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Prediction of subjective states from psychophysiology: A multivariate approach

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Abstract

Biocybernetic systems utilise real-time changes in psychophysiology in order to adapt aspects of computer control and functionality, e.g. adaptive automation. This approach to system design is based upon an assumption that psychophysiological variations represent implicit fluctuations in the subjective state of the operator, e.g. mood, motivation, cognitions. A study was performed to investigate the convergent validity between psychophysiological measurement and changes in the subjective status of the individual. Thirty-five participants performed a demanding version of the Multi-Attribute Task Battery (MATB) over four consecutive 20-min blocks. A range of psychophysiological data were collected (EEG, ECG, skin conductance level (SCL), EOG, respiratory rate) and correlated with changes in subjective state as measured by the Dundee Stress State Questionnaire (DSSQ). MATB performance was stable across time-on-task; psychophysiological activity exhibited expected changes due to sustained performance. The DSSQ was analysed in terms of three subjective meta-factors: Task Engagement, Distress and Worry. Multiple regression analyses revealed that psychophysiology predicted a substantial proportion of the variance for both Task Engagement and Distress but not for the Worry meta-factor. The consequences for the development of biocybernetic systems are discussed.

Keywords: EEG; ECG; Respiration; Subjective states; Mood

1. Introduction

Biocybernetic systems utilise real-time changes in psychophysiology as an adaptive control input to a computer system. For example, a biocybernetic loop may control the provision of automation within an aviation environment (Byrne and Parasuraman, 1996). This loop diagnoses the psychological status of the human operator based on psychophysiological activity and relays a control signal to initiate or relinquish system automation (Pope et al., 1995). The affective computing concept (Picard, 1997) represents an example of the same principle where psychophysiological monitoring/diagnosis enables computer software to respond to the subjective state of the user. It is envisaged that interaction with an "affective computer" will be interactive and intuitive, providing help when frustration is diagnosed or increasing the difficulty level of a computer game if the user is deemed bored or disinterested. The concept of biocybernetic control enables a wide range of applications (Allanson and Fairclough, 2004), from adaptive automation (Scerbo et al., 2001) to health-monitoring (Gerasimov et al., 2002) and biofeedback training tools (Pope and Palsson, 2001).

The use of psychophysiology to control system automation has a number of advantages over performance-based methods of monitoring the operator (Byrne and Parasuraman, 1996): (a) psychophysiology provides a continuous stream of data input whereas performance input may be discrete, (b) a performance-based diagnosis may not be available if the system is fully automated and (c) performance quality is relatively insensitive to implicit changes in user state which may be indexed via psychophysiology (O'Donnell and Eggemeier, 1986). This latter point is important as the sensitivity of biocybernetic control is based upon the capacity of these systems to monitor covert processes of psychophysiological regulation.

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The model of mental effort regulation proposed by Hockey (1993, 1997) captures this divergence between overt performance and covert changes in psychophysiological state. Within this framework, stable levels of performance may mask latent decrements that represent a covert process of mental effort regulation. Latent decrements include qualitative changes in performance strategy in conjunction with ‘‘compensatory costs’’ such as increased sympathetic activation of the ANS and negative affect, e.g. anxiety. There are numerous examples of these compensatory costs in response to increased task difficulty/psychological challenge. For instance, catabolic changes in the sympathetic nervous system instigate an orchestrated patterns of physiological activity, including: accelerated heart rate (Mathias and Stanford, 2003; Tomaka et al., 1997), increased systolic blood pressure (Blascovich et al., 1999; Suzuki et al., 2003), a rise of electrodermal activity (Gendolla and Krusken, 2001), a fast/shallow respiratory pattern (Boiten, 1998) and reduced eye-blink duration in conjunction with increased blink frequency (for predominantly visual tasks) (Veltman and Gaillard, 1996, 1998). Corresponding data are available from the subjective domain: students taking a college examination reported mood changes (e.g. increased fear and anxiety) compared to a typical day in class (Thayer, 1967). Similarly, participants exposed to high mental workload reported falling energy levels and negative affect in combination with increased tension (Matthews et al., 1990).

The goal of the biocybernetic control system is to operationalise psychological states via a ‘‘signature’’ pattern of psychophysiological activity. For instance, Pope et al. (1995) collected spontaneous EEG activity during the performance of a task, analysed these data into several ratio measures and selected one to represent the level of operator engagement associated with the task. This index captured the ratio of high-frequency EEG activity (β) to a combination of lower-frequency components ($\Theta + \alpha$). This EEG-based engagement index was used to drive biocybernetic control of adaptive automation in a laboratory study (Prinzel et al., 1995), i.e. system automation was only available if the operator was deemed engaged with the task. Further experiments with the same system demonstrated benefits in performance quality as well as reduced mental workload (Freeman et al., 1999; Prinzel et al., 2000). These positive findings have been replicated using prolonged periods of task performance (Freeman et al., 2000) and a vigilance task (Milkulka et al., 2002); for a recent summary of this research, see Scerbo et al. (2003).

The utility of biocybernetic control depends on a close association between psychophysiological activity and those subjective states that are relevant for task performance, e.g. engagement, anxiety, anger, boredom (Prinzel, 2002). The problem of mapping from psychophysiology to subjective experience and vice versa has direct implications for the introduction of biocybernetic control systems. The goal of the biocybernetic loop is to make system interventions that appear both timely and intuitive to the user. These qualities are important indicators of system reliability, which is an important determinant of trust in an automated system (Moray et al., 2000; Muir, 1994; Muir and Moray, 1996). Therefore, it is important that psychophysiological triggers for system intervention have a coherent and consistent relationship with the subjective state of the user.

