ARL-TR-8945 • Apr 2020

DEVCOM
ARMY RESEARCH
LABORATORY

Analysis of Facial Expressions: Explaining Affective State and Trust-Based Decisions during Interaction with Automation

by Catherine Neubauer, Gregory Gremillion, Kristin E Schaefer, Brandon S Perelman, Claire La Fleur, and Jason S Metcalfe

NOTICES

Disclaimers

The findings in this report are not to be construed as an official Department of the Army position unless so designated by other authorized documents.

Citation of manufacturer's or trade names does not constitute an official endorsement or approval of the use thereof.

Destroy this report when it is no longer needed. Do not return it to the originator.

ARL-TR-8945 ● APR 2020

Analysis of Facial Expressions: Explaining Affective State and Trust-Based Decisions during Interaction with Automation

Catherine Neubauer, Gregory Gremillion, Kristin E Schaefer, Brandon S Perelman, Claire La Fleur, and Jason S Metcalfe
Human Research and Engineering Directorate, CCDC Army Research Laboratory

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE *(DD-MM-YYYY)* April 2020	**2. REPORT TYPE** Technical Report	**3. DATES COVERED (From - To)** 2016–2020

4. TITLE AND SUBTITLE Analysis of Facial Expressions: Explaining Affective State and Trust-Based Decisions during Interaction with Automation	**5a. CONTRACT NUMBER**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) Catherine Neubauer, Gregory Gremillion, Kristin E Schaefer, Brandon S Perelman, Claire La Fleur, and Jason S Metcalfe	**5d. PROJECT NUMBER** W911-NF-12-2-0019
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) CCDC Army Research Laboratory ATTN: FCDD-RLH-FA Aberdeen Proving Ground, MD 21005	**8. PERFORMING ORGANIZATION REPORT NUMBER** ARL-TR-8945
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)**
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

ORCID ID(s): Catherine Neubauer, 0000-0002-6686-3576; Gregory Gremillion, 0000-0002-0205-688X; Kristin E Schaefer, 0000-0002-1342-3446; Brandon S Perelman, 0000-0001-6558-0286; and Jason S Metcalfe, 0000-0001-9086-9962

14. ABSTRACT

Trust is a critical factor in the development and maintenance of effective human-autonomy teams. This becomes more important as the technology advances in independent and interdependent decision-making with humans, especially in high-risk dynamic environments. As such, new processes are needed to classify an individual’s affective state change that could be related to either an accurate or a misaligned change in trust that occurs during collaboration. The task for the current study was a simulated leader–follower driving task with two different types of driving automation (Level 2: full vs. Level 1: speed only) and across two different automation reliability levels (good vs. bad). Facial expression analysis and subjective questionnaire measurement were evaluated to gauge group differences in affect-based trust. Through a novel analysis approach, results indicated that the participant sample was best described by four distinct group clusters based on demographics, personality traits, response to uncertainty, and initial perceptions about trust, stress, and workload associated with interacting with the driving automation. These groups showed marked differences in their level of subjective trust and affect via facial expressivity. This suggests that trust calibration metrics may not be equally critical for all groups of people.

15. SUBJECT TERMS

Driving Automation, Affective Computing, Affect-Based Trust, Trust-Based Decision-Making, Human-Autonomy Teaming

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON** Catherine Neubauer
a. REPORT Unclassified	**b. ABSTRACT** Unclassified	**c. THIS PAGE** Unclassified	UU	39	**19b. TELEPHONE NUMBER (Include area code)** 310-448-5354

Contents

List of Figures

List of Tables

Summary

Novel assessment practices and metrics for evaluating trust in human-autonomy teams are needed to develop and calibrate effective team performance. This report provides insights into new assessment practices that can help quantify affect-based trust by analyzing facial expressivity. Affect-based trust is an emergent attitudinal state in which the individual makes attributions about the motives of their robot partner[1,2] that can have a direct impact on comfort, satisfaction, and attitudes toward automation.[3] This is critical for future crew stations because each of these factors influences how and when we interact with autonomy-enabled systems.

