Towards a Computer Interaction-Based Mood Measurement Instrument

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Abstract

The purpose of this explorative research was to explore the mood of a computer user and his or her use of keyboard and mouse. Twenty-six users (13 programmers and 13 frequent computer users) took part in the study. A background software application executing on participants' computers logged the keyboard key press and mouse click events. The correlations between moods of the participants and their use of keyboard and mouse show that it might be possible to create individual tailor made mood measures based on individuals keyboard and mouse use. The highest and lowest significant correlations found were r (63) = 0.39, p<= 0.01 and r (73) = -0.24, p<= 0.05 respectively. About 31% of participants showed significant correlations towards valence whereas about 27% showed significant correlations toward arousal. Further, the data shows that experience and self discipline might be a factor to predict people who show significant correlation between their behaviour and valence level. Similarly dutifulness might help in predicting people who show significant correlation between their behaviour and arousal level.

1. Introduction

Human computer interactions follow the principles of recognition, interpretations and expressions of emotions that are similar in human-human interaction (Reeves and Naas, 1996). An affect recognizing computer can communicate in a more natural way and can have more effective human computer interaction (Zimmerman et al., 2003). Affect recognizing computers not only make certain tasks easier to do but also provide encouragement and comfort in order to significantly reduce frustration levels (Klein, 1999). Amongst computer users group, programmers' most often feel frustrations and become moody because of the deadlines and expectations to produce (Ross and Zhang, 1997). Programmers therefore might be an interesting group of participants for studying the impact of affects. Damasio (1995) argued that moods and emotions are necessary for reasoning and rational decision making. Programmers often need reasoning and decision making skills to resolve programming problems. There are also some studies like Khan et al., (2007) that suggest that programmer's mood might have an impact on their debugging performance. However the task of affect recognition is complex in nature and involves various overheads. There are various affect recognition methods like self-reports and physiological methods, another less explored way of affect recognition and measurement is also by monitoring the behaviour of people.

It seems reasonable to expect that behaviour based mood measurement is possible because mood is an affective state and has an impact on behaviour (Zimmerman, 2003). Moods last from minutes to hours and days. Since moods last for long-time their influence on behaviour is more prominent than emotions (Zimmerman, 2003). Moods may either have an informational impact on behaviour or directive impact on behaviour (Gendolla, 2000). Gendolla further stated that informational impact of moods effect judgemental and appraisal behaviours that lead to behavioural adjustments while directional moods influence behaviour preferences and interests for fulfilling hedonic motive[1].

[1] living and behaving in ways that mean you get as much pleasure out of life as possible

Andrade (2005) showed that the ability to judge quality, importance or amount of something based on affective reactions (evaluations) and controlling this mechanism (regulations) guide behaviour. When there are no mood changes, it might lead to monotonic increase in behavioural aims. However any expected activity might change the mood and thus evaluation and regulatory mechanism to produce some patterns. In addition moods are also known to affect several other aspects of behaviour like judgements and evaluative judgements (Siemer et al, 1998), intergroup discrimination (Forgas and Fiedler, 1996) and acceptance of certain risks (Isen and Nehemia, 1987). Similarly moods also affect helping (Manucia et al., 1984), helping tasks that are incompatible with good moods (Isen and Stanley, 1978), decision rules in risk (Nygren et al., 1996) and decision making (Pham, 1998).

Although the literature shows that moods have an impact on behaviours, the question of interest is how can we measure the moods from the users' behaviour with the help of computers? There is vast amount of literature available that shows that computers can measure moods and behaviour. Such work is mostly conducted in the areas of robotics and human computer interaction. For example Johnson et al. (1998) experimented to extract ordered sets of training data from human behaviour for computer learning purposes. These human behaviours included spatial behaviours like shake of hands, body movements. Other such human behavioural considerations are automatic facial recognition (Valstar et al., 2004), action recognition (Bobick and Davis, 1997) and recognition of human movement (Gavrila and Davis, 1995; Pentland, 1995).

Previous work has shown that it is possible to measure moods of a computer user but these methods needs complex software and algorithms as well as dedicated hardware like video cameras, pressure sensitive and physiological devices (Zimmerman et al., 2003). These methods can be a cause of disruptions in user attention. The use of keyboard and mouse data might reduce these overheads as these are the most basic devices used by computer users. Computer users are familiar with theses devices and there are no risks of external disruptions such as loss of concentration because of attached equipm`ent. The use of keyboard and mouse is also cheap as they are available with almost every computer. In addition keyboard and mouse data recording in log files is not difficult to implement (Zimmerman et al., 2003).