There is evidence of convergent validity between psychophysiology and mood states from previous research. For example, Thayer (1970) reported a significant correlation between a psychophysiological composite (heart rate + skin conductance) and a bipolar scale of general activation (lively–quiet). This finding was replicated by Matthews et al. (1990) who reported that skin conductance level was correlated with energy, whilst a composite variable (skin conductance + heart rate) was associated with tension. The search for psychophysiological predictors of emotional experience represents a similar line of investigation. A field study using ambulatory measures of blood pressure and heart rate found that both variables increased with the intensity of negative moods but were insensitive to positive affective states (Shapiro et al., 2001). Christie and Friedman (2004) measured psychophysiology during exposure to film clips designed to induce positive and negative emotional responses. These authors extracted two discriminant functions to describe the ANS response: an ‘‘activation’’ factor and an ‘‘approach–withdrawal’’ factor. Both ANS factors were combined to create a multivariate space wherein anger and amusement were distinguished on the ‘‘activation’’ scale, whilst anger and fear differentiated on the ‘‘approach–withdrawal’’ scale.

The psychophysiological response appears sufficiently differentiated to discriminate broad patterns of emotional response as well as quantitative fluctuations in mood. However, it is difficult to formulate the psychophysiological signature of each subjective state with the required degree of precision, as demonstrated by inconsistent findings from many studies in this area (Cacioppo et al., 1993). This disparity may stem from two sources: the inclusiveness of the psychophysiological response and the multifaceted experience of subjective states. Whenever the psychophysiological signature of an emotional state is captured, it contains a non-affective content (e.g. cognitive demands, motor activity) and a contextual element triggered by the functional goals associated with that emotion (e.g. approach or avoidance) as well as the emotional signature itself (Stemmler et al., 2001). This lack of specificity is mirrored by the experience and operationalisation of subjective states, which may involve a complex interplay between affective feelings, motivational desires and related cognitions (Matthews et al., 2002).

A partial solution to this problem is to adopt an inclusive definition of the subjective state that encompasses affective, motivational and cognitive dimensions of subjective experience as well as the psychophysiological response. This was the logic underlying the development of the

Dundee Stress State Questionnaire (DSSQ) (Matthews et al., 2002) that attempts to integrate aspects of subjective experience within a number of meta-factors. The DSSQ was derived via factor analysis of self-report questionnaires from a large sample (e.g. Fenigstein et al., 1975; Heatherton and Polivy, 1991; Matthews and Desmond, 1998; Matthews et al., 1990; Sarason et al., 1986). The factor analysis yielded three factors, each of which encompass at least three sub-scales: Task Engagement (energy, concentration, motivation), Distress (tension, negative affect, confidence) and Worry (self-focus, self-esteem, cognitive interference). Task Engagement was defined as an ‘‘effortful striving towards task goals’’ (Matthews et al., 2002, 1997); this factor increased during a demanding working memory task and declined when participants performed a sustained vigilance task (Matthews et al., 2002). The Distress meta-factor was characterised by ‘‘an overload of processing capacity’’ (Matthews et al., 2002, 1997) and tended to increase when participants experienced a loss of control over performance quality (Matthews et al., 1997). The third Worry meta-factor was concerned with rumination and negative self-evaluation (Matthews et al., 2002, 1997) and is based upon the S-REF model of anxiety (Wells and Matthews, 1996); the Worry factor was also found to increase when participants experienced a loss of control over performance (Matthews et al., 1997).

This study was performed to investigate the relationship between psychophysiology and the three meta-factors of the DSSQ. The purpose of the study was to derive psychophysiological correlates of subjective states for biocybernetic control. Participants were exposed to a demanding task over a sustained time period. The high level of demand was included to provoke Task Engagement, whilst the time-on-task manipulation was intended to eventually reduce engagement whilst inflating Distress and Worry.

2. Method

2.1. Participants

Thirty-five university students participated in the experiment (13 females and 22 males), and all received a monetary reward. The age of participants ranged from 18 to 40 years ($M = 24.1$ years, S.D. = 5.90). Potential participants were excluded if they were pregnant, on medication or reported any known cardiovascular problems. Participants were additionally requested not to consume large amounts of alcohol the night before, nor drink large amounts of caffeine or participate in strenuous exercise on the morning of the experiment.

2.2. Experimental task

The computer task used for the experiment was the Multi-Attribute Task Battery (MATB) (Comstock and Arnegard, 1992); this is a multitasking environment containing three sub-tasks: tracking, system monitoring and resource management. Each sub-task was pre-scripted to a high level of task demand (the parameters of which were tested and utilised in a prior experiment (Fairclough and Venables, 2004).

The compensatory tracking task was programmed to the default ‘medium’ demand setting provided by the software. (A prior pilot experiment demonstrated that the default ‘high’ demand setting encouraged extremely high levels of frustration, causing participants to disengage from the tracking sub-task.) Tracking efficacy was calculated as root-mean-square (RMS) error. For the system monitoring task, participants were required to detect pointer-deflections on a set of four gauges (with an event rate of 10 deflections/min) during the system monitoring task. Performance was calculated in terms of proportion of correct responses. The resource management task requires participants to maintain a specific level of fuel (i.e. 2500 units) within both the main tanks (A and B), which are constantly depleting. For a high level of demand, one to two pumps were scripted to fail (one pump failing for 4 min at a time and another failing for 30 s every minute). Performance in this task was calculated as the deviation from the required level of (2500) units in tanks A and B.

