Personality Traits in the Relationship of Emotion and Performance in Command-and-Control Environments

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***Abstract*—Affect-adaptive systems are capable of adapting human-machine interaction with respect to the current emotional user state and situational needs. To set the ground for a future affect-adaptive system, we examined interindividual differences in the relationship between emotional user states – composed of emotional valence and arousal - and performance in a command-and-control environment in a lab experiment (N = 51, 19-57 years, M = 32.75 SD = 9.8). We suspect that observed interindividual differences are caused by two personality traits: neuroticism and conscientiousness. We used personality, valence, and arousal to model task performance in a linear mixed-model and found significant effects for valence as a random effect and arousal as a fixed effect. Furthermore, we found interaction effects with neuroticism and conscientiousness. Our results suggest that future affect-adaptive systems may benefit from considering personality traits to address interindividual differences in the relationship of emotional user state and performance.**

Keywords–Affective computing; Affect-adaptive systems; Affective user state; Command-and-control; Personality traits.

I. INTRODUCTION

In human-machine interaction, critical user states, such as fatigue [1] or an incorrect focus of attention [2], may impair the performance of the human-machine system. Some adaptive systems permanently observe the user state and adapt their interaction mechanisms when critical or undesired states are detected to mitigate performance decrements [3]. This investigation focuses on the emotional user state as one of the dimensions in a multidimensional model of user state [4]. [5], such as command-and-control (C2) environments. Considering that emotion and performance are closely linked [6][7], a deeper understanding of the emotional user state and its correlation with performance is necessary for our goal of developing an affect-adaptive C2 system. In a simulated C2 task, we examined the influence of personality traits on this correlation. In accordance with [8], both the valence component and the arousal component of the emotional state were analyzed.

Following this introduction, we provide theoretical background regarding the correlation of emotional user state and performance and the role of personality (Section 2). Section 3 describes the method we used to investigate the research question. Section 4 presents the results of the statistical analyses that are then discussed in Section 5. The paper closes with our conclusions drawn from this investigation (Section 6).

II. BACKGROUND

In previous investigations [9][10], we observed remarkable interindividual differences in the correlation of the emotional user state and performance. While a state of low arousal and neutral valence was beneficial for many subjects, some benefitted from states of positive or negative valence. About 50% of the subjects did not show any association between emotional user state and performance. These results pose a challenge for affect-adaptive mechanisms as there may be a group of users that performs best in a state of neutral valence, while others thrive in a positive or negative emotional state. An affect-adaptive system that does not consider these individual differences in its adaptation mechanisms could actually hinder performance, for example by promoting neutral valence in a subject that performs best in a positive state of valence. We therefore aim at testing the feasibility of developing distinct *Affective Response Categories* of users that benefit from different emotional user states. An effective affect-adaptive system should be able to distinguish these categories, assign users to them, and adapt interaction accordingly.

Our approach to assign users to these categories is based on the Appraisal Theory of Emotion [11]. According to this theory, emotions are caused by the appraisal of a stimulus and matching it with individual goals and expectations. Multiple processes like bodily sensations and situational factors contribute to the emotional experience [12]. We suspect that the individual differences observed in our previous investigations emerge at the stage of appraisal. For example, if an individual tends to an anger-prone appraisal style, events are often appraised in a way that leads to an anger experience [13]. Previous research indicates that personality traits have a key role in this process [14][15]. Personality traits are associated with certain coping strategies for emotional states. Neuroticism, for example, has been associated with low perceived coping ability, experience of negative emotions such as anxiety, and emotion-focused coping strategies. Conscientiousness, on the other hand, appears to be correlated with problem-focused coping and high perceived coping ability [16]. These findings indicate that the personality-appraisal relationship differs between individuals and could offer an explanation for the interindividual differences in the correla-

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tion of the emotional user state and performance we found in earlier investigations [9][10].

Supporting evidence for the moderating effect of personality on emotional reactions is also provided by Brouwer, Van Schaik, Korteling, van Erp and Toet [17], who investigated the relationship between conscientiousness, stress sensitivity, and arousal. Subjects with a low conscientiousness score showed a higher increase in heart rate than subjects with a high conscientiousness score during a stressful situation. Additionally, Roslan et al. [18] found an increase in emotional arousal, measured by physiological correlates, for subjects scoring high on neuroticism. During a speaking task, subjects with high neuroticism scores showed a higher increase in skin conductance and heart rate than subjects with a low neuroticism score.

We therefore suspect that personality traits, particularly neuroticism and conscientiousness, moderate the interindividual differences and would like to test the feasibility of determining a user's Affective Response Category by his or her personality characteristics.