Limited research exists on the possibility of measuring moods based on the users' use of keyboard and mouse. For example Mahr et al. (2005) used mouse motions to detect emotions with some significant correlations in his thesis. Another example is Zimmerman et al. (2003) who designed experiments to store keyboard keystrokes and mouse movements in log files and later intended to find correlations of these events with affective state. Zimmerman (2003) results might not be published yet but this study intends to carry on the experiments on the possibility of mood measurement from computer user keyboard and mouse use.

The experiment presented in this paper is a first step toward measuring moods with the use of keyboard and mouse. The aim was to examine whether an individual tailor made mood measure could be established. This would be a first step toward a generalizable instrument that could be used across individual computer use. The next subsection will briefly describe moods, emotions, similarities and differences between moods and emotions. The next section will explain the experimental material, setup, participants, log files and results. The analysis will also look at a personal factor that would help to predict whether person behaviour correlates with mood. The last section present conclusions and a brief discussion on the similarities and differences of experimental procedures in this study and other studies reported in literature. The conclusions section will also expand on possible future studies.

1.1 Moods and Emotions

Emotions are affective states aroused by external stimuli, directed toward the particular stimulus in the environment that caused arousal and are activated by a physiological state. Emotions are induced after an object is seen or evaluated. Parkinson et al. (1996) consider both moods and emotions as affective states. Parkinson defined moods as "Affects which refer to mental states involving evaluative feelings, in other words psychological conditions when the person feels good or bad, and either likes or dislikes what is happening" (p. 4). Emotions exist for a short time (from seconds to minutes) are intense in nature and have a clear object and cause. Moods last for longer, are weaker in origin and have no clear object and cause of beginning (Fridja, 1993). It is possible to identify the events that caused emotions however it is difficult to identify events that caused a mood (Ekman, 2003). Researchers often consider moods and emotions as the same and study them under one term mood. Example of studies which did not distinguish between moods and emotions are: Kirchsteiger et al. (2006) and Kaufmann and Vosburg (1997). This unrecognized differentiation is because moods might be the results of preconceived emotions as people often are not aware of their moods until attention is drawn toward them (Zimmermann et al., 2003).

Some researchers consider moods as an affective state and have discrete form in nature. However most of the researchers' also consider moods as dimensional like Dienstbier (1984). Researchers such as Remington and Fabrigar (2000) and Russell (1980) consider moods to have at least two dimensions (a pleasure or valence dimension and an arousal dimension). The two-dimensional valence arousal mood models are gaining popularity and therefore are utilized in this study.

1.2 Two Dimensional Mood model

Two-dimensional valence arousal model gains its name from its use of valence and arousal. Sanchez (2005) defined valence as the degree of happiness or sadness whereas he defined arousal as a subjective state of feeling activated or deactivated. The representation of valence and arousal on X-axis and Y-axis forms a two-dimensional model of mood as proposed by Thayer (1989). Others like Morris (1995) prefer adding a third dimension to express the dominance (controlled, uncontrolled). This study used only a bidimensional model, with two dimensions, valence and arousal as these two dimensions are used in most emotional judgments (Bradley and Lang, 1994). Figure 1 explains some affective states and their correspondence to some valence-arousal combinations. For example, the "Rejoice" could be mapped as pleasant and high arousal state whereas "gloomy" could be mapped as unpleasant and low arousal state. Similarly, "terrified" could be mapped as unpleasant but high arousal state whereas "soothing" could be mapped as pleasant but low arousal state (Sanchez et al., 2005).

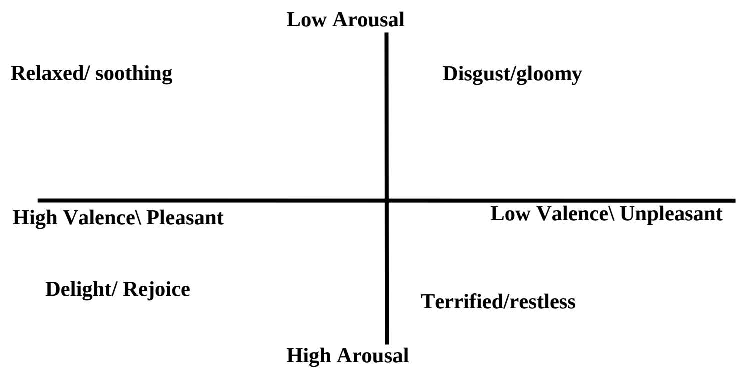


Figure 1*: Valence-arousal model with some examples of moods and emotions*

The use of two-dimensional models to examine a mood is gaining increasing acceptance (Thayer, Newman and McClain, 1994). Studies using two-dimensional mood emotions model also used self-report to measure their intensity. According to Lang (1980) self-reports are more reliable in multidimensional view of moods as in comparison to one-dimensional view. This study will use self-report measures and multidimensional approach to arousal and valence because of the following reasons:

1. Most research used a multidimensional model of emotions rather than discrete emotional states or single dimension of emotions (Picard, 1997).

