Facial Temperature Markers for Mental Stress Assessment in Human-Machine Interface (HMI) Control System

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Abstract: Mental state prediction is of great importance to human-machine interface (HMI) as far as both safety and reliability are concerned. In this paper, the use of facial temperature changes for predicting mental stress has been investigated. A carefully designed experiment of HMI has been performed on seven (7) healthy subjects, and the statistical analysis of the results has been provided, and the effectiveness of using facial temperature with the thermal camera to estimate the human mental stress has been established. The biomarkers developed from the data of facial temperature have exhibited a similar or even better ability to differentiate between the mental stress levels in comparison with the traditional biomarkers (e.g. heart rate variability (HRV), task load index (TLI) and pupil size). The mean nasal temperature has been shown to be sensitive to changes in the mental state, and the maximum facial temperature and the mean forehead temperature have also shown clear correlations with mental stress and task performance.

1 INTRODUCTION

The combination of an automatic system with a human operator has been widely implemented in many human-centered environments, including manufacturing, transportation and clinical medicine. However, the performance of such a combination has usually been compromised by increasing operational demands on the human operator, which can also threaten the safety and reliability of the whole system (Walter et al., 2014). Therefore, it is of paramount importance to introduce an effective interface between the human operator and the automatic system. The main aim of this interface is to help the automatic system to assign suitable tasks for the human operator depending on his or her mental stress level and to achieve the best overall task performance.

The human operator's performance in a certain task is dependent on his or her attention span, cognition, perception and execution, which all develop from the basic conditional reflex (Barrett, 2006; Barrett et al., 2007). Therefore, monitoring the activities of some specific neurons and subsystems they regulate has proved to be a valid approach to assess one's mental stress (Barrett, 2006; Barrett et al., 2007; Inzlicht et al., 2015). In the area of human-machine interface research, the assessment of the human operator's mental stress level usually combines peripheral physiology, startle response, central physiology and behaviour. The frequently used measurements cover electrocardiography (ECG), electroencephalography (EEG), pupil size, blood pressure, blood volume, blood volume pulse, respiration, muscle tension, electrodermal activity, galvanic skin and temperature signals (Mahfouf et al., 2007; Nassef et al., 2010; El-Samahy et al., 2015; Ting et al., 2010; Torres-Salomao et al., 2015; Torres-Salomao et al., 2017; Zhai and Barreto, 2006).

Heart rate variable (HRV) from ECG and task load index (TLI) from EEG are the most common and recommended mental stress biomarkers. HRV is consistently corresponding to cardio-respiratory system, which is susceptible to the changes of mental stress (Bernardi et al., 2000; Kuriyagawa and Kageyama, 1999). The aim of TLI is to calculate one's working memory (WM), which constitutes one's ability to maintain the focus on one specific task regardless of the surrounding interference (Gevins and Smith, 2003; Smith et al., 2001). However, EEG and ECG measurements are normally involved with using the electrodes to record voltage differences across the skin. Such a requirement has limited the movement and the range of movement of the human operator and disturbed his or her mental state

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as well. Meanwhile, the measurements here remain sensitive to the noise introduced by defective skin-electrode connections and surrounding electromagnetic fields. The high complexity of EEG and ECG measurements has limited the efficiency and safety of applying HRV and TLI in the real world situations. Therefore, it is important to design and integrate new mental stress biomarkers with the existing system to overcome these constraints.

Facial temperature recorded by infrared cameras has been recongised as a potential valid reflection of the human mental state nowadays. Infrared cameras have hitherto provided a reliable means of documenting the facial temperature in real time without body contact, and they usually have fewer requirements about the work environment compared with EEG and ECG. State-of-the-art research has demonstrated that both the hypothalamus and the parasympathetic-sympathetic nervous system have significant emotion induced influence on the human thermoregulation (Clay-Warner and Robinson, 2015; Hong and Hong, 2016). Such impact usually leads to changes in skin temperature and forms different periodic temperature cycles from seconds to minutes, which are observable with infrared cameras (Brengelmann, 2000; Charkoudian, 2003; Houdas and Ring, 2013). Previous studies have also proved that temperature readings from the forehead, the periorbital and the nasal regions are closely correlated with mental stress (Hong and Hong, 2016; Nhan and Chau, 2009; Nhan and Chau, 2010; Nozawa and Tacano, 2009). Thus, the biomarkers based on the facial temperature readings from the camera have great potential to provide accurate mental stress estimation instantaneously, and also retain adequate distance from the subject comparing to the HRV and TLI.