There are two major outcomes from this research that advance the science in this domain and provide direct support to Army initiatives, including the Human Autonomy Teaming Essential Research Program and Army Modernization Priority Next Generation Combat Vehicle (NGCV). First, we developed a new method for grouping individuals prior to engaging in an autonomous driving scenario based on demographics, personality traits, response to uncertainty, and initial perceptions about trust, stress, and workload associated with interacting with automation. Analyses showed that these groups (rather than individuals) had unique differences in their reported state-based trust and consequently different patterns of facial expressivity while interacting with different levels and reliability patterns of automation. These findings suggest that trust calibration metrics may not be equally critical for all groups of people, meaning that trust-based interventions (e.g., changes in user display features, communication of intent, etc.) may not be necessary for all individuals, or may vary depending on group dynamics.

This report is a more complete version of our published research as part of the 3rd International Conference on Intelligent Human System Integration (IHSI): Integrating People and Intelligent Systems in Modena, Italy, 19–21 February 2020.[4]

[1] Burke C, Sims DE, Lazzara EH, Salas E. Trust in leadership: a multi-level review and integration. Leadership Quarterly. 2007;18:606–632. doi:10.1016/j.leaqua.2007.09.006.

[2] McAllister D. Affect- and cognition-based trust as foundations for interpersonal cooperation in organizations. Academy of Management Journal. 1995;38:24–59. doi:10.2307/256727.

[3] Schaefer KE, Chen JYC, Szalma JL, Hancock PA. A meta-analysis of factors influencing the development of trust in automation: implications for understanding autonomy in future systems. Hum Fact. 2016;58:377–400.

[4] Neubauer C, Gremillion G, Perelman B, La Fleur C, Metcalfe J, Schaefer-Lay K. How analysis of facial expressions explain affective state and trust-based decisions during interaction with autonomy aids. Proceedings of the 3rd International Conference on Intelligent Human Systems Integration: Integrating People and Intelligent Systems; 2020 Feb 19–20; Modena, Italy.

1. Introduction

While trust has been shown to be critical for effective teaming, the methods and metrics needed to assess team trust need to be more fully developed. The traditional measurement practices for evaluating general trust are primarily associated with subjective feedback (Yagoda and Gillan 2012; Schaefer et al. 2016), with some research supporting behavioral or performance-based response (Freedy et al. 2007). More recently, there has been a push for integrating wearable sensing of the human to identify psycho-physiological signal differences during an interaction (Marathe et al. 2018); however, part of the difficulty in identifying new trust metrics and measurement practices is that trust in human-autonomy teams is a complex process.

Through a large review of the literature, it has been found that there are six identified types of trust that impact human-autonomy teams: *trust propensity*, *trustworthiness*, *affect-based trust*, *cognitive-based trust*, *situational trust*, and *learned trust* (Schaefer et al. Forthcoming 2020). For this work, we are interested in identifying possible assessment metrics for evaluating *affect-based trust* within human-autonomy teams. Affect-based trust is an emergent attitudinal state in which the individual makes attributions about the motives of the automation (McAllister 1995; Burke et al. 2007). The reason for this specific focus is that newer autonomy-enabled technologies, such as automation-enabled driving aids, are being designed to help alleviate high-task demands that lead to negative emotional states, poor performance, or even dangerous decision-making strategies. Further, simulated driving tasks are capable of eliciting large-scale changes in affective response (Neubauer et al. 2010); therefore, simulated driving is a valuable domain to identify new assessment practices for affect-based trust.