2.3. Psychophysiological variables

EEG was recorded across the four sites utilised by Pope et al. (1995) study: Cz, P3, Pz and P4 (with a ground site located midway between Cz and Pz). Each site was referenced to the left and right mastoid areas. The EEG signals were amplified (using four BIOPAC EEG100C differential, bio-electric potential modules). The high and low bandpass filters were set at 0.1 and 35 Hz, respectively. The EEG signals were analysed via Fast Fourier Transform (FFT) in steps of 2.65 s with an overlap of 0.5 s. Epochs with total power exceeding 200% of the average for that participant were identified as outliers and removed from subsequent analysis, i.e. a pilot exercise found this criterion to be highly associated with artifacts in the EEG record identified by visual inspection. Mean percent power values were obtained for: Θ (4.3–7.8 Hz), α (8.2–12.9 Hz) and β (13.3–21.9 Hz).

To assess vertical eye-blink activity, Ag/AgCl electrodes were placed above and below the left eye, with a ground electrode positioned in the centre of the forehead. The EOG signals were filtered at 0.05–35 Hz, and amplified by a BIOPAC EOG100C differential (high gain), corneal–retinal potential amplifier. Eye-blink frequency and duration were the parameters derived from a smoothed EOG signals.

Heart rate activity was recorded using a standard Lead II configuration, and amplified using vinyl electrodes positioned on the seventh intercostal space on the right and left sides of the body. A common ground electrode was placed on the sternum. ECG was measured using a BIOPAC TEL 100C differential (high gain) amplifier. The high and low bandpass filters were set at 0.5 and 35 Hz, respectively. R peaks of the ECG were detected offline, and the inter-beat interval (IBI) between successive R waves was calculated. These data were evaluated for missed and ectopic beats, the former were corrected via interpolation and the latter were discarded. HRV in mid-frequency (0.09–0.13 Hz) and high-frequency (0.14–0.40 Hz) bands were calculated from the IBI data by means of an FFT analysis with CARSPAN software (Mulder et al., 1995).

Respiration was monitored using two elasticated belts placed around the chest and diaphragm. Respiration signals were again amplified using a (differential, high gain) BIOPAC TEL100C remote monitoring module, with the filter settings at 0.05–35 Hz. The waveform signals of both chest and diaphragm expansion were added together using BIOPAC AcqKnowledge software, and peaks from the combined signal were detected and used for the calculation of respiration rate (i.e. breaths/minute).

Skin conductance level (SCL) was measured with two electrodes (which produce a continuous voltage electrode excitation of 0.5 V), attached to the side of the foot (Boucsein, 1992). These signals were amplified using a BIOPAC TEL100C remote monitoring module, and subsequently filtered (low pass) at 1 Hz to get rid of extraneous noise. Skin conductance values for mean and area were collected every 2 s and averaged over 4 min periods. The sample rate for all channels (i.e. ECG, SCL, EOG and respiration) was 500 Hz.

2.4. Subjective measures

Subjective state was measured using the Dundee Stress State Questionnaire (Matthews et al., 2002, 1997). This battery of questionnaires contains Likert scales derived from earlier research which have been grouped into three fundamental meta-factors: Task Engagement, Distress and Worry.

Task Engagement is concerned with "a commitment to effort" (Matthews et al., 2002, p. 335) and contains scales for: energetical arousal (5-point Likert scale) (alert–tired) (Matthews et al., 1990), motivation and concentration (5-point Likert scale) (Matthews and Desmond, 1998). The theme of those scales grouped under the Distress meta-factor is "an overload of processing capacity" (Matthews et al., 2002, p. 336). This factor contains scales for: tense arousal (5-point Likert scale) (tense–relaxed) and hedonic tone (5-point Likert scale) (sad–happy) (Matthews et al., 1990) as well as confidence/perceived control (Matthews and Desmond, 1998). The third meta-factor of the DSSQ is Worry and this factor is concerned with self-evaluation and self-focus; the Worry factor contains scales pertaining to: self-focus (5-point Likert scale) (Fenigstein et al., 1975), self-esteem (5-point Likert scale) (Heatherton and Polivy, 1991) and cognitive interference (5-point Likert scale) (Sarason et al., 1986).

Full details regarding the factor structure of the DSSQ, population norms and state responses to different types of psychological tasks may be found in Matthews et al. (2002).

2.5. Procedure

Upon entering the laboratory, participants were briefed about the nature of the experiment. Those who chose to participate were already fully informed as to the procedures involved in the recording of the physiological measures. Participants were prepared so their physiology could be recorded (e.g. the location of the electrode sites, the mild abrasion of skin, the attachment of the electrodes, etc.), and this was followed by a 15-min baseline period for all of the physiological variables. During this baseline period, the participants were asked to lie back and relax (with their eyes open) whilst their physiology was measured.

Following the baseline period, participants were presented with a 5 min training session to acquaint themselves with the keyboard/joystick controls. This was followed by a 20 min high-demand practice block. Participants then began the formal task session of 4×20 min (high-demand) blocks of MATB performance (80 min in total), i.e. a repeated measures design. The participants received no information about the duration of the experimental task prior to the formal task (i.e. the participants did not know how many 20 min blocks must be completed); in addition, participants were asked to surrender their watches to remove anticipation of task completion. Prior to the practice block, and again after each task block, participants were presented with a computerised version of the DSSQ. The DSSQ asked participants to rate their feelings and moods as perceived *at that moment*, i.e. no retrospective ratings were obtained. The DSSQ took between 3 and 5 min to complete. Upon completion, participants persisted with the next task block. This continued until all four blocks had been completed. The recording of the physiological measures was initiated at the same time as each task session was started.