2. Self-reports are more reliable with multidimensions than with the discrete categories such as anger or fear (Lang, 1980).

For the subjective assessment of moods on valence arousal model, the SAM (Self-Assessment Manikin) scale by Lang (1980) was used in this research. This scale is often used in research that applies self-reporting measures and has been presented as a promising solution to the problems associated with measuring emotional responses (Morris, 1995). SAM represents PAD (Pleasure arousal Dominance) along a nine-point scale using graphical characters. Valence is often represented on the X-axis whereas Arousal is often represented on the Y-axis. For valence the figures ranges from smiling happy figure to frowning unhappy figure. For Arousal the figures ranges from excited open eyes to sleepy closed eyes. Valence starts from 1 (High Valence) to 9 (Low Valence). Similarly the Arousal starts from 1 (High Arousal) to 9 (Low Arousal).

2 Experimental Material

The basic ideas of the experiment was to record keyboard and mouse events in log files with self-reported moods from the participants after a fixed interval and afterwards study the correlations between these two datasets. A keyboard and mouse event logging application was developed and executed on each participant computer as a background process. This application was able to detect computer user keystrokes and mouse movements and to store them in a log file. A mood rating dialogue box (see figure 2) appeared after every twenty minutes requiring the participant to rate their mood on SAM (Self-Assessment Manikin) scale. The application also provided various functionalities like: pause logging[2] for 5 and 10 minutes or for variable time in minutes. In addition participants were able to exit logging[3], stopping pop-up[4] dialogue box and uninstalling the application with all the participant data deleted, in case of withdrawal from the study. The study was setup for sample size of 86 mood rating data points for each participant. Participants were asked to complete at least 86 mood ratings. This sample size gave an 80% chance of finding at least medium size effect in the correlations with an alpha = 0.05. Therefore participants were instructed to answer at least 86 mood rating dialogues. Some figures that illustrate application are given in figure 2 and 3.

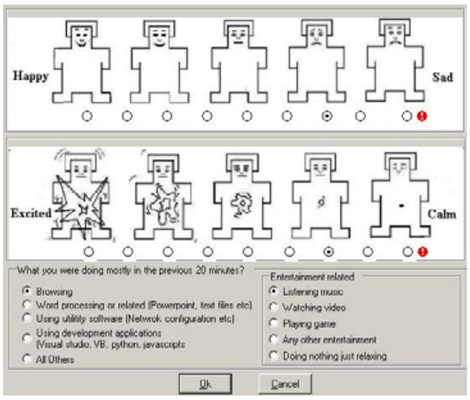


Figure 2*: Mood rating dialog with SAM (Self Assessment Manikin) scale*

[2] Participants were assured that application will not record any personal information. To further increase the trust pause logging functionality was provided so participants could pause logging of events for a specific time interval

[3] Participants were able to exit logging at any time. The application was developed to restart itself at the next computer boot up process; however participants were able to restart application without rebooting the computer.

[4] The appearance of pop-up dialog box after a fixed interval might be annoying specially when doing very important and concentration demanding work. This functionality was provided to stop appearance of pop-up dialogs until participant restart them again.

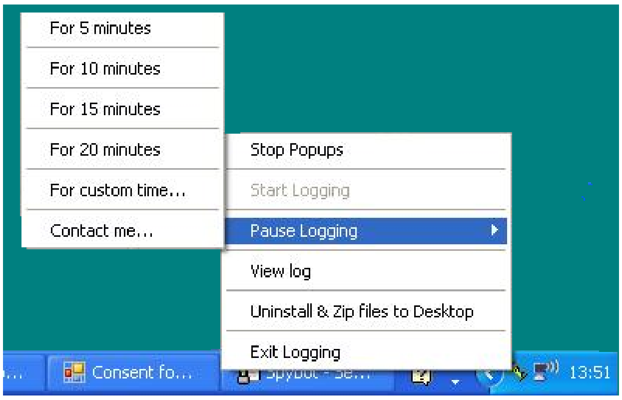


Figure 3*: Application menu and its further options*

2.1 Log files

This study used log files to record keystrokes and mouse clicks. Various researchers used log files in different computer related studies. For example Kukreja et al. (2005) developed a tool RUI (Recording User Interfaces) with a possibility of its use in human robot interaction studies as well as in human computer interaction studies by log file analysis. Haigh and Magarity (1998) used log analysis for measuring website use. Khan et al. (2008) used log files to measure users' personality whereas Ignatova & Brinkman (2007) also used log files to record interaction data for usability testing of different components in software. Log files used in this study record keyboard and mouse clicks to find a relationship between interaction data and moods. The events were recorded as: capital alphabets as 'Capital Alphabet', short alphabets as 'Short Alphabet', numbers as 'Numerical' and special characters like @ as 'Special Character'. This step was to protect participants' personal data and information. Figure 4 shows an example of the log file used in this study.