While the ultimate of this researchis to control the human-machine interface, the specific objectives are (1) to validate the effectiveness of using facial temperature for assessing mental stress in HMI, (2) to compare the efficiency of using facial temperature as a mental stress biomarker with other existing biomarkers, (3) to outline the limitation of current research and discuss the future development of the temperature biomarker within the human machine interface framework.

2 EXPERIMENTAL SETUP

2.1 Participants

Ten (10) healthy research students from the Automatic Control and Systems Engineering Department at the University of Sheffield (UK) were selected as suitable participants for the experiment. The volunteers included both genders, from 22 to 30 years old with an average age of 25.

2.2 Simulation of Human Machine Interaction

Mental arithmetic was selected as the simulation of HMI in this experiment. Mental arithmetic proved to be a simple efficient intuitive way of introducing physio-psychological stress (Garde et al., 2002; Hjortskov et al., 2004). The mental arithmetic assessment applied in this experiment was based on a Matlab GUI application, which was similar to the one implemented in previous HMI studies (Torres-Salomao et al., 2015; Torres-Salomao et al., 2017). The mental arithmetic task required the participant to complete the multiplication of two numbers within a certain amount of time.

2.3 Data Acquisition

EEG and ECG data were continuously monitored via the Biosemi Active Two System. EEG signals were collected with a 32+2 electrodes layout from a standard Biosemi 10/20 system. ECG signals were acquired from the 3-lead system that formed a triangle area covering the chest. Data was recorded with Biosemi ActiView software with a sampling rate at 2048 Hz. Pupil size was measured by a Gazepoint eye-tracking camera, and the acquisition was done by Gazepoint software during the experiment. Facial Temperature was captured with a FLIR P640 24 degree thermal imaging camera, which was placed horizontally to the subject's face with the emissivity of 0.98. The thermal imaging sequences were captured with a sampling frequency of 10 Hz by FLIR ResearchIR.

2.4 Data Analysis

The thermal imaging sequences were analysed in MATLAB® to extract the temperature changes in the regions of interest (ROI), which were the maximum facial temperature (around periorbital), the mean nasal temperature and the mean forehead temperature, see Figure 1.

The maximum facial temperature was calculated as follows:

$$MaximumFacialTemperature = \left\{\max(Temp_{(i,j)}) | \forall i \in L, \forall j \in W\right\}, \quad (1)$$

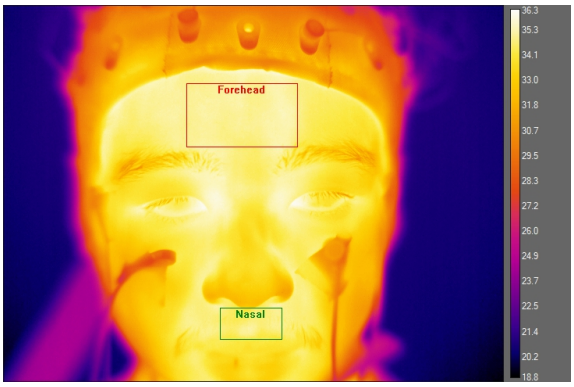


Figure 1: Regions of interest: periorbital, nasal and forehead.

where $Temp_{(i,j)}$ represents the average temperature recorded at pixel (i, j) for a period of 15 seconds, and L and W were the numbers of the columns and rows of pixels in a frame.