1) *Hypothesis 1:* The emotional user state is associated with task performance.

a) Higher pupil width is significantly associated with low performance for all subjects.

b) The relationship between emotional valence (positive, neutral, negative) and performance varies across subjects.

2) *Hypothesis 2:* Personality traits have a moderating effect on the emotion-performance relationship.

a) There are significant interaction effects of neuroticism with valence (I) and arousal (II).

b) There are significant interaction effects of conscientiousness with valence (I) and arousal (II).

c) There are significant interaction effects of neuroticism and conscientiousness with valence (I) and arousal (II).

The present investigation aims to test these hypotheses in a simulated C2 task as a step towards an affect-adaptive C2 environment that considers individual differences in the affective response.

III. METHOD

A laboratory experiment was conducted to test the hypotheses.

A. *Sample Description*

Fifty-one ($N = 51$) subjects aged 18 to 57 years ($M = 32.75$, $SD = 9.8$) participated in the experiment. All participants were employees of the Fraunhofer Institute for Communication, Information Processing and Ergonomics (FKIE) who were invited via e-mail. Thirty-three percent of the participants were female. Participation was not generally compensated, but the three best-performing subjects earned a voucher for motivational purposes.

B. *Experimental Task*

To simulate a C2 task, we used the Rich and Adaptable Test Environment for C2 (RATE) [19], a modular and scalable task environment that allows for flexible design of experimental tasks and customized performance scoring. Inspired by the Warship Commander Task [20], we developed an air defense task using a simulated radar display (Figure 1). In order to protect their own ship, participants had to perform three subtasks.

1) *Identify:* All unknown tracks need to be assigned an identification (hostile, neutral or friendly) according to certain parameters and rules.

2) *Warn:* Hostile tracks approaching the ship must be warned upon entering the outer safety zone.

3) *Engage:* Hostile tracks entering the inner safety zone despite prior warning must be engaged.

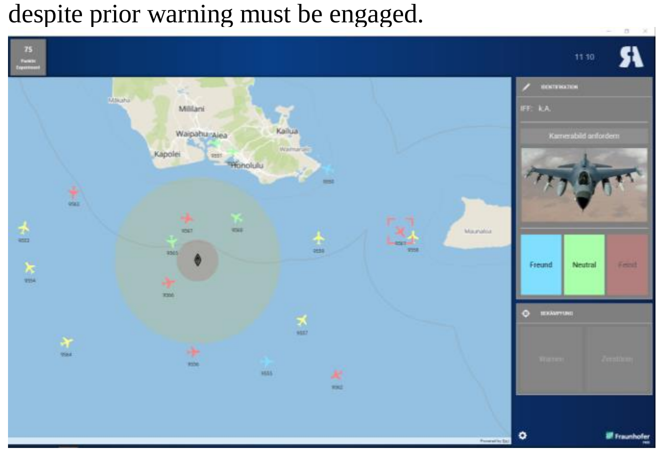

Figure 1. Rich and Adaptable Test Environment (RATE) for C2 [19].

All participants went through a training session followed by twelve scenarios of varying difficulty. Each scenario lasted 3:30 minutes. Based on the cognitive task load model validated in a C2 task by de Greef and Arciszewski [21], difficulty levels were determined by the total number of tracks and the relative proportion of enemy tracks. The number of tracks in each scenario was 6, 12, 18, or 24. The relative percentage of enemy tracks was 17%, 33%, or 47%. To avoid sequence effects, difficulty levels were randomized between subjects.

C. *Variables*

1) *Independent Variables:*

a) Big Five Personality Factors were assessed by the German version of the NEO-FFI [22]. In the present investigation, we focused on conscientiousness and neuroticism only.

b) Scenario difficulty varied across all twelve scenarios to cover a broad spectrum of difficulty levels.

c) Emotional valence was derived from facial expressions using Emotient FACET, an emotion detection tool that analyzes facial expressions in real time using a regular webcam.

d) Emotional arousal was indicated by pupil width, measured with a Tobii Pro Spectrum 300 Hz eye tracker.

2) Dependent Variables:

Performance was assessed via a performance score that considered priority of the tasks, accuracy, and response time [17]. The score was visible in the upper left corner of the screen (see Figure 1), so that participants were able to assess their own performance at all times.

D. Statistical Analysis

A linear mixed-model was calculated using the *lme4* package [23] in R (Version 4.0.5) [24]. Performance was included as the dependent variable. The median of a time window of 10 seconds was calculated for the performance score, emotional valence values, and pupil width, respectively. To control for confounding variables we included difficulty level, gaming experience and age as fixed effects before adding the emotional state. Pupil width was included as fixed effect as we expected that higher pupil width is associated with low performance across all subjects.