3 Participants

In this experiment we used an opportunity sample of 26 participants. The mean age of participants was 27 years with SD of 3. Their age ranged from 22 to 34 years. Fifty percent of the participants classified themselves as programmers, 42% as expert computer users and 8% as medium computer users. Their mean experience with computers was 5 years with a SD of 1.6 and ranging from 2 to 9 years. There were only two female participants in this study

4 The Experiment setup

The department ethics committee approved this experiment. Participants provided consent on a form before they could use the application. The application was installed on participants' computers as a background running process. Recorded data in the log files were in four different categories named as:

4.1 Window name

This data is used to identify the type of application in use at a specific event time. This data could help in identifying what keyboard and mouse behaviour computer users have on different applications. Special care was taken not to identify the document names. That means that the application recorded only specific application names like Microsoft Word, Internet Explorer, and Visual Studio.

4.2 Keyboard or mouse event

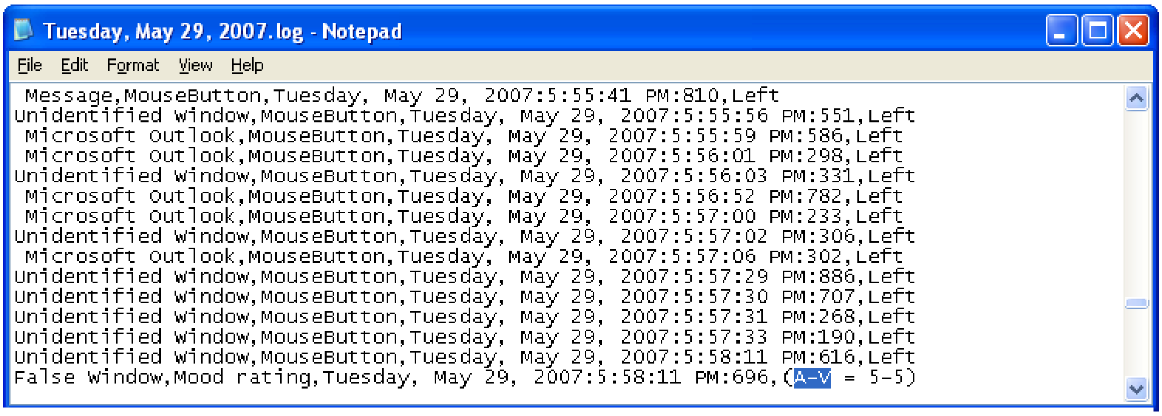
This data identified particular events. Events could either be mouse clicks or key press. Mouse clicks were recorded as "Mouse button" and key press events were recorded as "Key Up" or "Key Down" events.

4.3 Date and time of event

This data is used to records date and time of event and later on was used to find the time difference between events.

4.4 Category of event

This data stores the category of the event occurred. It stores “Left” or “Right” if a mouse button was clicked and stores “Short Alphabet”, “Capital Alphabet”, “Numeric key”, “Special Character”, if a key was pressed.



Tuesday, May 29, 2007.log - Notepad

File Edit Format View Help

```
 Message,MouseButton,Tuesday, May 29, 2007:5:55:41 PM:810,Left
Unidentified Window,MouseButton,Tuesday, May 29, 2007:5:55:56 PM:551,Left
 Microsoft Outlook,MouseButton,Tuesday, May 29, 2007:5:55:59 PM:586,Left
 Microsoft Outlook,MouseButton,Tuesday, May 29, 2007:5:56:01 PM:298,Left
Unidentified Window,MouseButton,Tuesday, May 29, 2007:5:56:03 PM:331,Left
 Microsoft Outlook,MouseButton,Tuesday, May 29, 2007:5:56:52 PM:782,Left
 Microsoft Outlook,MouseButton,Tuesday, May 29, 2007:5:57:00 PM:233,Left
Unidentified Window,MouseButton,Tuesday, May 29, 2007:5:57:02 PM:306,Left
 Microsoft Outlook,MouseButton,Tuesday, May 29, 2007:5:57:06 PM:302,Left
Unidentified Window,MouseButton,Tuesday, May 29, 2007:5:57:29 PM:886,Left
Unidentified Window,MouseButton,Tuesday, May 29, 2007:5:57:30 PM:707,Left
Unidentified Window,MouseButton,Tuesday, May 29, 2007:5:57:31 PM:268,Left
Unidentified Window,MouseButton,Tuesday, May 29, 2007:5:57:33 PM:190,Left
Unidentified Window,MouseButton,Tuesday, May 29, 2007:5:58:11 PM:616,Left
False Window,Mood rating,Tuesday, May 29, 2007:5:58:11 PM:696,(A-V = 5-5)
```

