

Evaluation of Mental Workload and Familiarity in Human Computer Interaction with Integrated Development Environments using Single-Channel EEG

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Abstract. With modern developments in sensing technology it has become possible to detect and classify brain activity into distinct states such as attention and relaxation using commercially available EEG devices. These devices provide a low-cost and minimally intrusive method to observe a subject's cognitive load whilst interacting with a computer system, thus providing a basis for determining the overall effectiveness of the design of a computer interface. In this paper, a single-channel dry sensor EEG headset is used to record the mental effort and familiarity data of participants whilst they repeat a task eight times in either the Visual Studio or Eclipse Integrated Development Environments (IDEs). This data is used in conjunction with observed behaviour and perceived difficulties reported by the participants to suggest that human computer interaction with IDEs can be evaluated using mental effort and familiarity data retrieved by an affordable EEG headset.

Keywords: Electroencephalography (EEG), Human-Computer Interaction (HCI), Integrated Development Environment, Programming, Interface

1 Introduction

Advances and widespread adoption of technology in the workplace have resulted in more information being presented to people, this has ultimately resulted in a higher cognitive demand for the processing of the information presented to extract key data and information pertinent to the task being performed. This increased cognitive demand and large amount of information can cause confusion, inhibit comprehension, and lead to mistakes being made or have consequences to personal health such as mental stress. Although there are methods available to monitor performance such as completion times, error rates, and qualitative feedback form questionnaires etc., these only look at the observable metrics. Physiological measures can also be implemented to monitor mouse movement, eye motions and gaze, heart rates, and galvanic skin response, but again these neglect cognitive processing effort. Generally, the attempt to observe this cognitive effort has resulted in clever experimental design and questioning but does not directly relate to cognitive workloads or cognitive strategies used (Cutrell & Tan, 2008).

The interaction between humans and machines and the cognitive learning of this process has given rise to various methods of understanding the underlying mechanisms behind them. One such example would be to include GOMOS (Goals, operations, methods and selection rules) (Wolpert, Ghahramani, & Jordan, 1995). When humans are initially presented with a new tool to learn they generally do not have the skills to use it effectively. This is due to lack of knowledge of the operation and purpose of the tool, the situation(s) to use it, or the results obtained from the use of the tool itself. Studies have shown that the process of learning to use a new tool can be summarised as developing an internal model (Wolpert et al., 1995). This internal model provides a neural representation of how the body responds to a command at a

given velocity and position, and prior to the acquisition of this model, the user cannot use the tool skilfully as this internal model does not exist within the brain. However, after building this model the skill level increases (Kitamura, Yamaguchi, Hiroshi, Kishino, & Kawato, 2003). It is logical to propagate this internal model from the use of a new tool to using and interfacing with a computer program. This logical extension would also lead to performing familiar tasks using a differing software.

Most neuroscience research on interaction and learning has focussed on imaging the brain using MRI scans (Sakai et al., 1998; Imamizu et al., 2000; Kitamura et al., 2003), whilst this provides exact positioning of the areas of activation in the brain and their respective durations, it is also very expensive to conduct, as it requires specialist equipment and is difficult to achieve experimental results where the person is free to perform tasks as they would in the workplace or at home. This restricts the application of this technology to the analysis of specific tasks and not everyday activities. Electroencephalography (EEG) is another technology that allows the activity of the brain to be studied. EEG is less expensive, less restrictive, and widely used within research and clinical studies as it is a passive technology which is safe for extended use.

The brain is a complex organ which consists of a network of nerve cells connected via neurons, with each of these connections communicating messages via electrical signals. This electrical transmission can be detected and classified using a series of electrodes that are placed on the scalp with minimum intrusiveness. The very weak signals detected from the brain, usually within the $5 - 100\mu V$ range (Lee & Tan, 2006) are amplified and compared to a reference voltage by the use of a differential amplifier, this then forms the basis for frequency analysis. The results of the EEG produce a frequency spectrum subdivided into delta ($1 - 4Hz$), theta ($4 - 8Hz$), alpha ($8 - 12Hz$), beta ($15 - 30Hz$), and gamma ($30 - > 40Hz$), with each band providing levels of wakefulness or sleep and even “levels” of these states (Strijkstra, Beersma, Drayer, Halbesma, & Daan, 2003). In general terms, the lower frequencies (delta and theta) are not seen in the waking state and the majority of activity occurring when the subject is awake can be found within the alpha, beta, and gamma ranges (Miller, 2007). This makes it possible to determine the levels of wakefulness and the cognitive load (Antonenko, Paas, Grabner, & van Gog, 2010), which in conjunction with the ability to provide a minimally intrusive method of data collection makes the use of EEG a distinct appealing prospect for Human Computer Interaction (HCI) research.

The adoption of EEG has developed from expensive research and clinical equipment to a more consumer oriented technology. This reduction in the cost of EEG devices has led to the use of low cost equipment to research HCI issues such as task classification (Lee & Tan, 2006), games (Nijholt, Tan, Allison, del R Milan, & Graimann, 2008), and in adaptive user interfaces (Cutrell & Tan, 2008). Specific examples of the use of low cost EEG devices can be found in Wang, Sourina, and Nguyen (2010), where EEG is used to create a game for medical applications, or (Chu & Wong, 2014) where a player’s attention is measured whilst playing a mobile based game. Another example of the use of low cost EEG devices can be found in Mak, Chan, and Wong (2013a) and Mak, Chan, and Wong (2013b), where EEG is used to measure the mental effort and familiarity of participants when tracing shapes using their non-dominant hand. One such low cost device is the Neurosky Mindwave headset. This is an ergonomic, minimally intrusive, lightweight, and single-channel dry sensor EEG device capable of distinguishing the delta, theta, alpha, beta, and gamma frequencies as well as “attention” and “relaxation” states with data communication via Bluetooth.