The current work extends the state of the art by explicitly evaluating facial expressions in response to the level and degree of reliability of the automation during a leader–follower driving task. We seek to investigate the following two research aims: (**Aim 1**) quantify the effects of a simulated drive on facial expressivity in response to the level and reliability of the aid and (**Aim 2**) robustly model trust-based responses using multimodal data streams relating to subjective response, demographic and individual difference clustering, and facial expressivity.

2. Autonomous Driving Background

Army modernization is demanding increased implementation of driving automation, up to and including full autonomy, as a fundamental capability for Next Generation Combat Vehicles (Army Modernization Priority #2: NGCV; see Purtiman 2018). Though the implementation of driverless technologies has long been a goal of Army science and technology efforts, autonomous driving platforms have not enjoyed widespread integration into tactical ground-based platforms. In the civilian sector, however, the ever-increasing number of drivers on the road, along with added daily demands on our everyday lives, requires humans to juggle several tasks with limited bandwidth (often while driving). This inevitably results in an increase in the amount of traffic and roadway accidents.

As such, negative emotional states, such as stress and fatigue, can arise while driving. When fatigued, drivers may have difficulty regulating their emotional responses, especially in conditions where task-underload is present. Here, drivers may cope with low-task demands by withdrawing effort, resulting in a state of passive fatigue (Matthews and Desmond 2002; Desmond and Matthews 2009). Additionally, stress causes driver attention to narrow, which may interfere with concentration and appropriate decision-making and may lead to aggressive driving and distraction. The National Highway and Transportation Security Administration estimated that there were over 72,000 crashes involving drowsy drivers from 2009 to 2011 (National Center for Statistics and Analysis 2011), while the estimate of stress-related accidents remains unknown. For this reason, it is essential that active monitoring systems are developed to alert drivers of unsafe driving conditions. Within this domain, technologies relating to computer vision have long been employed for enhancing safe driving through detection and alerting systems for fatigue (Dong et al. 2011) and emotions relating to stress and impatience (Lisetti and Nasoz 2005; Nass et al. 2005).

Recently, there has been an increased push toward developing intelligent vehicles (Little 1997). One such technology that has become increasingly popular is the use of automation-enabled assisted driving aids. Examples of these systems include adaptive cruise control, hazard detection, and lane monitoring or correcting systems. It appears that such systems may promote safer driving by reducing a driver's workload and in turn decreasing stress and fatigue. However, it is also possible that these technological advances may result in poorer performance by decreasing task engagement (Hancock and Verwey 1997; Desmond et al. 1998) and shifting the driver's attention to personal discomfort and stress symptoms during full vehicle automation (Stanton and Young 2005; Neubauer et al. 2012). Additionally, prolonged automation use may reduce situation awareness, whereby reaction times may increase in response to unexpected events in the roadway (Young and Stanton 2002; Young and Stanton 2007; Saxby et al. 2013). Continuous automation use may be particularly dangerous when drivers quickly need to take back manual control of the vehicle in the case of automation failure (Desmond et al. 1998; Saxby et al. 2013; Neubauer et al. 2014). Finally, automation level and transparency are two factors that may leave the human feeling “out of control”, which may decrease situation awareness and, in turn, trust in the system.

Although the benefits and potential dangers of automation use in driving have been extensively researched (Desmond et al. 1998; Desmond and Hancock 2001; Young and Stanton 2007; Neubauer et al. 2012; Saxby et al. 2013; Neubauer et al. 2014), a further issue revolves around the adequate development and assessment of trust. As more of the functional tasks of daily life are being changed by the integration of autonomy-enabled systems, human-autonomy teaming will be commonplace. A misaligned level of trust in the system (i.e., when expectations do not match system behaviors) typically results in unnecessary or preemptive human intervention, essentially rendering the system ineffective (Parasuraman and Manzey 2010). Mitigating this effect, denoted as miscalibrated trust (Sarter et al. 1997), requires accurate estimation of underlying psychological traits and states that relate to trust, and trust-related decisions.