***Figure 4**: An example of log file*

Log files also recorded mood rating from the mood rating dialogue. The participant was also able to select a category of application they were working on and the type of entertainment (music, games etc) they were enjoying before the mood rating dialogue. An example of this recording is given below with an example of log file in figure 4 where A-V stand for Arousal-Valence rating from the participant.

5 Results

5.1 Preparation of data

On average every participant events were monitored over 8 days. All log files created by the application during these days were merged into a single log file. Each participant log file contained an average of 0.1 million lines of event recordings. An application was developed to extract the required information from the log files. The application extracted self-reported arousal and valence from these log files and keyboard\mouse behaviour within six and ten minute windows around these mood ratings. Figure 5 below illustrates the way application extracts the data around the mood ratings within the six and ten minute windows.

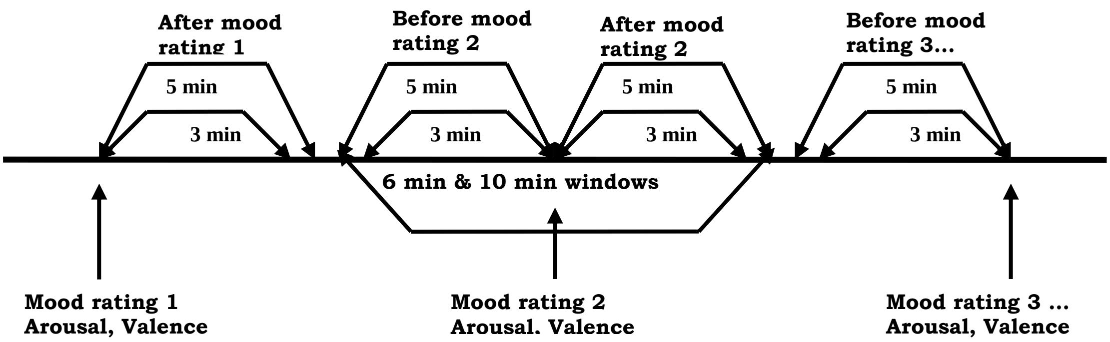


***Figure 5**: Window for taking events to analyze correlations between events and valence/arousal*

Eighty-six arousal valence ratings were required from participants however some of the participants provided fewer. The basic measures taken for each window were:

- Self-reported valence and arousal that participant recorded at mood rating dialogue.
- Total number of events around a particular mood rating
- Average time between these events
- Total windows switched
- Standard Deviation of the time between events
- Number of backspace and delete key events
- Number of alphabetical and numerical key events
- Number of mouse clicks
- Number of all other keys

In preparation of the data all those window slots were removed where the number of events was fewer than or equal to 10. The threshold value of the 10 was selected because participant might not be active on keyboard and mouse as they were busy in some other tasks like reading text from websites. Another filter was based on the key press and mouse click rates. All the key press and mouse click events with less then 50 milliseconds difference with previous event were filtered. Card et al. (1983) showed that novices have a typing speed of 1000 milliseconds per character whereas champion typists have an average speed of 60 milliseconds per character. Champion typists were considered as a lower limit and data having differences of less than 50 milliseconds were filtered out. All the key press and mouse clicks with a difference of more then 20,000 milliseconds (20 seconds) with previous event were also filtered out. The reason was that people waiting more than 20,000 milliseconds to type a key press might be involved in some other activity besides interacting with the computer.

5.2 Analysis

For each participant Pearson correlations were calculated between valence and log variables and between arousal and log variables. The Table 1 showed that 7 out of 26 (27%) participants had significant correlations with valence in a six minutes window. Similarly 7 out of 26 (27%) participants showed significant correlations with arousal in a six minutes window as is clear from Table 2. The data analysis on the 10-minute window showed that 8 out of 26 (31%) participants had significant correlations on valence (Table 3) whereas 6 out of 26 (23%) participants had significant correlations on arousal (Table 4).