The mean nasal temperature was calculated as follows:

$$MeanNasalTemperature = \left\{ \frac{1}{N} \sum Temp_{(i,j)} | \forall i \in X, \forall j \in Y \right\}, \quad (2)$$

where $Temp_{(i,j)}$ represents for the average temperature recorded at pixel (i, j) from the selected region for a period of 15 seconds, and X and Y were the numbers of the columns and rows of pixels in the selected region.

The mean forehead temperature was calculated as follows:

$$MeanForeheadTemperature = \left\{ \frac{1}{N} \sum Temp_{(i,j)} | \forall i \in M, \forall j \in N \right\}, \quad (3)$$

where $Temp_{(i,j)}$ represents for the average temperature recorded at pixel (i, j) from the selected region for a period of 15 seconds, and M and N were the numbers of the columns and rows of pixels in the selected region.

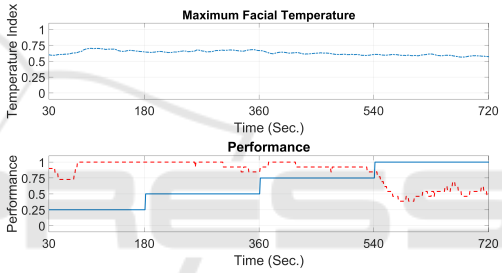
2.5 Procedure

The whole experiment for one subject lasted approximately 40 minutes, including two 12-minute mental arithmetic Sessions and one 12-minute comparison Session in the interval, with 2-minute breaks in between Sessions. Within each mental arithmetic Session, there were four 3-minute sub-sessions of varying difficulty levels. The difficulty level was determined by the digit of the numbers and the time allocated for answering the questions, and the order of them was altered after the first arithmetic Session to separate the physiological changes introduced by the mental state from the normal daily activities.

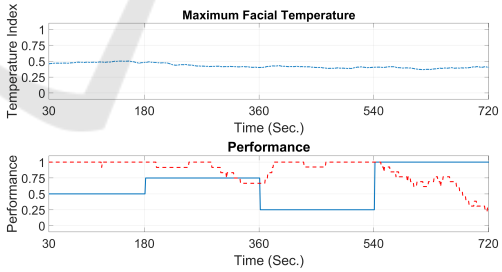
3 RESULTS

3.1 Maximum Facial Temperature

The overall average value of the maximum facial temperature for all the volunteers was 36.0334 °C. Changes in temperature for different Sessions were mostly around 0.10 °C, and below 0.10 °C for any two adjacent sub-sessions. However, compared to the period of the control Sessions, the maximum temperature of the experimental Sessions has demonstrated a certain degree of deviation from the initial values recorded at rest.



(a) Normalised maximum facial temperature (-.-), accuracy (- -) and difficulty level (-) plots for participant 1. Session 1 with elevated difficulty levels



(b) Normalised maximum facial temperature (-.-), accuracy (- -) and difficulty level (-) plots for participant 1. Session 3 with randomised difficulty levels

Figure 2: Maximum Facial Temperature.

In the primary experiment with ten participants, the maximum facial temperatures of six subjects were consistently correlated with their task performance for both increasing and random difficulty order, see Figure 2. Among the six participants, four of these showed negative correlations between the temperature and the accuracy, while the other two demonstrated positive correlations. Thus, the mental state

induced change of the maximum facial temperature was predominantly affected by the individual.

3.2 Mean Nasal Temperature

The general mean value of the mean nasal temperature for all test subjects was 33.6021 °C. The change of temperature over the different Sessions ranged from 0.30 up to 2.20 °C, and from 0.02 to 0.54 °C for any two nearby sub-sessions. Apart from the temperature difference within the control Sessions and the experimental Sessions, the increases and decreases of the mean nasal temperature were also closely related to the rise and fall of the subjects' accuracy, which supports the findings from previous research mentioned in the literature review, see Figure 3 for example.