This paper proposes to use the Neurosky headset to gather EEG data from a sample of 12 subjects performing a set of tasks related to programming. The users will perform a series of simple tasks using differing Integrated Development Environments (IDEs) with the cognitive functions being recorded. The subject will then complete a questionnaire pertaining to the level of effort and difficulty to complete the tasks in conjunction with observations made by the

facilitator. This data is then correlated with the brain activity to determine the mental effort and the brain activity when performing the set tasks.

The rest of this paper is organised according to the following. Section 2 describes the method used for this study, including the configuration of the experiments, the methods used for data collection, and the techniques used for the processing of the data. Section 3 presents and discusses the results from the experiments. Section 4 concludes the paper with summary of the findings and suggestion for future research direction.

2 Methods

2.1 Experiments

A sample of twelve volunteers were recruited and considered in this study. The volunteers consisted of all males aged between 22 and 37 years old. All participants were reported to have normal or corrected-to-normal vision, and have no known history of neurological or psychological disorder. Participants have given their informed consent before taking part in the experimental procedure, which was approved by the ethics committee at the Bournemouth University in the United Kingdom. Participants were reported to have not previously used the Integrated Development Environments (IDEs) they were assigned for the experiment.

Each participant was asked to perform eight trials involving Human Computer Interaction (HCI) with one of two considered software IDEs. Each trial required the participant to follow clearly defined instructions to complete tasks in either of the considered IDEs. To complete the task successfully, participants were required to acquire a new set of interface associations, for example, creating a new project in either of the considered IDEs. The details of these trials have been presented in Figures 9 and 10 which illustrate the exercise sheets handed to the participants.

Each participant was asked to complete only one of the exercise sheets, resulting in six participants who completed the exercise sheet for the Visual Studio IDE, and six participants who completed the exercise sheet for the Eclipse IDE. There were no crossover of participants between IDEs.

The IDEs considered were Visual Studio by Microsoft, and Eclipse by the Eclipse Foundation, the specific details of these two IDEs are listed in Table 1.

Table 1. Configurations and specific information regarding the IDEs considered during the experiment.

	Visual Studio	Eclipse
Full Name	Visual Studio Community 2013	Eclipse IDE for Java Developers
Version	12.0.31101.00 Update 4	Luna Service Release (4.4.2)
Operating System	Microsoft Windows 7	Microsoft Windows 7

Two shell scripts were developed and executed after each task was completed by a participant in order to reset the configurations and environments of the IDEs before the next task.

Two computers were used during the experiment, each with the configuration listed in Table 2. Two computers were used to separate the EEG data collection software (which ran on Visual Studio) from the software used by participants, and to allow real-time analysis of the mental effort and familiarity data.

There were two facilitators; one was observing the performance of the participants and monitored the progress of the task while the other facilitator was monitoring the data acquisition of the user interface software and ensuring that the subjects headset maintains connection.

Table 2. Hardware and software configurations of the computers by participants to complete the tasks, and by the facilitators to collect the EEG data.

Configuration name	Configuration value
Architecture	Windows x64
RAM	16 GB
CPU	Intel(R) Xeon(R) CPU E5-1620 @ 3.70GHz ×16
Total CPU Cores	8
MATLAB version	R2014b (8.4.0.150421) 64-bit (win64)

2.2 Data Collection

EEG data was acquired using a commercially available, single-channel mobile headset developed by NeuroSky Inc. This headset is shown in Figure 1 and consists of a single non-invasive electrode that presses against a subject’s forehead approximately an inch above the left eyebrow, and a ground/reference electrode that clips on to the ear lobe. This headset is capable of acquiring raw EEG signals at up to 512Hz and contains an advanced Application-Specific Integrated Circuit (ASIC) module that performs noise filtering of both EMG and 50/60Hz AC power interference.



Fig. 1. The NeuroSky MindWave Mobile headset

The EEG headset was connected via Bluetooth to a separate PC from the one used for the tasks described in Section 2.1 to avoid any interference with the use of the IDEs. Figure 2 shows a block diagram of the system architecture for the data acquisition system used in this paper.

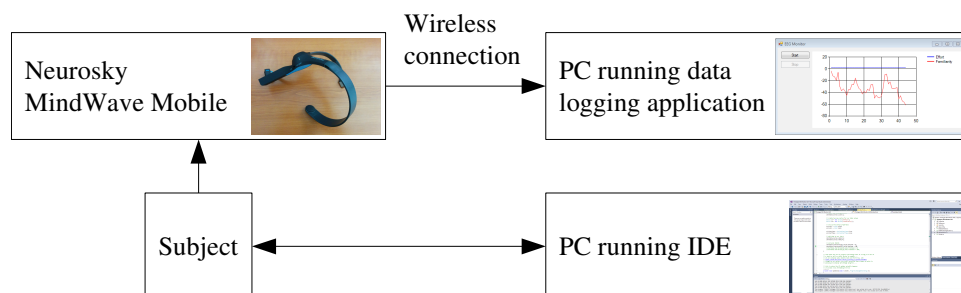


Fig. 2. System architecture for the EEG data acquisition system

To acquire the EEG data relating to the mental effort required to navigate the graphical interfaces of the development environments considered in this paper, a simple data logging application was developed on top of the API provided by NeuroSky (*Neurosky Developer Tools 2.5 PC/Mac*, 2015). This API provides a simple interface for connecting to the EEG headset and acquiring data, as well as implementations of the mental effort and task familiarity algorithms that calculate task related spectral power variations (Mak et al., 2013a, 2013b). The API also helps process the raw EEG data and remove artefacts, such as that produced by eye movement or eye blinks, using wavelet analysis (Zikov, Bibian, Dumont, Huzmezan, & Ries, 2002).