3. Results

Experimental data were analysed using Statistica 6.1 (Statsoft Inc.). Outliers (defined as values lying at least three standard deviations outside the group mean) were excluded from all analyses. Multivariate analysis of variance (MANOVA) was used to analyse effects where several dependent variables were available, and repeated-measures analysis of variance (ANOVA) was used to investigate effects associated with one variable. Violations of sphericity were detected using Mauchly's Test and F-values corrected using the Greenhouse–Geisser adjustment where necessary. Post hoc testing was performed using a Bonferroni procedure for both MANOVA and ANOVA. For reasons of brevity, significant main effects between dependent variables are not reported for MANOVA analyses, i.e. these

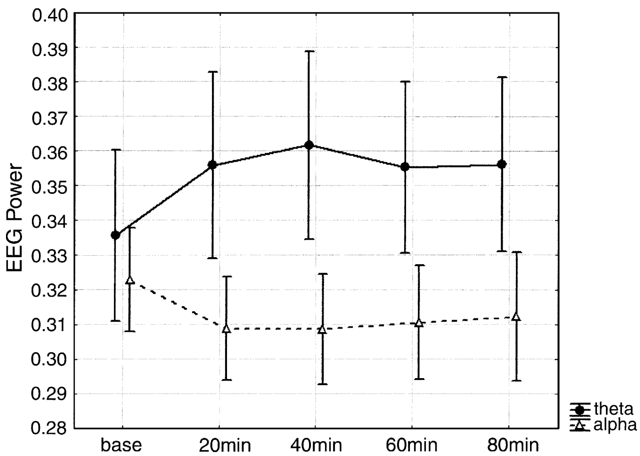

Fig. 1. Mean values and standard errors for EEG power in Θ and α bandwidths across time-on-task ($N = 35$).

effects simply represent different units of measurement used for each dependent variable.

3.1. The effect of time-on-task on performance

Performance on the MATB was quantified via several variables to represent each of the three MATB sub-tasks, specifically: (a) root-mean-square error was used to represent tracking performance, (b) the deviation from the target value of 2500 was measured to assess performance on the fuel management task and gauge monitoring performance was measured via (c) accuracy (percent correct responses as a proportion of all responses). The time-on-task effect on MATB performance was analysed via a 4×3 multivariate analysis of variance (time-on-task $\times$ MATB variable) that revealed no significant differences. Therefore, performance on all three sub-tasks of the MATB was stable over 80 min of performance, although a trend was apparent for the fuel management task (Table 1).

3.2. The effect of time-on-task on EEG activity

Power in the three EEG bandwidths was quantified for each site and subjected to a $4 \times 3 \times 5$ MANOVA (site $\times$ EEG bandwidth $\times$ time-on-task). The time-on-task factor included the baseline condition. This analysis revealed only a significant interaction between EEG bandwidth $\times$ time-on-task [$\Lambda(8,27) = 0.61$, $p < 0.01$, $\eta^2 = 0.519$]. Post hoc Bonferroni tests revealed significant trends in the data for each of the three EEG bandwidths. Power in the Θ band significantly increased from baseline over the initial 40 min of performance and stabilised for the second half of the task ($p < 0.05$). The mean power in the α bandwidth significantly decreased from baseline during task performance ($p < 0.01$). Both trends are illustrated in Fig. 1. There was no significant change in the β bandwidth.

3.3. The effect of time-on-task on cardiovascular activity

Three ECG variables (mean IBI, 0.1 Hz sinus arrhythmia, vagal tone) were analysed via 3×5 MANOVA (ECG variable $\times$ time-on-task) which yielded a significant main effect for time-on-task [$\Lambda(4,31) = 0.65$, $p < 0.01$] interaction between variable and time-on-task [$\Lambda(8,27) = 0.35$, $p < 0.01$, $\eta^2 = 0.771$]. Post hoc Bonferroni testing revealed significant changes for both heart rate and vagal tone; specifically: mean IBI was reduced during the initial two periods of performance ($M = 863.2$ and 874.3) compared to baseline ($M = 891.1$) ($p < 0.05$), and vagal tone was significantly suppressed throughout all four periods of task performance ($M = 7.12$, 7.19, 7.20 and 7.27) compared to baseline ($M = 7.65$) ($p < 0.05$).

3.4. The effect of time-on-task on skin conductance level

Data from the SCL were analysed via a repeated-measures ANOVA procedure. Two participants were excluded from the SCL analysis due to artifacts in the data record. The ANOVA on the remaining SCL data revealed a significant effect for time-on-task [$F(4,30) = 3.42, p < 0.02, \eta^2 = 0.313$]. Post hoc Bonferroni testing revealed that SCL increased significantly from baseline during performance and declined with time-on-task. This trend is illustrated in Fig. 2.

3.5. The effect of time-on-task on respiration rate

Data from respiration rate were analysed using a repeated-measures ANOVA. The presence of artifacts meant that two participants were excluded from this analysis. The rate of breathing showed a significant increase during task performance ($M = 19$, 18.5, 18.4 and 18.3 breaths/min) compared to the baseline condition ($M = 16.7$ breaths/min) [$F(4,30) = 9.59$, $p < 0.01$, $\eta^2 = 0.236$].