As fixed effects, we added difficulty level, gaming experience, age, and pupil width. Since previous investigations showed individual differences in emotional valence, classification outcome for neutral, positive, and negative valence was included as random effects. Moreover, conscientiousness and neuroticism were included as fixed effects to test the moderating effect of personality on the emotion-performance relationship.

The *lmerTest* package [25] was used to test for the significance of fixed effects. The Akaike information criterion (AIC) was used to compare models. All independent variables were centered within subjects to perform group-mean centering before running the statistical analysis. All models were fitted with the maximum-likelihood estimation.

IV. RESULTS

In this section, we describe the results of our analyses.

A. The fixed effect model:

The Intraclass-Correlation-Coefficient (ICC) of the random-intercept-only-model was 0.21, showing that 21% of the observed variance in performance can be attributed to between-subject factors. The AIC of the first model was 86092.62. The estimate of the significant intercept was 72.87, representing the average performance value of all subjects across all levels of difficulty. The second model included difficulty level as a fixed effect. The AIC of the second model decreased to 75851.911, ANOVA comparison between the random-intercept-only-model and the second model showed a significant increase in model fit on a $p < 0.001$ level. Gaming experience was added as the second fixed effect to the third model. The AIC decreased significantly ($p < 0.01$) from 75651.911 to 75646.272. The fourth model included age as a fixed effect. The AIC of the fourth model decreased significantly ($p < 0.001$) from 75646.272 to 75631.464. The fifth model included pupil width as a fixed effect. The AIC decreased from 75646.272 to 74162.670 and was a significant improvement in model performance ($p < 0.001$), confirming H1a.

B. The random effect model

The addition of positive valence as a random effect decreased the AIC to 73765.647, the addition of neutral valence decreased the AIC to 73532.586, and the addition of negative valence decreased the AIC to 73449.612. ANOVA comparison showed a significant improvement ($p < 0.001$) of each model, respectively, confirming H1b.

C. The interaction model

The interaction models tested the moderating effects of the personality traits conscientiousness and neuroticism on the relationship between emotions and performance. We tested for model improvement using ANOVA comparisons between the random effects model and interaction model of interest.

*1) Neuroticism * emotional valence*

The addition of an interaction term between positive valence and neuroticism to the model increased the AIC to 73452.544. The interaction between neutral valence and neuroticism increased the AIC to 73455.242. The interaction between negative valence and neuroticism showed an AIC of 73455.387. None of the interactions models showed a significant improvement in model fit compared to the random effects model that included valence as a random effect. Therefore, the moderating influence of neuroticism on the relationship between valence and performance stated in H2a (I) was not confirmed in the current experiment.

*2) Conscientiousness * emotional valence*

The addition of an interaction term between positive valence and conscientiousness to the model increased the AIC to 73450.694. The interaction between neutral valence and conscientiousness increased the AIC to 73452.165. The interaction between negative valence and conscientiousness showed an AIC of 73452.277. Similar to the interaction between neuroticism and valence, none of the interactions models showed a significant improvement in model fit to the random effects model. The moderating effect of conscientiousness on emotional valence stated in H2b (I) was not confirmed in the current experiment. As neither of the personality traits interacted with valence, H2c (I) was rejected.

*3) Neuroticism * arousal*

Although neuroticism had no direct influence on performance as a fixed effect, it significantly influenced pupil width. The model including an interaction between neuroticism and pupil width demonstrated an AIC of 73439.335, representing a significant increase in model fit on a $p < 0.001$ level compared to the random effects model, confirming H2a (II). In low-arousal conditions, as indicated by smaller pupil size, participants with a low neuroticism score performed better than subjects with a high neuroticism score (see Figure 2).

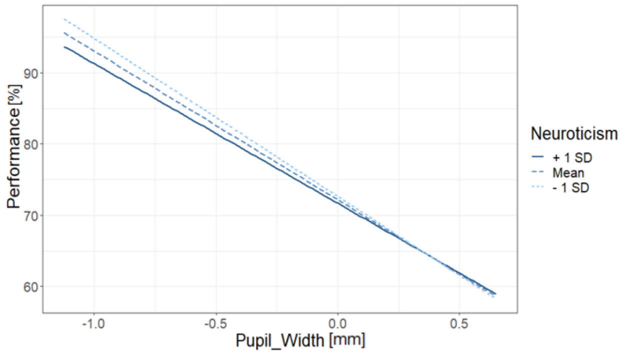

Figure 2. The Interaction between Pupil Width and the Personality Factor Neuroticism.