The mental effort algorithm measures the workload exerted on a subject's brain by the task that they are performing. Raw EEG signals from a single channel frontal EEG device are sampled at 512Hz and filtered to remove both eye movement artifacts and electromagnetic interference are acquired and the band powers (i.e. the power spectral densities of each EEG band) calculated. The band power of the upper alpha band EEG signals (11-14Hz) in particular is then used to calculate the mental effort of the subject performing the task. Mak et al. (2013a) have shown that these upper alpha band EEG band powers exhibit consistent, statistically significant increases in mental workload. Mak et al. (2013a) have shown that there is some correlation between theta band power and mental workload, but these are only statistically significant at the beginning of difficult tasks.

The task familiarity algorithm measures how well a subject is learning a specific task. As a subject learns how to perform common tasks in an IDE for example, they become more familiar with it and thus the task familiarity measurement increases. To calculate task familiarity, the raw EEG signals are processed in the same way as for Mental effort (i.e. they are sampled and filtered to remove common artifacts). Mak et al. (2013b) have shown that, as a subject becomes more familiar with a given task, EEG activities in all frequency band decrease. However, decreases in the delta and gamma bands were particularly significant - though in the case of gamma waves this decrease was only statistically significant ($p < 0.05$) at the start of tasks.

A UML activity diagram for the data logging application used in this research is provided in Figure 3 showing the work-flow through the application. One of the key activities within this work-flow is the initial calibration of the mental effort and task familiarity metrics. This involves the subject relaxing with eyes open for 60 seconds before starting the task to allow for the calculation of initial baseline values for both mental effort and task familiarity. These baseline values can then be used as a reference for comparing later values. New values for mental effort and task familiarity are calculated continuously every 10 seconds. It should also be noted that the application also checks the signal quality every second to ensure that the headset is connected and positioned properly - if a poor signal quality indicator is detected then no data is collected and the trial facilitator is notified so that they can help readjust the headset.

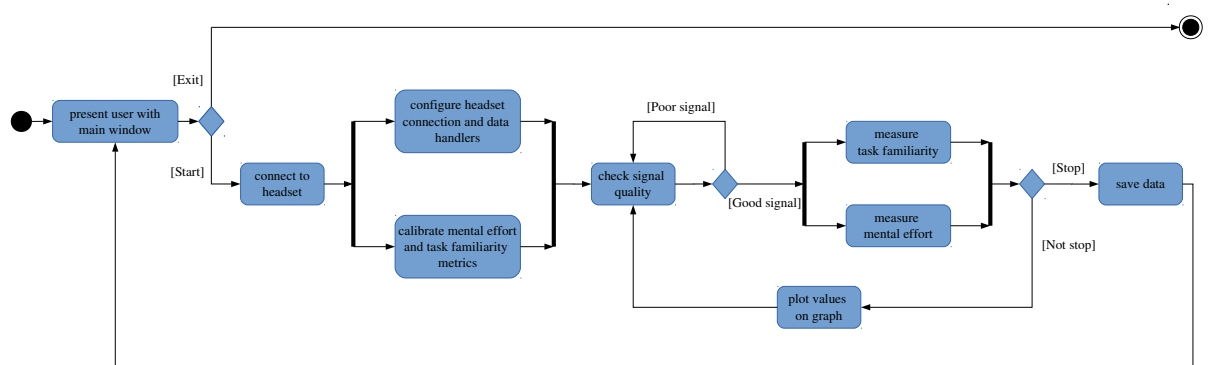


Fig. 3. UML activity diagram for the data acquisition application

In order to aid the experiment facilitators in monitoring the progress of tasks and ensuring that the subject's headset connection is correct, a simple user interface has been created which plots the last 300 values obtained for mental effort and task familiarity. This user interface is shown in Figure 4 and also allows the facilitator to temporarily suspend the trial. This was useful in the event that the head-set signal was lost.

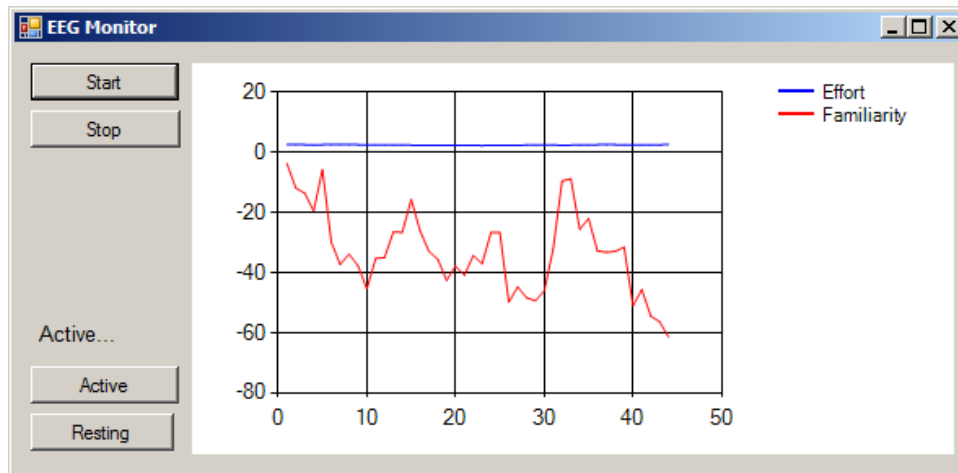


Fig. 4. Graphical user interface for the data acquisition application

Observations made by a facilitator were recorded in conjunction with the collection of EEG data during each task for every participant. These observations included noting:

1. When a participant had made an error.
2. When a participant had stopped referring to the exercise sheet.
3. When a facilitator was required to intervene in the task.
4. Comments made by the participant throughout the experiment.

