about stress, joy, boredom, excitement, interaction levels, anticipation, decision making. The higher the peaks, the higher the arousal and the more there is a change in the phasic component patterns the more interaction takes place (Rico-Olart et al. 2020).

Table 1. *Physiological Sensor Data and It's Analysis*

Sensor (Signal)	Analysis approach	What it helps to determine	Reference paper
EEG (voltage from 7 points)	event-related potentials (ERP)	attention, learning, sense of complexity, language-related cues	Huang et al., 2020
	Wavelet decomposition	challenge level, need of skill level, engagement, stress, focus	Miyauchi & Kawasaki, 2018; Conrad & Bliemel, 2016
GSR (Skin Conductance)	Phasic and Tonic state separation	Emotional cues related with excitement and stress levels	Rico-Olart et al., 2020

In our current approach, we utilized the frequency band processes as well as EDA data variability to gather info about engagement, excitement, focus, interest, stress levels, and cognitive load during the given task. When this info is further analyzed through statistical comparison methods, it would characterize the individual differences in the thinking task in its different phases.

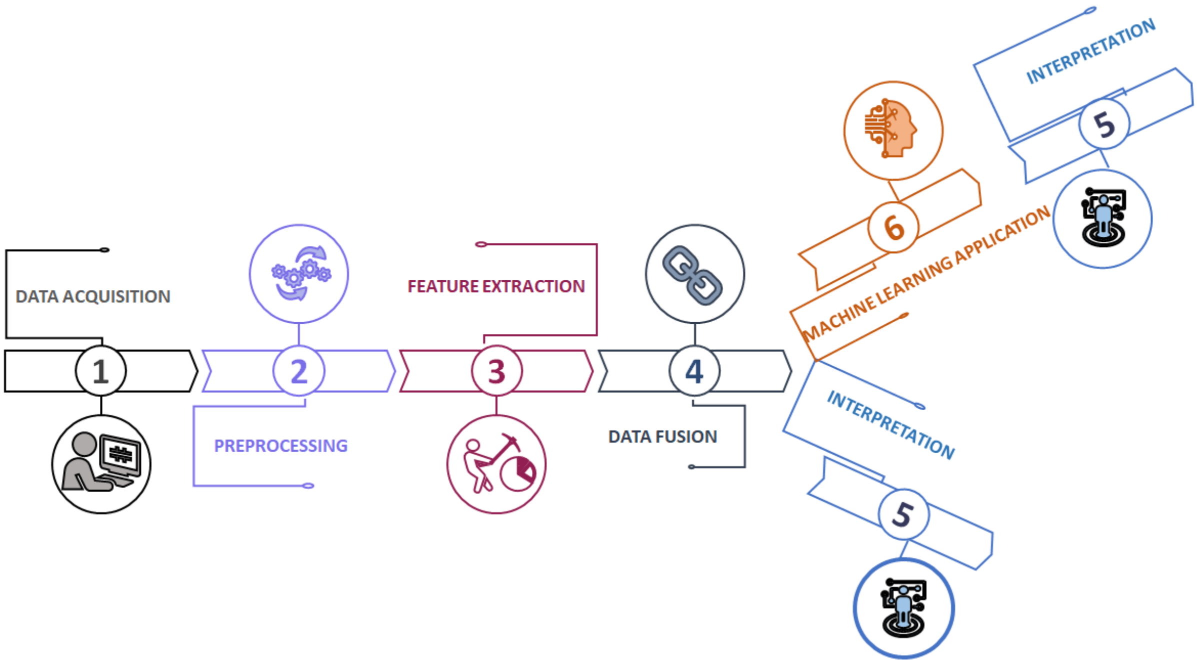

Figure 8. Data processing flow

Further analysis approach includes the utilization of other features of the collected sensor and possibly fusing the information together to then interpret. At this stage additional analysis and data tagging with emotional cues are possible through the preset machine learning algorithms. The data processing flow including all steps are depicted in Figure 8.

4.3 Current Challenges and Limitations

This pilot made us aware of the current challenges and limitations of the data and experimental setting as follows. Since the task was designed as a problem solving task related to executing critical thinking, it is more complicated than a perceptual task that is often the usual settings of the experiments used in the literature using physiological sensors. Thus the processing and interpretation of the data is not straightforward and requires specific mapping of the analysis masks to the given context. Further, given the complexity of the task and the time taken to attempt it, there is a lot of room for individual differences in responding. That makes it challenging to compare the data within subjects. Due to those individual differences, each subtasks denoted by the masked phases in figure 6 are also not uniform in the time space. For the pilot study there were a limited number of subjects, and often the data gathered from the sensors had high noise or unexpected data loss, thus any statistical procedures can not be applied for comparison.

4.4 Contribution and Future Works

This is an initial exploration to collect multimodal data during a critical thinking task. Both the task environment design and the data analysis was done from the perspective of (inter)actions involved in thinking. We have created a platform and data pipeline for synthesising physiological, behavioral and interaction data during such an activity. Here we presented the visualised data collected during the pilot session as a demonstration of the variation of the trends of the signals along with the progress of the task.

Next we aim to analyse the details of the physiological and behavior data of the participants. The processing of the EDA data and the EEG data would be done to find whether there are any differences in the level of physiological activities in the information interaction and the artefact creation phases to characterise the critical thinking activity from the perspective of the ENaCT framework.

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