Many metrics to measure operator state exist and typically include questionnaire assessment; however, these are taken after an operator performs a task, requires them to remember how they felt in a given moment, and may reflect subjective bias. Additionally, unimodal streams of data may not accurately capture all aspects of an affective state or decision. Most of the published research on computer vision approaches to operator state detection have focused on fatigue assessment and typically relied on analyses focused on eye tracking and head movements (Gu and Ji 2004; Zhang and Zhang 2006; Dong et al. 2011). While the relationship between trust and facial expressivity has not been studied thoroughly during driving, we posit that these methods for measuring emotional response will provide more directed insight on understanding affect-based trust. This line of research is critical because it will be necessary to develop autonomy-enabled systems that can robustly perceive and respond to our emotions as we interact with them if human–agent teams are to be successful (Bartlett et al. 2004). In this context, it is vital that automated agents not only accurately perceive our affective state but also respond appropriately to avoid misinterpreting social cues during collaboration to improve decision-making and performance (Scheutz et al. 2006).

3. Method

The current study was conducted on an immersive 6-degree-of-freedom motion platform equipped with a full driving control interface and a three-screen visual presentation system at the US Army Combat Capabilities Development Command

(CCDC) Ground Vehicle Systems Center[*]. The following section describes the experimental design, participants, and measures used (see Fig. 1a for a view of the apparatus setup).

3.1 Experimental Design

A simulated leader–follower driving task was created using SimCreator (Real-Time Technologies, Royal Oak, Michigan), which allowed participants to operate a simulated vehicle on a two-lane closed-circuit roadway. During this drive, participants were instructed to safely navigate the roadway while avoiding collisions with all vehicles and pedestrians. Though the participants were not explicitly instructed to make any particular use of the driving automation (when available), they were encouraged to make their own decisions as to whether using the autonomous assistant would be beneficial to the goal of maintaining lane position and headway with respect to the lead vehicle. This joint human-automation driving task was conducted while simultaneously performing a secondary pedestrian classification button-press task (see Figs. 1b and 1c for roadway circuit and experimental display).

The design was a 2 *level of automation* (level 1 automated speed control only; level 2 full control of speed and steering) × 2 *automation reliability* (good; bad) within subjects design. Throughout this report, these four driving conditions are referred to as speed, good (SG) (i.e., level 1 speed control, high automation reliability); speed, bad (SB) (i.e., level 1 speed control, low automation reliability); full, good (FG) (i.e., level 2 full control of speed and steering, high automation reliability); and full, bad (FB) (i.e., level 2 full control of speed and steering, low automation reliability). In addition to the automated driving conditions, participants also completed one manual (no automation) drive as a baseline (referred to as the *MM* driving condition). The average drive time around the course for each condition lasted approximately 12 min. Full methods including additional information about participants, task descriptions, and all measures and procedures can be found in Drnec and Metcalfe (2016) and Gremillion et al. (2016).

[*] Prior to 2019, the CCDC Ground Vehicle Systems Center was referred to as the US Army Tank and Automotive Research, Development and Engineering Center.