Also in conjunction with the collection of EEG data, the participant was asked to complete a questionnaire after completing each of the eight tasks. This questionnaire would simply ask:

1. Was this task difficult? Answers: Not difficult; Indifferent; Difficult.
2. Did you make any mistakes? Answers: Yes; No.
3. Did the facilitator intervene? Answers: Yes, No.

2.3 Data Processing

The EEG data recorded by the software was stored in comma separated log files per participant. EEG data for each task was identified using a boolean value which would indicate whether a participant was “Resting” or “Active” (completing a task). The sequence for each log file would alternative from “Resting” to “Active” eight times (for each task) and finish on a final “Resting” state. This data would be copied to a MATLAB data structure with clear separation of the “Active” states and “Resting” states.

All EEG data for mental effort and familiarity has been normalised (between 0 and 1) to account for variance in calibration and base mental effort and familiarity for each participant. The loss in the raw range and magnitude of data as a result of the normalisation is not considered an issue as this study is interested in the relative increase or decrease of mental effort and familiarity across eight tasks for all participants. 1-D data interpolation was achieved by cubic convolution in MATLAB R2014b (using the “v5cubic” method). This allowed the mental effort

and familiarity data for each task to be contrasted between participants who completed the tasks in different amounts of time.

The observations made by the facilitator have been translated into binary matrices indicating which tasks had mistakes that were made by the participants, and at which task the participants stopped referring to the exercise sheet. The perceived difficulty of the tasks by the participants have also been translated into binary matrices indicating which tasks were perceived as difficult. These matrices will be used when plotting the data to aid the explanations of the behaviour of the recorded mental effort and familiarity, as it is expected that if a mistake is made in a task it will result in anomalous readings.

3 Results

This mental effort and familiarity data has been plotted in Figures 5 and 6 for Visual Studio respectively, and Figures 7 and 8 for Eclipse respectively. The plots include the mean averages of mental effort and familiarity data over each task as well as a plot of the linear best fit and indication of the slope.

Overall, the mean average results for familiarity across both the Eclipse and Visual Studio IDEs show the trend of moving from familiarity readings, which are descending in the initial tasks, to familiarity readings which are ascending in the later tasks. This is in accordance with the prediction that over time, a participant will become more familiar with the task which they have been asked to repeat for a total of eight times. In the samples taken and illustrated in Figures 8 and 6, it can be observed that on average the participants did not begin to show signs of increased familiarity with the Visual Studio IDE until the third task, and in contrast it can be observed that on average the participants began to show signs of increased familiarity with the Eclipse IDE after the first task. This observation is supported further by the observed mistakes and perceived difficulty matrices illustrated in the Figures, where it can be seen that five of the six participants for the Visual Studio IDE made mistakes in task 2, where as only one of the six for the Eclipse IDE made a mistake in the same task.

In addition, only two out of the six participants who were completing the Visual Studio IDE exercises reported occurrences of perceived difficulty for the first task. This sample group reached a total of 23 mistakes throughout the experiments. In contrast, four out of the six participants who were completing the Eclipse IDE exercises reported occurrences of perceived difficulty for the first task. This sample group reached a total of only 16 mistakes throughout the experiments.

Overall, the mean average results for mental effort across both the Eclipse and Visual Studio IDEs show the trend of moving from mental effort readings, which are ascending in the initial tasks, to mental effort readings which are descending in the later tasks. This is again in accordance with the prediction that over time, a participant will become more familiar with the task which they have been asked to repeat for a total of eight times, and therefore require less of a mental effort to complete the tasks.

The figures show that the majority of the Eclipse IDE participants stop referring to the exercise sheet at task 3, where as the majority of Visual Studio participants stop referring to the exercise sheet at task 4. Once participants stopped looking at the exercise sheets, the majority of Visual Studio IDE participants began to make mistakes soon after. This resulted in the mental effort for Visual Studio IDE participants to increase in task 4, where four of the six participants made a mistake. This caused an anomaly in the descending mental effort trend as the tasks were repeated. A similar event occurred for the Eclipse IDE participants on task 6, where three of the participants made a mistake and as a result the average familiarity reading for that task showed a descending slope.