*4) Conscientiousness * arousal*

Similar to neuroticism, conscientiousness had no direct influence as a fixed effect on performance. However, the addition of the interaction term between conscientiousness and pupil width also gained a significant increase in model performance. The AIC decreased significantly from 73439.335 to 73436.082 ($p < 0.05$), supporting H2b (II). In high arousal conditions, as indicated by higher pupil size, low conscientiousness is associated with low performance.

*5) Neuroticism * conscientiousness * pupil width*

Given that both personality traits interacted with pupil width in the current experiment, a three-way interaction between neuroticism, conscientiousness, and pupil width was investigated as well. Compared to the model including both two-way interactions terms, the current model showed an AIC of 73433.829. This increase in model fit of the three-way interaction model compared to the model including both two-way interactions was significant ($p < 0.05$), supporting H2c (II). Subjects scoring high on neuroticism and low on conscientiousness demonstrate in highly arousing states, as indicated by a higher pupil size, an association with low performance.

D. *The final model*

The final model (see Table 1) includes the fixed effects of difficulty level, gaming experience, pupil width, and age, the random effects of emotional valence and the three-way interaction between neuroticism, conscientiousness, and pupil width. While difficulty level is a negative predictor of performance with an estimate of -2.58, gaming experience shows a positive influence on performance with an estimate of 2.89. Furthermore, pupil width and age are negative predictors of performance with an estimate of -34.42 and -0.41, respectively. While the interaction between neuroticism and pupil width is still significant on a $p < 0.01$ level, the interaction between conscientiousness and pupil width was no longer significant. However, the higher order interaction between neuroticism, conscientiousness, and pupil width explains that finding. We therefore limit the interpretation to the higher-order interaction. Figure 3 visualizes this three-way interaction effect. The influence of neuroticism on pupil width in the two-way interaction was positive with an estimate of 11.66. The inclusion of conscientiousness within the three-way interaction moderates this relationship by shifting the estimate to -3.35.

In instances of low performance, participants with a high neuroticism score and a low conscientiousness score demonstrate a higher pupil width than subjects with a high neuroticism score and a high conscientiousness score (see Table 1 and Figure 3).

TABLE I. RESULTS OF FIXED EFFCTS, RANDOM EFFECTS, AND THE INTERACTION BETWEEN PUPIL WIDTH AND PERSONALITY

Final Model

	Performance		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	103.45	75.11 – 131.78	**<0.001**
Difficulty_Level	-2.58	-2.61 – -2.54	**<0.001**
Gaming_Experience	2.89	1.06 – 4.71	**0.002**
Age	-0.41	-0.59 – -0.24	**<0.001**
Pupil_Width	-34.42	-49.17 – -19.66	**<0.001**
Conscientiousness	-0.42	-9.19 – 8.34	0.925
Neuroticism	3.07	-11.55 – 17.68	0.681
Pupil_Width * Conscientiousness	3.61	-1.31 – 8.52	0.150
Pupil_Width * Neuroticism	11.66	4.02 – 19.30	**0.003**
Conscientiousness * Neuroticism	-1.34	-6.30 – 3.62	0.597
(Pupil_Width * Conscientiousness) * Neuroticism	-3.35	-6.03 – -0.67	**0.014**
Random Effects			
σ^2	68.88		
τ_{00} Subject	39.34		
τ_{11} Subject.Positive_Valence	14.54		
τ_{11} Subject.Neutral_Valence	56.68		
τ_{11} Subject.Negative_Valence	67.33		
ρ_{01}	-0.05		
	-0.04		
	0.20		
ICC	0.36		
N Subject	51		
Marginal R^2 / Conditional R^2	0.636 / 0.769		
AIC	73433.829		

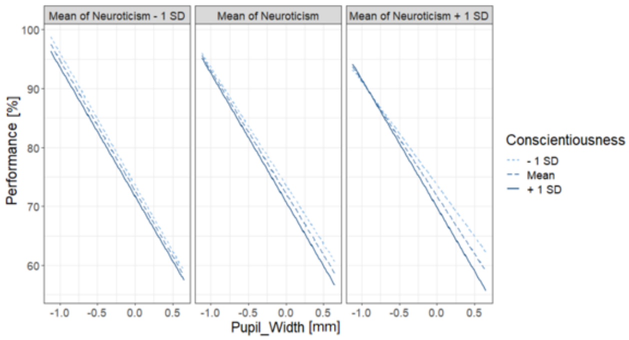

Figure 3. The Interaction between Pupil Width and the Personality Factors Neuroticism and Conscientiousness.