Table 1*: Correlations of different variables with participants' valence with six minutes data around a* valence rating;

Participants	N	Window Switching	SD Time between events	Backspace delete	Mouse Clicks
1	73			0.26*	
2	49				-0.31*
8	54		-0.30*		
9	56			-0.30*	-0.32*
17	46		0.34*		
19	45	0.32*			-0.31*
20	31	0.38*			

Note: *** sign. Correlation significant at 0.01 levels, * sign. Correlation significant at 0.05 levels, N. Number of mood valence ratings*

***Table 2**: Correlations of different variables with participants' arousal with six minutes data around an arousal rating:*

Partici pants	N	Average time between events	Windows switching	SD between events	Other keys	Alphabets Number keys	Mouse clicks
1	73				-0.24*		
10	18		-0.50*				
11	69		-0.25*	0.26*		-0.30*	-0.28*
13	37					0.44*	
19	45	0.28*					-0.33*
20	52	0.42*					
25	32						0.35*

Note: ** sign. Correlation significant at 0.01 levels, * sign. Correlation significant at 0.05 levels, N. Number of mood valence ratings

***Table 3**: Correlations of different variables with participants' valence with ten minutes data around a valence rating:*

Partici pants	N	Events	Window Switching	Average time between events	SD TIME between events	Back-space Delete	Mouse clicks	Others
1	83					0.25*		
3	76		-.24*				-0.31*	
8	56			-0.28*				
9	63	-0.26*			0.34*	-0.34**	-0.39**	
11	72			-0.24*				
14	66		0.28*					
15	73	0.38**		-0.29*	-0.31**	0.26*	0.35**	0.37**
19	57		0.27*				-0.30*	

***Note:** ** sign. Correlation significant at 0.01 levels, * sign. Correlation significant at 0.05 levels, N. Number of mood valence ratings*

***Table 4:** Correlations of different variables with participants' arousal with ten minutes data around an arousal rating:*

Particip ants	N	Events	Average Time between events	Window Switching	Back-space Delete	Alphabets Numbers	Mouse Clicks	Others
1	83		0.23*				-0.23*	
10	21		0.44*	-0.53*		0.44*		
18	62	0.26*				0.25*		
19	57	-0.32*			-0.30*		-0.36**	-0.28*
20	37		0.37*					
26	77						-0.24*	

***Note:** ** sign. Correlation significant at 0.01 levels, * sign. Correlation significant at 0.05 levels, N. Number of mood valence ratings*

The results above revealed that some participants' keyboard and mouse behaviour have significant correlations with their mood ratings. Out of 26 participants only about 30% showed these patterns. An analysis on 6 and 10 minutes window reveal that in both intervals mouse click events correlate negatively most of the times with that of valence and arousal. However all other data is a mixture of both positive and negative correlations. Therefore it might can be predicted that a decrease in mouse clicks events is related to an increase in valence or arousal whereas an increase in mouse click events is related to a decrease in valence or arousal.

5.3 Conservative analysis

This study analysed eight different behavioural variables. To test whether all these variables differ significantly, a comparison (post-hoc) test was conducted to ensure that the possibility of committing Type I error does not exceed a pre-specified alpha value that is reasonably low (for example $\propto = 0.05$). Introduction of tougher alpha levels control the potential biases. Although post-hoc analysis is mostly used in case of ANOVA, this study looked on the possibility of using more conservative levels in case of correlations also.

Researchers are not in total agreement on the suitable way to use these comparisons (Sheskin, 1996). In planned analysis, comparisons are decided at the beginning of the study. In post-hoc tests data analysis is conducted to explore which groups or variables contributed statistically to significant results (Maxwell and Delaney, 2004). The equation formulated below helped were utilized to decrease the possibility of committing Type I error for a multiple comparison:

$$\propto_{Pc} = 1 - \sqrt[C]{1 - \propto_{FW}} \qquad = 0.006$$

Here $\propto_{FW} = 0.05$ and $C = 8$ as number of behaviour variables is eight. The note $\propto_{FW}$ represent family wise type I error rate and is the chance of at least one Type I error in C comparisons. $\propto_{PC}$ is a comparison Type I error rate and is the chance of Type I error in any single comparison.

By substituting values in equation one, we get $\propto$ of 0.006. Although reducing the alpha value decreases the possibility of committing Type I error, it increases the possibility of committing Type II error. Below are the tables for the participants having significant correlation between behaviour variables and mood rating at 0.006 levels?