3.6. The effect of time-on-task on eye-blink frequency and duration

Both eye-blink rate and blink duration were subjected to a 2×5 MANOVA analysis (EOG variable $\times$ time-on-task)

Table 1
Mean values and standard error in brackets for MATB performance (tracking, fuel management, system monitoring) across time-on-task ($N = 36$)

MAT variable	20 min	40 min	60 min	80 min
RMS error	70.58 (2.77)	70.19 (3.04)	71.11 (3.14)	69.36 (3.29)
Deviation from target level	164.00 (36.14)	148.41 (33.43)	148.41 (33.21)	145.10 (41.85)
Accuracy (%)	79.83 (3.22)	82.38 (2.81)	82.32 (2.87)	82.28 (2.98)

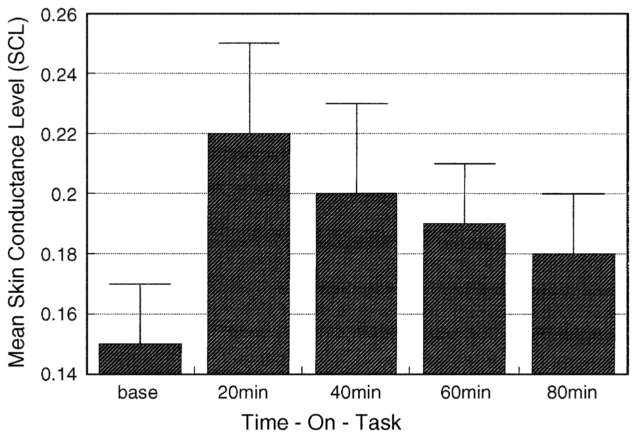

Fig. 2. Time-on-task trend for mean skin conductance level ($N = 33$).

that revealed an interaction effect of marginal significance [$\Lambda(4,31) = 0.76$, $p = 0.06$, $\eta^2 = 0.287$]. Post hoc Bonferroni tests revealed no significant effect of time-on-task associated with mean eye-blink frequency. By contrast, eye-blink duration was significantly suppressed during task performance (M = 895.5, 898.8, 934.3 and 937.4 ms) compared to baseline (M = 1060.7) ($p < 0.05$).

3.7. The effect of time-on-task on subjective states

Nine scales from the DSSQ were divided into three groups based on the factor analysis reported in (Matthews et al., 2002). This categorisation divided the DSSQ into three meta-factors: Task Engagement (energetical arousal, motivation, concentration), Distress (tense arousal, hedonic tone, confidence) and Worry (self-focus, self-esteem, task-irrelevant thoughts). The z-change score from each scale of the DSSQ was calculated where: z-change = (score − group_mean from previous time period)/(standard deviation of group from previous time period). This transformation is based upon the one reported by Temple et al. (2002) and is intended to standardise change scores across all DSSQ scales.

The transformed values from those three scales associated with the Task Engagement meta-factor were analysed via a 3 × 4 MANOVA (DSSQ scale × time-on-task). This analysis revealed an interaction effect of marginal significance [$\Lambda(6,29) = 0.763$, $p = 0.06$, $\eta^2 = 0.321$]. Mean values for each component of the Task Engagement meta-factor are shown in Table 2. Post hoc Bonferroni analyses revealed that energetical arousal showed a large decrement after 40 min of performance compared to other periods ($p < 0.01$). Similarly, motivation levels fell at a higher rate during the first half of performance compared to later periods ($p < 0.01$). The decrement associated with concentration was reduced during the final period of performance compared to previous periods ($p < 0.01$).

The 3 × 4 MANOVA for the Distress meta-factor revealed a significant main effect for time-on-task [$\Lambda(3,32) = 0.69, p < 0.05, \eta^2 = 0.253$]. Descriptive statistics for three scales comprising the Distress meta-factor are shown in Table 3. Both tense arousal and hedonic tone exhibited negative and positive change scores over time, but the magnitude of these changes was insignificant. Post hoc Bonferroni testing revealed a significant effect for only the confidence factor, which declined sharply during the final 20 min of performance ($p < 0.05$).

A 3 × 4 MANOVA was conducted on the three components of the Worry meta-factor. This analysis revealed a significant interaction effect only [$\Lambda(6,29) = 0.75, p < 0.02$, $\eta^2 = 0.382$]. Post hoc analyses of the DSSQ scales indicated that self-esteem showed a significant increase after 40 min of performance ($p < 0.01$). In addition, the rate of task-irrelevant thoughts was highest after 20 and 60 min compared to the remaining time periods ($p < 0.01$). Descriptive statistics for these analyses are shown in Table 4.

3.8. Multiple regression analyses

Psychophysiological data were standardised using a z-change score transformation (described in the previous section) prior to regression analyses. The z-change transformation was performed on psychophysiological data averaged over the final 5 min of each 20 min period of task performance: this period was selected to achieve maximum coherence with the subjective self-report scales (i.e. participants were asked to report how they felt at that moment), which were administered at the end of each 20 min period.

The transformed psychophysiological data were averaged across all four time periods and subjected to a correlation analysis. This analysis was performed to estimate the degree

Table 2
z-Change means and standard errors in brackets for the Task Engagement meta-factor across time-on-task ($N = 35$)

	20 min	40 min	60 min	80 min
Energetical arousal	−0.20 [0.16]	−0.41 [0.18]	−0.20 [0.15]	−0.26 [0.20]
Motivation	−0.41 [0.18]	−0.46 [0.18]	−0.26 [0.18]	−0.11 [0.18]
Concentration	−0.56 [0.22]	−0.40 [0.19]	−0.51 [0.25]	−0.26 [0.19]

Table 3
z-Change means and standard errors in brackets for the Distress meta-factor of the DSSQ across time-on-task ($N = 35$)