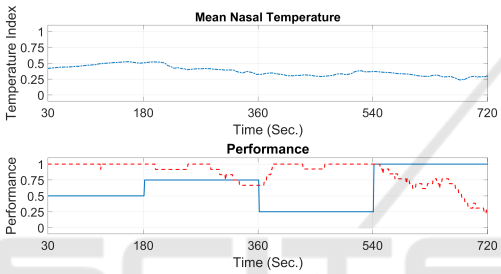
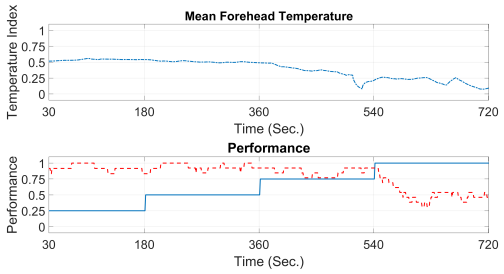


Figure 3: Normalised mean nasal temperature (-.-), accuracy (- -) and difficulty level (-) plots for participant 1. Session 3 with randomised difficulty levels.

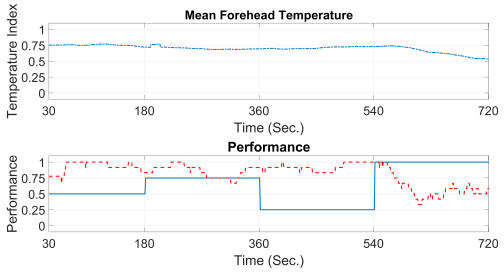
3.3 Mean Forehead Temperature

The overall mean value of the forehead temperatures across all volunteers was 33.9252 °C. The mean temperature difference between the Sessions ranged from 0.01 to 1.50 °C, and were mostly around or below 0.10 °C between any two neighbouring sub-sessions. Compared to the maximum facial temperature, the forehead temperatures of the experimental Sessions have shown a similar degree of deviation from the value of the control Sessions. Also, six out of the seven participates have demonstrated consistent correlations between their task performance and their mean forehead temperature, for the experiment Sessions with both ordered and randomised difficulty levels. An example is provided in Figure 4.

In the previous six volunteers, the mean forehead results of five subjects showed positive correlations with their accuracy, and remaining subject showed a negative correlation. Therefore, it can be concluded that, similarly to the maximum facial temperature, this change of mean forehead temperature was influenced by the individual variation as well.



(a) Normalised mean forehead temperature (-.-), accuracy (- -) and difficulty level (-) plots for participant 7. Session 1 with elevated difficulty levels



(b) Normalised mean forehead temperature (-.-), accuracy (- -) and difficulty level (-) plots for participant 7. Session 3 with randomised difficulty levels

Figure 4: Mean Forehead Temperature.

3.4 Comparison with Other Biomarker

Heart rate variability (HRV) and task load index (TLI) were previously recommended as the biomarkers for the mental state estimation for years, and the pupil diameter marker (PDM) has been validated as an effective biomarker for the mental stress (Bernardi et al., 2000; Kuriyagawa and Kageyama, 1999; Gevins and Smith, 2003; Smith et al., 2001; Torres-Salomao et al., 2015; Torres-Salomao et al., 2017). Therefore, the two-sample T-test was introduced to compare the efficiency of using facial temperature as a suitable stress biomarker with HRV, TLI and PDM. According to the two-sample T-test, each biomarker was tested for its ability to distinguish different mental stress levels. For H = 0, then there were no significant differences observed with a 5% confidence level. For H = 1, there were significant differences between the data from two sub-sessions. The details about the test results were provided in the Appendix, and a summary presented in Table 1.

The distribution of a valid biomarker's readings must demonstrate a certain amount variation corresponding to the varying mental stress that introduced by the different task difficulty levels. The two-sample T-test has provided a quantitative measurement for this type of the variation, and the higher H value represents the better differentiation ability of the

Table 1: Mean H Values for T-test Summary.