Table 5: *Behavioural variables with significant correlations at 0.006 level with valence and arousal*

P-ID	N	Mood Dimension	Time Window	Backspace Delete		Mouse Clicks		Number of events		Other keys	
				r	*p*	*r*	*p*	*r*	*p*	*r*	*p*
9	63	Valence	10 Min	-0.34	0.006	-0.39	0.001				
15	73	Valence	10 Min			0.35	0.002	0.38	0.001	0.37	0.001
19	57	Arousal	10 Min			-0.36	0.006				

This table shows that it is unlikely that the significant results obtained from some participants were obtained by chance alone. The most important part that emerges in this analysis is the mouse clicks which are significant at 0.006 levels for all three participants. This can be the result of high arousal or of high valence. Analysis and results also show this. First two participants in the table above showed significant correlations with valence and had low average valence rating of 5.75 while all other participants had an average high valence rating of 4.74. This might suggest that sadder participants' keyboard and mouse click correlates more negatively with their valence level. Earlier it was also established that almost all participants showing some correlations with behavioural keyboard mouse data showed negative correlations with mouse clicks. Analysis also showed that participant 19 arousal rating was 7.14, which is an indication of low arousal as compared to average arousal rating (5.14) of the other two participants. This seems to support that low arousal and mouse clicks might be negatively correlated with each other.

5.4 Logistic Regression

The analysis found significant correlations between the mood rating and the behaviour for some of the participants only. Therefore the next step of the analysis was to determine potential factors that could help finding the mood of a specific person by looking at his or her keyboard and mouse use. Two Logistic Regression analyses were conducted: one with as dependent variable whether a significant correlation was found between a person's arousal rating and his or her behavioural measures. The other with as dependent variable whether a significant correlation was found between a person's valance rating and his or her behavioural measures. Independent variables were gender, user type as categorical variables. Independent variables also included age and personality scores on five personality main traits and 30 personality subtraits. To get personality scores 20 out of 26 participants completed short version of the IPIP-NEO personality test (Buchanan et al., 2005). The analyses used a logistic regression forward method with likelihood ratio.

Valence logistic regression model showed that 85% of participants showing correlations could be correctly classified with a significant model (χ^2 (2, N = 20) = 9.56, $p < .01$). Table 6 shows variables which might be useful in predicting participants, who might show correlations of their keyboard and mouse use with their moods. The predicting variables include experience in number of years approaching to an alpha level of 0.05 (*p = 0.06)* and self-discipline. Table 7 show some explanation regarding how predictions can be made. From table 7 we can notice that as the experience of the participants' increases there is more possibility of predicting that we can detect their valence from their behaviour. Similarly it might be more difficult to detect valence from the keyboard mouse use of disciplined participants compared to participants with less self-discipline.

Arousal logistic regression model, showed that 65% of participants could be correctly classified which is significant (χ^2 (1, N = 20) = 7.05, $p < .008$). Table 8 shows that this model which includes only dutifulness as significant predictor that explains that participants with more sense of dutifulness might show significant correlations between their arousal and use of keyboard and mouse.

Table 6*: Summary of Logistic Regression Analysis for Variables Predicting participants that might show correlations in valence; Have correlation (n = 11) and No correlations (n = 9)*

Predictor	*B*	*df*	*SE B*	e^B
Experience	0.931	1	0.49	2.54
Self Discipline	-0.1*	1	0.05	0.90
Constant	1.23	1	2.41	3.42
χ^{2**}		9.56		
df		2		
% Correct predictions for participants having correlations			50%	
% Correct predictions for participants with no correlations			35%	
Overall Correct predictions			85%	

Note: e^B = *exponentiated B, *p < 0.05, **p < 0.01*

Table 7*: Predictor Variables showing possibility of predicting participants who might show correlations or no correlations with use of keyboard and mouse and their valence level*

Predictor Variable	Correlation (Yes/No)	Mean	Standard Deviation	Out Comes
Experience in years	No	4.5	0.41	More experience might result in correlations
	Yes	5.6	0.53	
Self Discipline	No	64.33	5.70	Not Disciplined to Self Disciplined (1 to 100)
	Yes	48.92	4.92	

***Table 8**: Summary of Logistic Regression Analysis for Variables Predicting participants that might show correlations in arousal; Have correlations (n = 8) and No correlations (n = 12)*

Predictor	*B*	*df*	*SE B*	e^B
Dutifulness	0.07*	1	0.03	1.07
Constant	-4.26*	1	1.93	0.01
χ^2**	7.05			
df	1			
% Correct predictions for participants having correlations			20%	
% Correct predictions for participants with no correlations			45%	
Overall Correct predictions			65%	