All participants using the Visual Studio IDE found it difficult to create a C# project; instead they made the mistake of creating a Visual Basic project. A facilitator intervened whenever there

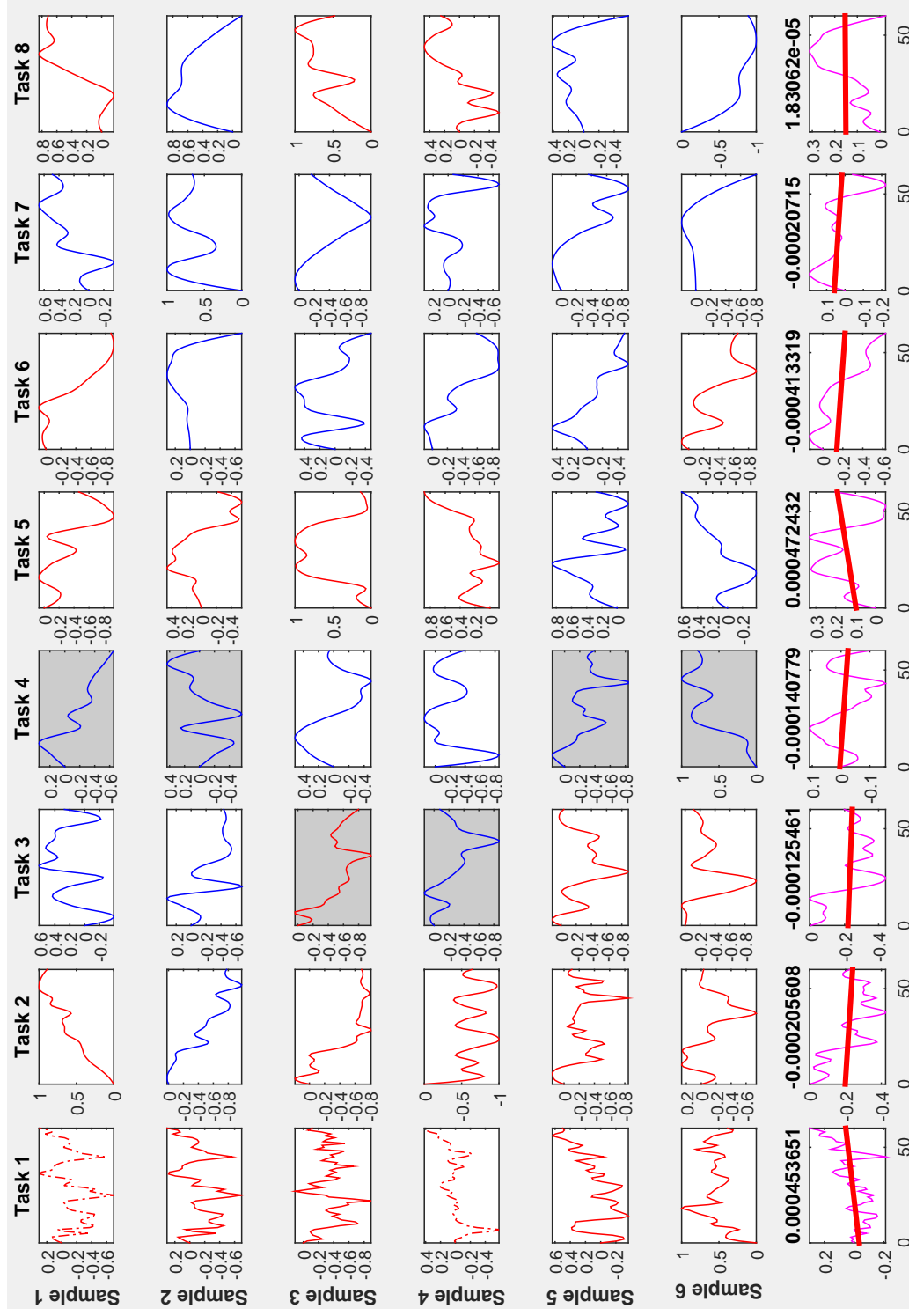


Fig. 5. Plots of the post-processed Mental Effort data over time obtained from the EEG head-set for participants using the Visual Studio IDE. Red lines indicate an error observed by the facilitator. Dashed lines indicate a perceived error by the participant. Shaded backgrounds indicate the task from which a participant stopped referring to the exercise sheet. Final row indicates mean average of task data, linear best fit, and gradient of the slope.