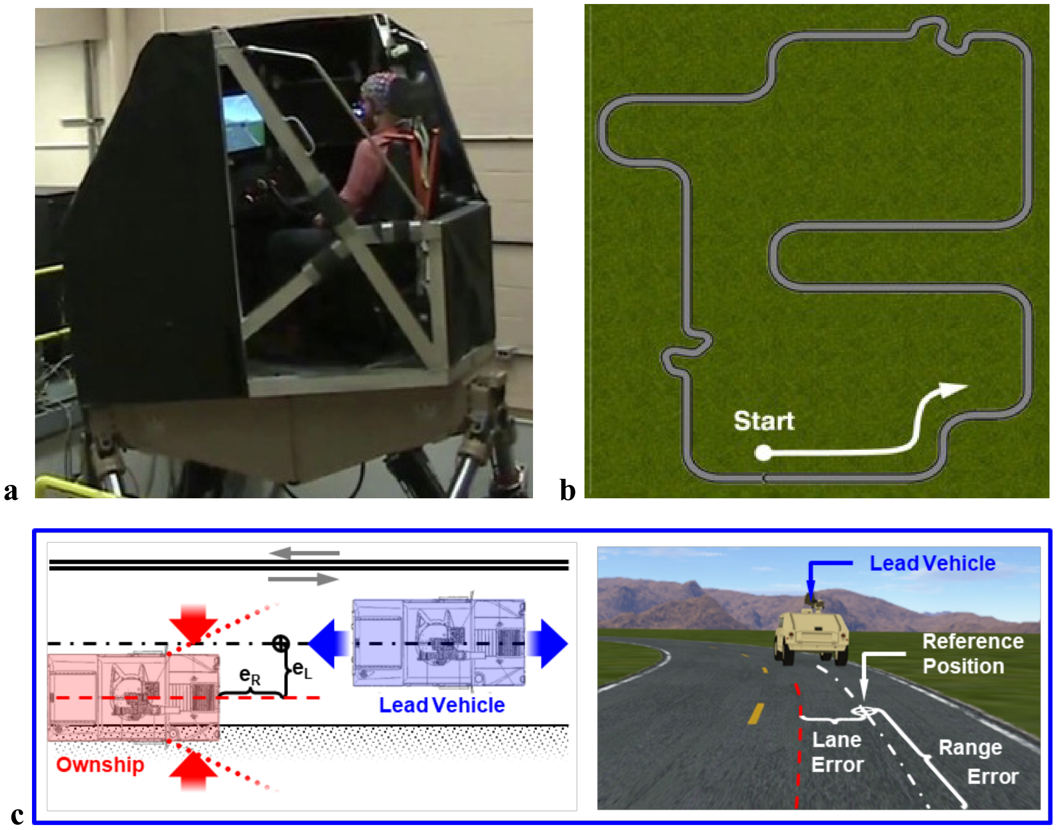

Fig. 1 (a) Ride Motion Simulator; (b) simulated roadway circuit; (c) example view of leader–follower simulation trajectory and participant view of display, respectively

3.2 Participants

Twenty-four participants, ages 18–65 years with normal-to-corrected vision to normal vision were recruited. Only participants who had completed all sections of data collection were included for this analysis, resulting in a sample size of 19 participants.

3.3 Measures

The larger intention of the paradigm from which the data were obtained was to develop a robust set of measures that could detect online changes in the human drivers of trust in the driving automation. Given that trust is subject to significant individual differences, it was deemed important to record a variety of measures spanning the range from subjective self-report to objective behaviors as well as the intervening physiological indicators of the underlying psychological processes. For a full discussion and rationale behind the paradigm design and measures, see Drnec and Metcalfe (2016) and Metcalfe et al. (2017). The following descriptions are those included in data analysis for this report; however, this set does not comprise all variables that were recorded per the study design.

1. *Demographics:* Although several demographics were collected, only age is reported due to the results of the cluster analysis.
2. *Personality*: The Big Five Inventory (BFI) is a 44-item questionnaire that indexes personality traits relating to extraversion, openness to experience, agreeableness, conscientiousness, and neuroticism (John et al. 1991; 2008).
3. *Uncertainty*: The Uncertainty Response Scale (URS) is a trait measure that contains 48 items designed to predict individual differences in coping with uncertainty (Greco and Roger 2001). The URS has three subscales: Emotional Uncertainty (EU), Desire for Change (DFC), and Cognitive Uncertainty (CU).
4. *Trust*: Two scales were used to measure trust—a four-item version of the Muir and Moray trust scale (Muir and Moray 1996) and the Checklist for Trust in Automation (Jian and Bisantz 1998).
5. *Workload*: The NASA-Task Load Index (NASA-TLX) is a standard measure of subjective workload based on ratings of task demands and is widely used in human performance research (Hart and Staveland 1988).
6. *Stress*: The Stress Visual Analogue Scale (SVAS) is a one-item analogue scale to identify task-based stress.
7. *Analysis of Facial Expressivity*: The participant's face was continuously recorded throughout the task via a webcam mounted to the simulation screen. Measures relating to emotional expression were automatically extracted through the OpenFace freeware (Baltrušaitis et al. 2018). More specifically, OpenFace yields frame-by-frame evidence of facial action unit (AU) evidence, which corresponds to specific muscle movements of the face. Facial expressions relating to both positive and negative affect (i.e., emotions such as happiness, sadness, surprise, fear, anger, and contempt) were calculated on a frame-by-frame basis separately for each task, using computations of single AU evidence following the Facial Action Coding System (Ekman and Friesen 1978). Table 1 outlines the specific AUs needed to calculate each universal emotion.