***Note**: e^B= exponentiated B, *p < 0.05, **p < 0.01*

***Table 9**: Predictor Variables showing possibility of predicting participants who might show correlations or no correlations with use of keyboard and mouse and their arousal level*

Predictor Variable	Correlation (Yes/No)	Mean	Standard Deviation	Out Comes
Dutifulness	No	45.50	6.12	undutiful to dutiful 1 to 100
	Yes	71.63	6.54	

6 Conclusions, limitations and future research

6.1 Conclusions

The results of this study suggest that it might be possible to measure computer users' mood from their use of keyboard and mouse. There were some significant correlations which Cohen (1992) would classify as medium and large effects to support this. However not every participant data showed similar correlation patterns and therefore these findings cannot be generalized even in this opportunity sample. However the significant correlations found for some participants' could be promising for future extensive experimentation. From the logistic regression analysis in results section we can also assume that it might be possible to predict whether a participant would show significant correlations between their valence, arousal and their use of keyboard and mouse or not.

6.2 Limitations

There were some limitations also in the study. The participant mood ratings with low standard deviation differences of both valence and arousal showed that participants' moods were of less intensity. This might be because that natural condition was used without experimentally controlled mood induction. Figures 6 and 7 show that mean of valence is 4.80 with a SD of 0.94 and that of arousal is 5.19 with a SD of 1.15 which is near 5 the centre point of both ratings.

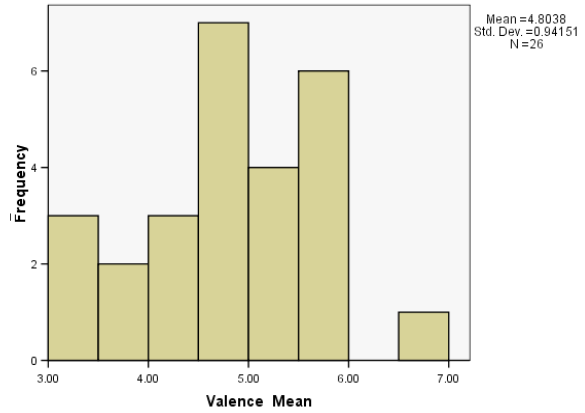


***Figure 6**: Valence Histogram*

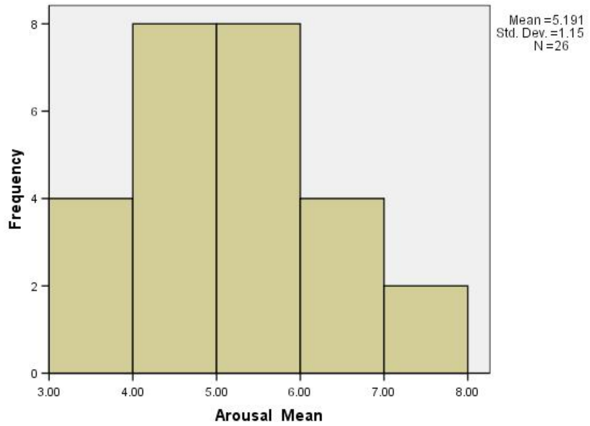


***Figure 7**: Arousal Histogram*

Another limitation which a couple of participants mentioned is related to the mood rating dialogue. They considered mood rating dialogue a distracter as it was designed to appear after every 20 minutes. Participants were informed prior of the experiment about mood rating dialogue and they were encouraged to e-mail if they want to send some suggestions or complaints. Only two participants commented about the mood rating dialogue as a distracter and could be a cause of insignificant results. Yet another limitation could be cancelling the mood rating dialogue by participants in either high arousal or low arousal. Calculations showed that participant cancelled 27% of their dialogues on average. Another limitation was that only two female participants took part in this study which is clearly an under representation of the female population.

6.3 Future research

This study was an explorative study which used natural conditions. In future such studies could be designed which experimentally induce moods and then analyse computer user behaviour on keyboard and mouse. This might produce clearer results. As relationship were found between moods and keyboard\mouse use patterns, putting these patterns into neural networks and other learning algorithms might increase the percentage of affective state measurement. Zhai and Barreto (2006) considered such work. They extracted some features from Skin Responses (GSR), Pupil Diameter (PD), and Blood Pressure Volume (BPV) and put these features into three learning algorithms named as: Naïve Bayes Classifier, Decision Tree Classifier and Support Vector Machine (SVM). They found an accuracy of 78.65%, 88% and 90.1% respectively in measurement of affective states. Future studies can take a step further in not only classifying the states but also rating their affective states in a specific dimension of valence and arousal; something results in this study suggest might be possible for at least some people.

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