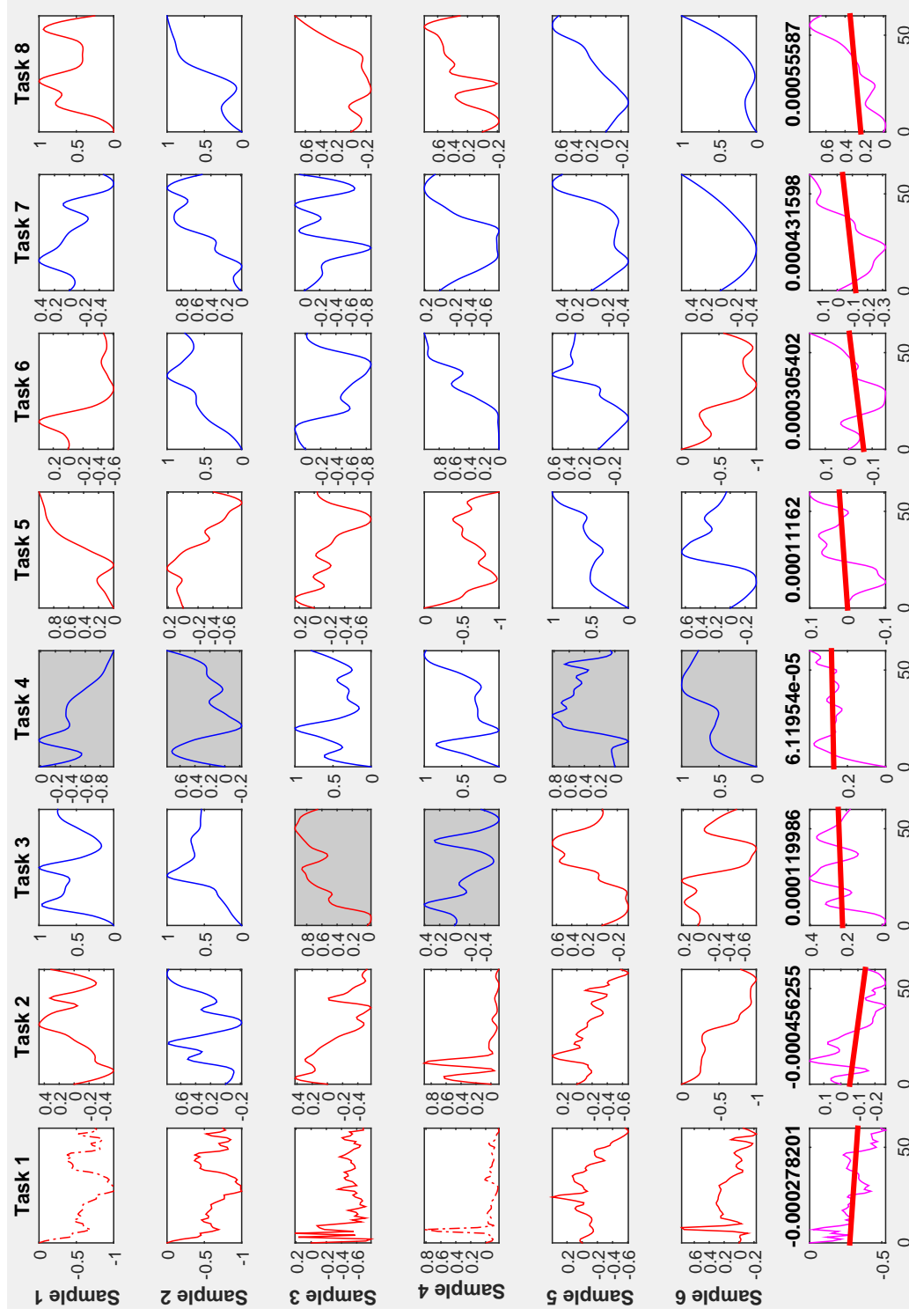


Fig. 6. Plots of the post-processed Familiarity data over time obtained from the EEG head-set for participants using the Visual Studio IDE. Red lines indicate an error observed by the facilitator. Dashed lines indicate a perceived error by the participant. Shaded backgrounds indicate the task from which a participant stopped referring to the exercise sheet. Final row indicates mean average of task data, linear best fit, and gradient of the slope.