Biomarkers	Session 1	Session 2
Facial	1.0000	1.0000
Nasal	0.9762	1.0000
Forehead	0.9762	0.9762
HRV1	0.9722	0.9444
HRV2	1.0000	1.0000
TLI1	0.7619	0.8571
TLI2	0.9167	0.9524
PDM	0.8690	0.8571

biomarker towards the mental stress. The biomarkers developed from the data for facial temperature have exhibited similar or even better ability to differentiate the mental stress level in comparison to the traditional biomarkers. This mainly contributes to the higher sensitivity of the facial temperature towards the minor mental stress changes in low pressure state comparing to the other biomarkers. In general, the biomarkers based on the facial temperature were more susceptible to the minor alteration of the mental state between two close sub-sessions, especially for the maximum facial temperature and the mean nasal temperature.

4 DISCUSSIONS

The experiments have studied the relationship between the facial temperature and the human mental stress. It has been identified that the facial temperature recorded by the infrared cameras is correspondingly correlated with the mental stress. Furthermore, it can provide an accountable indication for the human mental stress estimation. This promises the facial temperature great potential without the limitations that HRV and TLI suffer from. The effectiveness and efficiency of using the facial temperature to estimate the mental stress level have been validated with the experiments, yet in practice, these biomarkers were still limited by two major problems: auto-calibration of the camera and subjects' head movement.

Auto-calibration was designed to deal with the problem of thermal drift in the data recording. The thermal drift was related mainly to the abnormal temperature shifts in the recordings, and it was introduced by the changing temperature of the camera itself. The process was automatically programmed to calibrate the camera depending on the temperature change of the camera. During the one or two seconds of auto-calibration, the camera measured the temperature within itself rather than the outside target. As a consequence, the recording was disturbed by the sudden fluctuations that needed to be manually removed during data processing. The lack of actual data in those periods of time affected the ability of biomarkers to reflect the mental state at those precise moments. The effect of the calibration was limited by switching on the camera at least ten minutes before each experiment. However, this method only reduced the number of calibration for a 12-minute recording instead of eliminating calibration. Better cameras may well provide more effective solutions to this problem in the future.

Both FLIR ResearchIR and MATLAB®were only able to support fixed windows for data extraction. However, the subject's head movement was unavoidable for such a long experiment. Therefore, windows with fixed positions and fixed shapes were not capable of handling the displacement and distortion caused by this movement. Therefore, due to the failure of tracking regions of interest, the biomarkers based on the data were not able to faithfully represent the actual temperature changes in those areas, and thus their efficiency was constrained. Unfortunately, and in contrast to the object tracking in the normal RGB images, the thermal image lacked enough contrast of shape for the normal tracking algorithm to follow. Since there was little research on thermal image tracking and barely any actual algorithm, the participants were advised to be conservative with their head movements, which in this case caused distortions of the results.

The tracking of the region of interest seems to represent the toughest challenge among all the other above challenges. However, a new tracking algorithm based on particle-filter may be a useful solution to this problem (Dowdall et al., 2007; Driessen and Boers, 2008; Levin et al., 2008; Wu et al., 2012; Zhou et al., 2009; Zhou et al., 2013). The algorithm, built on the Matte algorithm that is based on the pixel dependence, can deal with nonlinear motion within the predict-update cycle in a simple way. Despite the limitations of the current thermal imaging technique, the facial temperature has proved to be a reliable tool for mental stress measurement in HMI. Therefore, Figure 5 shows the proposed scheme that integrates the facial temperature within the HMI system for optimising monitoring/control performances.