V. DISCUSSION

We investigated the correlation of the emotional user state and performance in a C2 environment, as well as the influence of personality traits on this correlation. All three classifiers of emotional valence were associated with performance and contributed significantly to the performance model as random effects. This replicates our earlier findings of interindividual differences in the correlation of emotion and performance [9][10] and confirms H1b. Unsurprisingly, low performance was associated with high difficulty level, low gaming experience, and high age. As hypothesized in H1a, low performance was also associated with high pupil width, indicating higher arousal during more demanding scenarios. Although conscientiousness and neuroticism showed no significant main effect on performance, participants with a higher neuroticism score tend to perform better on the task.

We found significant improvements of model performance when including arousal and emotional valence. Previous findings regarding the association between low conscientiousness [17] as well as high neuroticism [18] with increased arousal are in line with the results of the present study. Thus, it would be beneficial for affect-adaptive C2 systems to consider both these dimensions of the emotional user state. However, this investigation only analyzed the correlational relationship of emotion and performance. To ensure that emotions causally influence performance, we suggest an experimental design that includes the induction of emotional user states.

We earlier proposed to create Affective Response Categories to cluster users based on what emotional user states are most beneficial for their performance. This would allow affect-adaptive systems to adapt interactions in an appropriate manner based on category membership. Our results suggest that a categorization based on personality traits may be possible, given that we observed interaction effects of (1) neuroticism with arousal and performance, and (2) neuroticism and conscientiousness with arousal and performance. In conditions of low arousal, participants that score higher on the neuroticism scale show lower performance compared to participants that score lower on the neuroticism scale. Therefore, we assumed that subjects with a tendency to neuroticism put in less effort in less demanding situations. We confirmed this hypothesis by analyzing the interaction effect of difficulty level, neuroticism, and pupil width on performance. The results indicate that affect-adaptive systems should monitor participants with higher scores on neuroticism closely, as they tend to lower performance in low arousal conditions.

In order to further investigate this subgroup of participants, we analyzed the interaction of pupil width, neuroticism, and conscientiousness on performance. Subjects with high neuroticism scores and high conscientiousness scores showed higher arousal during low performance than those with low conscientiousness scores. This three-way interaction was significant with a negative estimate of – 3.35. Therefore, we suspect that more conscientious subjects in the subgroup of high neuroticism tried harder to counter the low performance state than those who are less conscientious.

We proposed that interindividual differences observed in our previous investigations emerged at the stage of appraisal and that personality traits have a key role in this process [14][15]. Based on the reported results, appraisal theory offers an explanation for differences in the correlation of arousal and performance. Participants that scored higher on neuroticism and higher in conscientiousness performed worse when arousal was high. Possibly, more conscientious participants executed tasks more carefully and required more time than less conscientious subjects. Especially in high workload scenarios that demand fast task execution in order to avoid score deductions, less conscientious subjects might have had an advantage. To test this theory, a closer look at accuracy and response time would be necessary to analyze the speed-accuracy trade-off [19].

VI. CONCLUSIONS

Our results indicate that people who differ in their personality characteristics also differ in their correlation of emotional arousal and performance. Participants scoring high on neuroticism and low on conscientiousness exhibit a higher arousal level than participants scoring low on neuroticism and high on conscientiousness. Hence, we conclude that the proposed categorization by personality traits shows promising potential for further research.

A starting point for how to consider personality in interactive systems is offered by Sarsam and Al-Samarraie [26], who demonstrated the benefits of integrating a user's personality trait into the design of the user interface. Users scoring high on neuroticism prefer calm colors as well as more structured and divided texts. Furthermore, the use of a personality-tailored interface also increased visual attention during a learning task.

An affect-adaptive system that considers Affective Response Categories to adapt interactions according to the user's individual emotional needs could assist in achieving consistently high performance in a human-machine-system. For example, in a high workload scenario, a user belonging to the subgroup of high neuroticism and high conscientiousness might need extra support in executing the tasks at the required speed, as compared to a user with high neuroticism but low conscientiousness. In a low workload scenario, if the current user belongs to the "high neuroticism" subgroup, it may be possible – according to our results – to avoid performance decrements by increasing arousal. An appropriate adaptation strategy might be to decrease the use of automation. With increasing workload, this user's arousal would increase and performance would improve. In contrast, a user in the "low neuroticism" subgroup may not require adaptive intervention in the same situation.

The preliminary parameters of the Affective Response Categories outlined herein demonstrate the feasibility for the creation of distinct categories and offer a starting point. In order to construct more holistic categories, further associations of individual characteristics and the correlation of emotion and performance will be necessary.

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