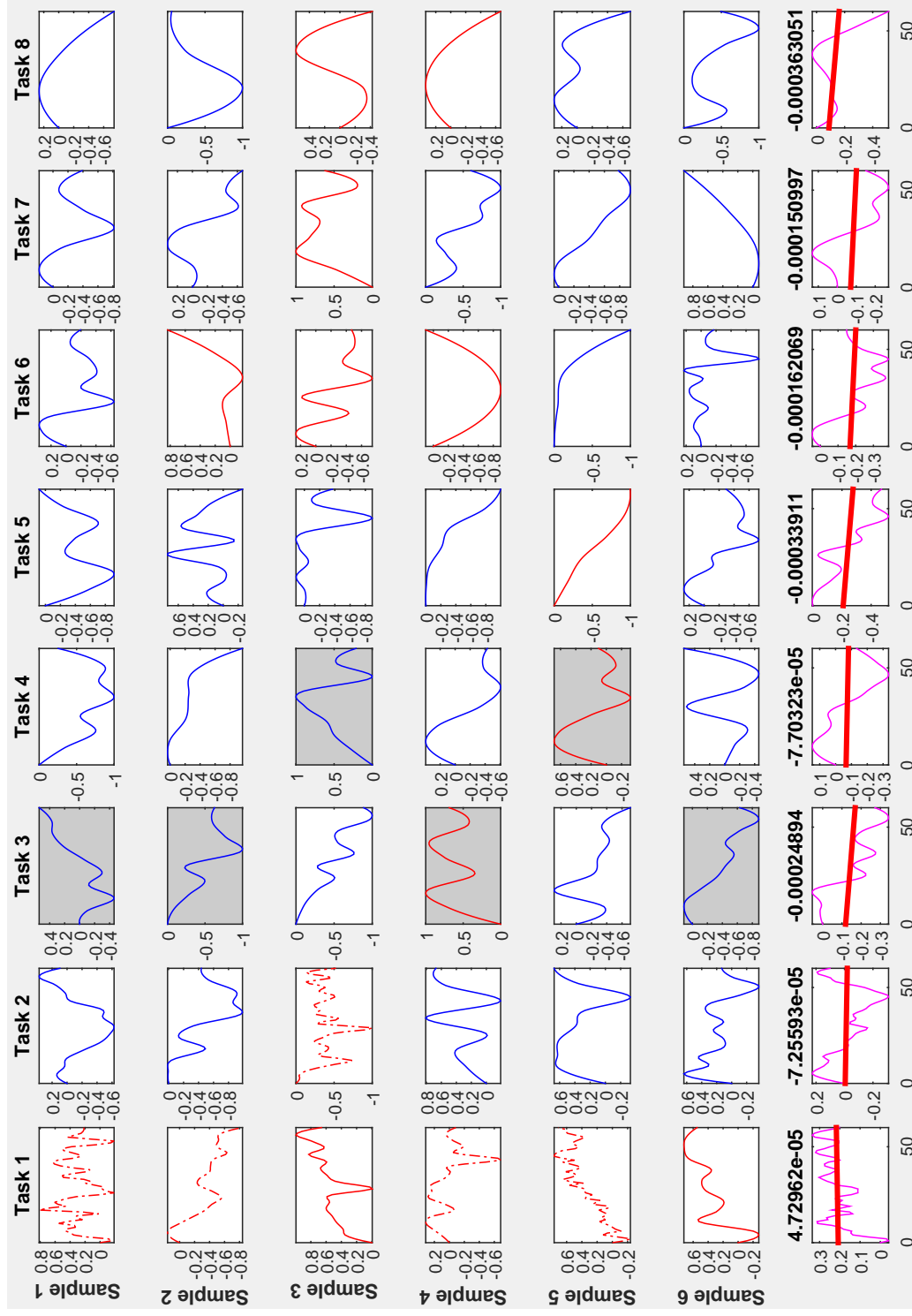


Fig. 7. Plots of the post-processed Mental Effort data over time obtained from the EEG head-set for participants using the Eclipse IDE. Red lines indicate an error observed by the facilitator. Dashed lines indicate a perceived error by the participant. Shaded backgrounds indicate the task from which a participant stopped referring to the exercise sheet. Final row indicates mean average of task data, linear best fit, and gradient of the slope.

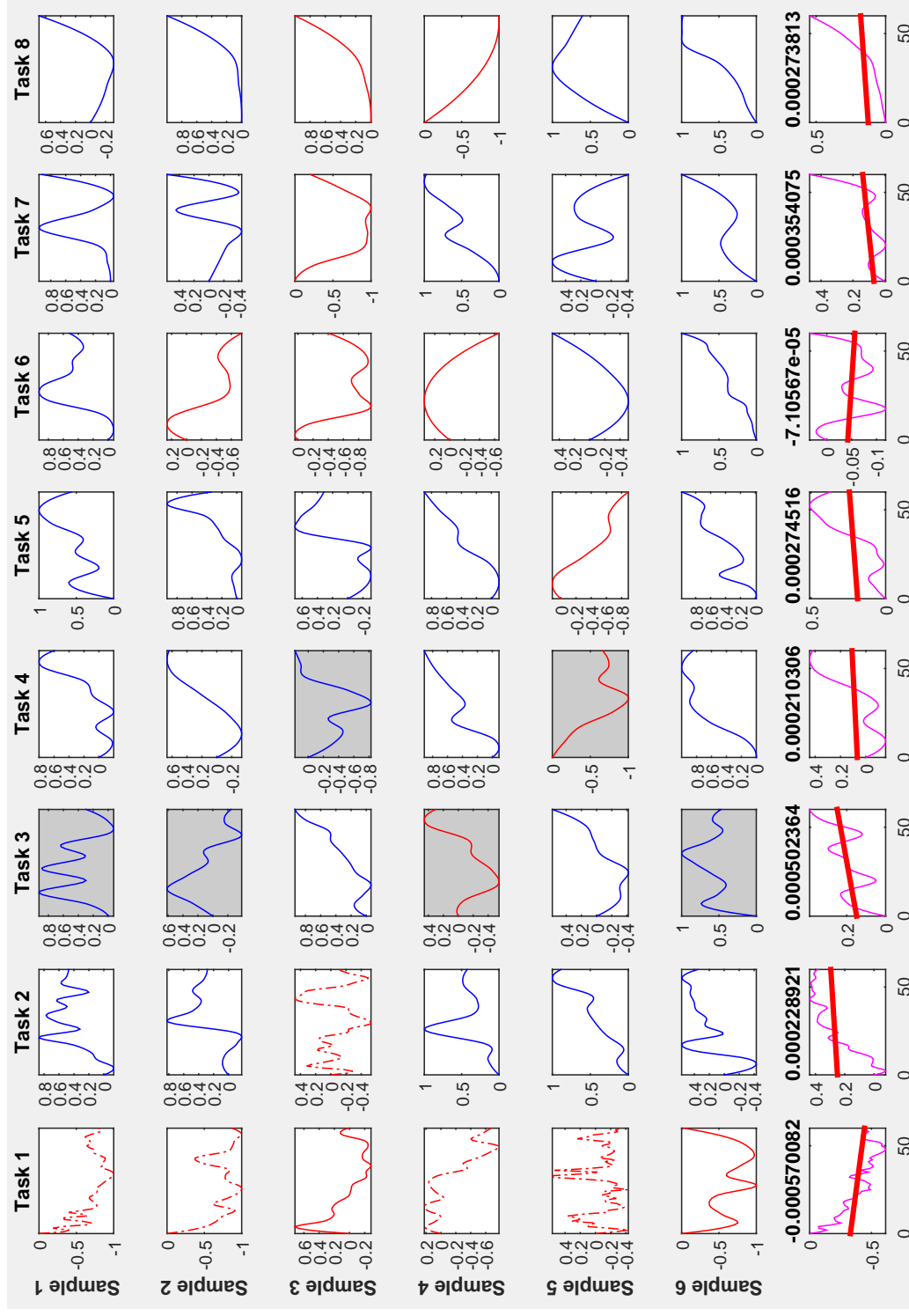


Fig. 8. Plots of the post-processed Familiarity data over time obtained from the EEG head-set for participants using the Eclipse IDE. Red lines indicate an error observed by the facilitator. Dashed lines indicate a perceived error by the participant. Shaded backgrounds indicate the task from which a participant stopped referring to the exercise sheet. Final row indicates mean average of task data, linear best fit, and gradient of the slope.

was a clear departure from the exercise sheet. Most of the participants found it difficult to create a class.