5 CONCLUSIONS

In conclusion, the experimental results of the facial temperature have validated the effectiveness and the efficiency of using thermal imaging for mental state estimation. Such a method proposes a more reliable

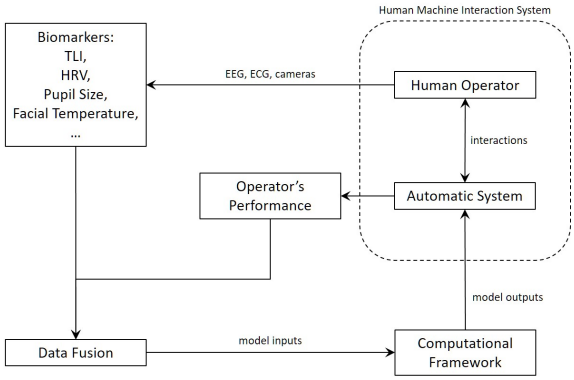


Figure 5: The Proposed Human Machine Interaction System.

marker for assessing the psychophysiological state of the operator. Furthermore, the combination of the facial temperature and other well-known biomarkers can significantly increase the robustness of the system and the precision of the prediction, as the facial temperature measurement requires no body contact and is more sensitive to the changes within the low mental stress states.

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APPENDIX

Summary of two sample T test

Table 2: Overall Maximum Facial Temperature T-test Results for Experimental Session 1.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	1.0000	1.0000	1.0000	0.0000

Table 3: Overall Maximum Facial Temperature T-test Results for Experimental Session 2.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	1.0000	1.0000	1.0000	0.0000

Table 4: Overall Mean Nasal Temperature T-test Results for Experimental Session 1.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	0.8571	1.0000	1.0000	0.0000

Table 5: Overall Mean Nasal Temperature T-test Results for Experimental Session 2.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	1.0000	1.0000	1.0000	0.0000

Table 6: Overall Mean Forehead Temperature T-test Results for Experimental Session 1.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	1.0000	1.0000	0.8571	0.0000

Table 7: Overall Mean Forehead Temperature T-test Results for Experimental Session 2.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	0.8571	1.0000	0.0000	
Phase 4	1.0000	1.0000	1.0000	0.0000

Table 8: Overall DEFP T-test Results for Experimental Session 1.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	0.8571	0.0000		
Phase 3	0.7143	0.5714	0.0000	
Phase 4	1.0000	1.0000	1.0000	0.0000

Table 9: Overall DEFP T-test Results for Experimental Session 2.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	0.8571	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	0.8571	0.8571	0.8571	0.0000

Table 10: Overall HRV1 T-test Results for Experimental Session 1.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	0.8333	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	1.0000	1.0000	1.0000	0.0000

Table 11: Overall HRV1 T-test Results for Experimental Session 2.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	0.8333	0.0000		
Phase 3	1.0000	0.8333	0.0000	
Phase 4	1.0000	1.0000	1.0000	0.0000

Table 12: Overall HRV2 T-test Results for Experimental Session 1.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	1.0000	1.0000	1.0000	0.0000

Table 13: Overall HRV2 T-test Results for Experimental Session 2.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	1.0000	1.0000	1.0000	0.0000

Table 14: Overall TLI1 T-test Results for Experimental Session 1.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	0.7143	0.0000		
Phase 3	0.8571	0.8571	0.0000	
Phase 4	0.8571	0.8571	0.4286	0.0000

Table 15: Overall TLI1 T-test Results for Experimental Session 2.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	0.5714	0.8571	0.0000	
Phase 4	1.0000	0.8571	0.8571	0.0000

Table 16: Overall TLI2 T-test Results for Experimental Session 1.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	1.0000	1.0000	0.0000	
Phase 4	1.0000	0.8333	0.6667	0.0000

Table 17: Overall TLI2 T-test Results for Experimental Session 2.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	1.0000	0.0000		
Phase 3	0.8571	1.0000	0.0000	
Phase 4	1.0000	1.0000	0.8571	0.0000

Table 18: Overall PDM T-test Results for Experimental Session 1.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	0.8571	0.0000		
Phase 3	0.8571	1.0000	0.0000	
Phase 4	1.0000	0.8333	0.6667	0.0000

Table 19: Overall PDM T-test Results for Experimental Session 2.

H value	Phase 1	Phase 2	Phase 3	Phase 4
Phase 1	0.0000			
Phase 2	0.8571	0.0000		
Phase 3	1.0000	0.7143	0.0000	
Phase 4	0.8571	0.8571	0.8571	0.0000