	20 min	40 min	60 min	80 min
Tense arousal	−0.04 [0.19]	−0.14 [0.17]	0.02 [0.16]	0.09 [0.18]
Hedonic tone	0.05 [0.18]	−0.18 [0.15]	−0.19 [0.21]	−0.13 [0.18]
Confidence	−0.01 [0.16]	−0.11 [0.16]	−0.08 [0.18]	−0.30 [0.19]

Table 4
z-Change means and standard errors in brackets for the Worry meta-factor of the DSSQ across time-on-task ($N = 35$)

	20 min	40 min	60 min	80 min
Self-esteem	0.07 [0.15]	0.30 [0.12]	0.02 [0.18]	0.07 [0.16]
Self-focus	−0.11 [0.15]	−0.09 [0.16]	−0.01 [0.17]	−0.09 [0.18]
Task-irrelevant thoughts	0.57 [0.22]	0.12 [0.27]	0.26 [0.17]	0.10 [0.22]

Table 5
Inter-item correlation between the five psychophysiological variables selected as independent variables for multiple regression ($N = 35$)

	α	IBI	SA	RR	BR
α		0.15	−0.14	−0.01	−0.16
IBI			−0.19	0.08	0.13
SA				−0.17	−0.09
RR					0.16

of redundancy between different psychophysiological measures and to identify variables for inclusion in the regression analyses. A probability level of <0.10 was used for this analysis in order to identify both moderate as well as high levels of correlation. Based on this correlation, five psychophysiological variables with low levels of inter-item correlations were selected as independent variables for the multiple regression analyses; these variables were alpha power in the EEG (α), inter-beat interval of the heart rate (IBI), sinus arrhythmia (SA), respiration rate (RR) and rate of eye-blink frequency (BR). A correlation matrix of these variables is shown in Table 5.

The variables from the DSSQ were averaged into three meta-factors described by Matthews et al. (2002): Task Engagement, Distress and Worry. Task Engagement was calculated by combining z-change scores from three DSSQ components: energetical arousal, concentration and motivation. To calculate the Distress factor, z-change scores for hedonic tone and confidence/control were reversed and combined with the z-change score for tense arousal; therefore, increased Distress was represented by rising tension in combination with negative affect and falling confidence. The Worry factor involved a combination of z-change scores for frequency of task-irrelevant thoughts and self-focus in conjunction with a reversed score for self-esteem, i.e. Worry = increased cognitive interference and self-focus in conjunction with falling self-esteem. The rationale for these formulations may be found in Matthews et al. (2002).

A series of multiple regressions were performed to investigate if Task Engagement, Distress and Worry were predicted by psychophysiological variables. Four multiple regression analyses were conducted for each meta-factor using data from each period of performance. The results of the Task Engagement analysis are presented in Table 6.

The regression analyses revealed a statistically significant relationship between Task Engagement and psychophysiological variables, which was sustained throughout the period of task performance. Psychophysiological variables predicted between 32 and 53% of the variance associated with Task Engagement. The most consistent predictor of Task Engagement was respiration rate which had a positive relationship with Task Engagement. Mean power in the α bandwidth, the 0.1 Hz component of sinus arrhythmia and eye-blink frequency exhibited a negative relationship with Task Engagement during the latter periods of the task activity.

The results of the stepwise regressions on the Distress meta-factor are presented in Table 7. Psychophysiological variables predicted between 28 and 42% of the variance associated with Distress. It was apparent that both α activity from the EEG and the 0.1 Hz component of sinus arrhythmia had a positive relationship with levels of Distress.

None of the psychophysiological predictors achieved statistical significance during the multiple regression to

Table 6
Results of the multiple regression using psychophysiological predictors of the DSSQ meta-factor Task Engagement ($N = 33$)

	20 min	40 min	60 min	80 min
Regression	Adj. $R^2 = 0.32$ $F(5,30) = 3.82$ $p < 0.01$	Adj. $R^2 = 0.43$ $F(5,30) = 5.20$ $p < 0.01$	Adj. $R^2 = 0.41$ $F(5,30) = 4.98$ $p < 0.01$	Adj. $R^2 = 0.53$ $F(5,30) = 7.62$ $p < 0.01$
Significant predictors, $p < 0.05$	RR = 0.57 [0.59]	RR = 0.69 [0.69]	RR = 0.32 [0.40] α = −0.62 [−0.63] SA = −0.34 [−0.40]	RR = 0.47 [0.55] α = −0.66 [−0.69] SA = −0.35 [−0.42] BR = −0.31 [−0.42]

A summary of the regression is provided in the upper panel and significant predictors are listed in the lower panel with their β weights and partial correlations in brackets. *Note*: RR: respiration rate, BR: eye-blink rate, SA: 0.1 Hz component of sinus arrhythmia, α: EEG alpha power.

Table 7
Results of the stepwise regression using psychophysiological predictors of the subjective meta-factor Distress ($N = 35$)

	20 min	40 min	60 min	80 min
Regression	Adj. $R^2 = 0.26$ $F(5,30) = 2.87$ $p < 0.05$	Adj. $R^2 = 0.42$ $F(5,30) = 5.26$ $p < 0.01$	Adj. $R^2 = 0.42$ $F(5,30) = 5.31$ $p < 0.01$	Adj. $R^2 = 0.38$ $F(5,30) = 4.51$ $p < 0.01$
Significant predictors, $p < 0.05$	α = 0.36 [0.34]	α = 0.38 [0.46] SA = 0.72 [0.68]	α = 0.67 [0.66] SA = 0.57 [0.59]	α = 0.64 [0.63]

A summary of the regression is provided in the upper panel and significant predictors are listed in the lower panel with their β weights and partial correlations in brackets. *Note*: SA: 0.1 Hz component of sinus arrhythmia, α: EEG alpha power.

predict the Worry meta-factor. This pattern of null findings was repeated across all four periods of task performance for the Worry meta-factor.