The majority of participants using the Eclipse IDE were unable to close the Eclipse welcome tab, this prevented them from seeing the project they had just created. The Eclipse welcome tab appeared to cause the greatest confusion for participants, one participant was quoted to say “I’m not entirely sure where the project is located after creating it”.

4 Conclusion

It was observed that the Eclipse users finished quicker than Visual Studio users. Eclipse users also made fewer errors than Visual Studio users. Generally, the participants found the Eclipse user interface easier to use. The EEG data recorded for mental effort and familiarity also suggest that the Visual Studio Integrated Development Environment (IDE) participants took longer to become familiar with the interface and required a higher mental effort when repeating the same task eight times.

The mental effort and familiarity data recorded by the EEG headset shows trends which correlate with the observations made by both the facilitator and the perceived difficulties of the participant. The results suggest that this method of evaluating Human Computer Interaction (HCI) in terms of familiarity and mental effort with IDEs is feasible using a low-cost EEG headset solution.

A drawback to this approach is the unpredictable behaviour of participants who undertake the tasks. Participants will at some point stop referring to the exercise sheets (in particular when repeating tasks) which will cause unpredictable readings. This is also the case with the unpredictable readings produced when a participant makes a mistake or a facilitator has to intervene. Future research should focus on the consideration of these events when processing the data.

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Appendix

Calibration

The method used for data acquisition requires that the participant is connected to the headset for an initial calibration. The facilitator will ask that you position yourself (seated) and look out the window towards the sky. This will last for 60 seconds whilst the calibration completes, during which time you will be required to:

1. Deliberately relax all muscles.
2. Clear mind of any specific thoughts.
3. Let mind wander and drift.
4. Relax your breathing.
5. Keep eyes open but relaxed.

Tasks

Please complete the following tasks. A facilitator will intervene after you complete each task to reset configurations for the next task. A facilitator may intervene to correct your actions in completing tasks.

Task 1

Please complete the following instructions:

1. Please open the **Visual Studio** IDE from the desktop, and follow the interface instructions until you are presented with the main IDE interface (no obstructing dialogue boxes).
2. Please create a new **Visual C# Console Application Project**. Please name the project **"Task 1"**
3. Please **Add** a new **C# class** file and name the class file **"Task1"**
4. Please copy the following code into the code editor within **Program.cs**, after `static void Main(string[] args){`:
System.Diagnostics.Debug.WriteLine("Hello Task1");
5. Please Run the code and note the output generated by the above code.

Task 2

Repeat Task 1, using **"Task 2"** as your project name, and **"Task2"** as your class file name.

Task 3

Repeat Task 1, using **"Task 3"** as your project name, and **"Task3"** as your class file name.

Task 4

Repeat Task 1, using **"Task 4"** as your project name, and **"Task4"** as your class file name.

Task 5

Repeat Task 5, using **"Task 5"** as your project name, and **"Task5"** as your class file name.

Task 6

Repeat Task 6, using **"Task 6"** as your project name, and **"Task6"** as your class file name.

Task 7

Repeat Task 7, using **"Task 7"** as your project name, and **"Task7"** as your class file name.

Task 8

Repeat Task 8, using **"Task 8"** as your project name, and **"Task8"** as your class file name.

Fig. 9. The exercise sheet for completing the eight trials for the Visual Studio IDE. These were presented to the participants of the experiments.

Calibration

The method used for data acquisition requires that the participant is connected to the headset for an initial calibration. The facilitator will ask that you position yourself (seated) and look out the window towards the sky. This will last for 60 seconds whilst the calibration completes, during which time you will be required to:

1. Deliberately relax all muscles.
2. Clear mind of any specific thoughts.
3. Let mind wander and drift.
4. Relax your breathing.
5. Keep eyes open but relaxed.

Tasks

Please complete the following tasks. A facilitator will intervene after you complete each task to reset configurations for the next task. A facilitator may intervene to correct your actions in completing tasks.

Task 1

Please complete the following instructions:

1. Please open the **Eclipse** IDE from the desktop, and follow the interface instructions until you are presented with the main IDE interface (no obstructing dialogue boxes).
2. Please create a new **Java Project**. Please name the project “**Task 1**”
3. Please **Add** a new **Java class** file and name the class file “Task1”. **Please check the “public static void main(String[] args)” box.**
4. Please copy the following code into the code editor within **Task1.java**, after “*public static void main(String[] args) {*”:
System.out.println(“Hello Task1”);
5. Please Run the code and note the output generated by the above code.

Task 2

Repeat Task 1, using “Task 2” as your project name, and “Task2” as your class file name.

Task 3

Repeat Task 1, using “Task 3” as your project name, and “Task3” as your class file name.

Task 4

Repeat Task 1, using “Task 4” as your project name, and “Task4” as your class file name.

Task 5

Repeat Task 5, using “Task 5” as your project name, and “Task5” as your class file name.

Task 6

Repeat Task 6, using “Task 6” as your project name, and “Task6” as your class file name.

Task 7

Repeat Task 7, using “Task 7” as your project name, and “Task7” as your class file name.

Task 8

Repeat Task 8, using “Task 8” as your project name, and “Task8” as your class file name.

Fig. 10. The exercise sheet for completing the eight trials for the Eclipse IDE. These were presented to the participants of the experiments.