4. Discussion

The study demonstrated a dissociation between performance quality and psychophysiology/subjective states over time-on-task. Participants maintained stable performance levels (Table 1) despite fluctuating levels of psychophysiological activity (Figs. 1 and 2) and changes in subjective state (Tables 2–4). This dissociation is predicted by the model of mental effort regulation proposed by Hockey (1997), i.e. stable performance is achieved via a strategy of mental effort investment which provokes compensatory costs from psychophysiological and subjective domains.

Patterns of EEG power in the Θ and α bandwidths showed the expected response to task activity (Fig. 1): Θ power was augmented and α activity was suppressed during task performance (Brooking et al., 1996; Fournier et al., 1999; Gevins and Smith, 2003; Gevins et al., 1998; Gundel and Wilson, 1992; Klimesch, 1999). The augmentation of Θ activity was sustained throughout the task relative to baseline as was the suppression of α power (Fig. 1).

The analysis of other psychophysiological measures reflected changes in sympathetic activation throughout time-on-task. An increase of sympathetic activation was indicated by the escalation of mean skin conductance level relative to baseline (Fig. 2) and increased heart rate during the initial 40 min of performance. However, a decline of sympathetic activation over time-on-task is indicated by the SCL which consistently fell with each consecutive period of performance (Fig. 2). Parasympathetic inhibition was indexed by vagal tone that represents the influence of the vagus nerve on heart rate and is mediated by breathing rate (Berntson et al., 1997; Porges, 1992, 1995). The analysis of vagal tone indicated a suppression of this component during task performance and this trend was sustained throughout the entire period of task performance. An identical pattern was apparent for respiration rate which increased during task performance (from baseline) and was not significantly influenced by time-on-task. These analyses indicate an uncoupled pattern of sympathetic activation and parasympathetic inhibition over time-on-task (Berntson et al., 1991, 1994), i.e. falling levels of sympathetic activation in conjunction with a stable but suppressed level of parasympathetic inhibition.

The DSSQ data were analysed as change scores to represent time-on-task trends relative to the previous period of task performance. The analysis of Task Engagement revealed a consistent decline for all three scales over time-on-task (Table 2), i.e. reduced engagement with sustained performance. The influence of time-on-task on the Distress factor was modest by comparison (Table 3). The combination of high task demand and sustained performance failed to significantly increase tense arousal or induce negative affect via the hedonic tone factor; however, it was significant that confidence levels fell dramatically after the final period of performance (Table 3). The sudden decline of confidence suggests that participants reached the limits of successful coping after the fourth session (participants were not told when the task would end) and Distress may have been augmented if the task period had been extended. The Worry meta-factor was also relatively unaffected by the experimental task (Table 4). The frequency of task-irrelevant thoughts increased with each period of performance; therefore, participants had more difficulty focusing attention on the task as time progressed. The significant increase of self-esteem after 40 min of performance (Table 4) was unexpected and is assumed to represent a perception of increased task mastery. The absence of any significant effect on self-focus was anticipated; the high temporal demands associated with multitasking MATB performance discourage rumination or a shift of attention from the task to the self (Matthews et al., 2002).

The main goal of the study was to investigate whether psychophysiological measures could predict changes in subjective states as represented by the DSSQ. The multiple regression analyses (Tables 6 and 7) provided some support for the predictive validity of psychophysiology, but with several important caveats. Psychophysiological variables predicted between one-third and one-half of the variance associated with the Task Engagement meta-factor over the four periods of performance (Table 6). Respiration rate was a consistent, positive predictor of engagement, i.e. higher breathing rate = increased Task Engagement. A number of other variables made a significant contribution to the regression equation during the latter periods of performance (Table 6). Suppression of both α activity and the 0.1 Hz component was associated with Task Engagement, both of which have been associated with increased mental effort (Gevins et al., 1998; Mulder, 1986). This finding suggests that covariation between psychophysiology and subjective self-report may be moderated by changes in sympathetic activation related to the investment of mental effort. The general pattern of the Task Engagement regression was an accumulation of psychophysiological predictors with increased time-on-task; for instance, a suppression of eye-blink frequency was also associated with Task Engagement during the final period of performance (Table 6). This pattern may be indicative of increased mental effort as a compensatory strategy to counteract the influence of fatigue on performance (Hockey, 1997).

The prediction of the Distress meta-factor was modest during the initial period of performance (Table 7). This multiple regression presented a positive association between Distress and both the 0.1 Hz component and α activity (Table 7). The Distress factor represents "an overload of processing capacity" (Matthews et al., 2002); in the context of the current study, any overload of capacity was induced by a failure to sustain performance over time-on-task.

The effect of task activity was to suppress the level of α activity (Fig. 1), which has been associated with mental effort investment (Gevins et al., 1998), and the Distress factor was associated with a failure to sustain α suppression. The positive association with the 0.1 Hz component indicated that Distress was associated with a tendency to reduce or conserve mental effort (Hockey, 1997), i.e. the 0.1 Hz component is suppressed when mental effort is invested. Therefore, the Distress meta-factor was associated with a "giving up" pattern from the psychophysiological domain.

This explanation posits that Task Engagement and Distress (and their psychophysiological predictors) were independent throughout task performance. However, the presence of common predictors (e.g. α activity and the 0.1 Hz component) points to a degree of convergence. This explanation is supported by a higher-level correlation between both Task Engagement and Distress meta-factors which developed with time-on-task (Table 8). This convergence does not indicate any shortcomings on behalf of the psychophysiological predictors or the regression procedure, but represents the possibility that the predictive role of both α activity and the 0.1 Hz component may be spurious due to higher-order correlations between the DSSQ meta-factors (Matthews et al., 2002).

None of the psychophysiological measures used in the study could successfully predict the Worry meta-factor. This null finding may stem from the failure of the independent variables to induce Worry in the participants (Table 4) as already discussed. In addition, the Worry meta-factor is characterised by attentional/cognitive scales and it is possible that the psychophysiological variables used in the study failed to tap this cognitive dimension. The Worry meta-factor may have been predicted by measures of cognitive psychophysiology such as evoked-cortical potential variables, e.g. the P300 component (Prinzel et al., 2003).

The current study had at least two major weaknesses. The first concerns the range of psychophysiological variables used during the study, which excluded several important measures such as blood pressure and facial EMG. The former has been used to differentiate states between states of challenge and threat (Blascovich and Tomaka, 1996; Tomaka et al., 1997), two states that bear a resemblance to the DSSQ concepts of Task Engagement and Distress used in the current study. Facial EMG has demonstrated consistent changes in response to pleasant and unpleasant stimuli, particularly in the corrugator muscles above the eyebrow (Cacioppo et al., 1990), and EMG activity from these sites has been used to differentiate between positive and negative affects (Bradley et al., 1996; vanOyen Witvliet and Vrana, 1995). The inclusion of these measures may have increased the explanatory power of the regression analyses in the current study. The regression analyses indicated that psychophysiology explained between 26 and 53% of variance in the subjective states data (Tables 6 and 7); the average was approximately 40%, leaving more than half the variance unexplained. Future research could investigate how to improve the explanatory power of regression analyses by supplementing psychophysiology with other data sources, e.g. real-time performance, cognitive models. For example, individual traits such as age and personality may play a role in the prediction of subjective states. The influence of both coping style and neuroticism on Distress from the DSSQ has been demonstrated (Matthews et al., 2002) and other more transitory variables such as sleep quality and time-of-day may also play a role.

The second weakness of the study concerns the choice of time-on-task as an independent variable and the difficulty level of the MATB. It was obvious from the analysis of the Distress meta-factor (Table 3) that the combination of high demand and sustained performance in the current study failed to provoke the expected increase of tension and negative affect. It may have required an additional independent variable such as loss of control or the threat of financial punishment to provoke increased Distress. This shortcoming is associated with another potential problem—the use of the one independent variable (time-on-task) to provoke changes across three meta-factors representing the subjective state. The current design may have created the convergence of psychophysiological predictors for both Task Engagement and Distress (Table 8). This finding also begs the questions regarding the generalisability of our results, e.g. would α activity have played such a prominent role as a psychophysiological predictor if time-on-task had not been used as an independent variable? A fundamental concern exists that those psychophysiological predictors listed in Tables 6 and 7 are specific to the independent variable (time-on-task) and do not represent generic fluctuations of Task Engagement or Distress. These issues will be resolved by future research which extends both the range of independent variables and the types of tasks under investigation.

Table 8
Pearson correlation coefficient between Task Engagement and Distress meta-factors over time-on-task ($N = 35$)

	R-values between Task Engagement and Distress
20 min	−0.33
40 min	−0.23
60 min	−<u>0.48</u>
80 min	−<u>0.56</u>

Underlined values are significant at $p < 0.01$.

5. Conclusions

The study demonstrated that performance quality was relatively insensitive to a time-on-task manipulation compared to psychophysiological and subjective variables. This finding confirms the sensitivity of psychophysiological measures and supports the potential utility of biocybernetic control. The multiple regression analyses demonstrated a degree of convergent validity between psychophysiology and subjective states, e.g. Task Engagement and Distress. These analyses broadly support the position that changes in subjective states may be operationalised by psychophysiology within the biocybernetic control loop. However, psychophysiology often failed to account for more than half of the variance associated with the subjective state in our study and the incorporation of additional variables (from performance, psychophysiology and personality) is required to improve predictive validity.

The current study provides the foundation of psychophysiological algorithms to describe uni-dimensional scales of Task Engagement and Distress. Key variables such as 0.1 Hz sinus arrhythmia and α activity were prominent predictors for both Task Engagement and Distress, but this finding may be an artifact due to higher-order correlations between the subjective meta-factors.

Task Engagement and Distress are relevant dimensions of subjective state for biocybernetic control as both have implications for performance and the wellbeing of the human operator. The current study operationalised engagement and Distress using the meta-factors devised by Matthews et al. (1997, 2002) which integrate mood, motivation and cognition within unitary factors. This level of specificity is sufficient to represent the subjective state of the operator as a two-dimensional space and construct a biocybernetic loop designed to counteract low levels of Task Engagement and high Distress. This characterisation should suffice for many applications where performance is important such as adaptive automation, computer games and educational software. However, this level of specificity will not suffice for those biocybernetic systems that require a more detailed level of mapping, e.g. between distinct emotional states and psychophysiology.

The rationale underlying the development of biocybernetic control is that these systems can deliver timely and intuitive system interventions. The fact that psychophysiology was capable of explaining a substantial amount of the variance associated with both Task Engagement and Distress in the current study provides momentum for the continued development of these systems. However, it is difficult to predict how this degree of convergent validity will translate into operators' perceptions of system reliability and influence related variables such as trust. A detailed understanding of how the mapping between psychophysiology and the subjective state influences user perceptions of biocybernetic control is a topic for future research.

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