Table 1 Facial expression emotion calculation from single AUs (Ekman and Friesen 1978)

Emotion classification	Action units
Anger	4+5+7+23
Contempt	R12A+R14A
Disgust	9+15+16
Fear	1+2+4+5+7+20+26
Happiness	6+12
Sadness	1+4+15
Surprise	1+2+5B+26

3.4 Clustering Approach

It is known that individual differences impact trust development (Schaefer and Scribner 2015; Schaefer et al. 2016); however, how the understanding of individual differences should (or should not) directly feed into the trust calibration process is unknown. Given the current state of the literature in this domain, it is difficult and in many cases impossible to completely individualize trust-based interventions when working with autonomy-enabled systems. Because of this, we employed a model-based clustering method to determine the trust-based patterns that emerge over subgroups of people in our sample rather than individuals. The process described here provides a data-driven means to infer clusters of participants within datasets. This analysis approach provides an attractive alternative to k-means clustering and related approaches since the analysis does not require a priori knowledge of underlying groups and can work with a relatively small sample size (see Perelman et al. 2019).

We employed a mixture modeling approach aimed at revealing subgroups within our sample, defined by their traits and state responses to experimental stimuli. This statistical technique was selected on the basis that it defines these subgroups in a data-driven fashion; this is a contrast to traditional experiment design in which groups are experimenter-defined. Flexible mixture modeling (FMM) fits a mixture of Gaussian models to the data using expectation maximization (E-M) iteratively by minimizing a criterion value. Because mixture models are inherently probabilistic, they are amenable to Bayesian analyses. Specifically, when these models are generated in a stepwise fashion (i.e., stepwise FMM), exploring a range of mixture models containing different numbers of components, the resulting mixture models can be compared to one another to prevent overfitting.

We used an implementation of stepwise FMM from the R Flexmix package (Leisch 2004; Gruen and Leisch 2007). First, we selected a wide range of data upon which to cluster participants, including participant demographics (age), personality traits (BFI), response to uncertainty (URS), baseline perceived trust (both trust scales), workload (NASA-TLX), and subjective stress response (SVAS). Second, we selected a model driver that was specifically designed to handle continuous data (adapted from Tan and Mueller 2016). Next, we generated mixture models containing 1 through *n*-1 components. Fixed variance in the process was set relatively low (σ = 0.1), and 200 E-M iterations were permitted to ensure convergence to an acceptable solution. Finally, we compared all of the resultant mixture models, which contained a range of components, on the basis of Bayes Information Criterion (BIC), which balances the model fit against the number of components. This process allowed us to determine the number of underlying subgroups present in the data, without specifying an overly complex model or overfitting the data.

4. Results

This section includes results of the flexible mixture modeling approach to clustering, and the associated changes in trust ratings and results relating to global changes in facial expressivity according to group cluster and driving condition.

4.1 Clustering Analysis

Results of the clustering analysis indicated that the participant sample was best described by four distinct groups indicated by the Akaike Information Criterion, BIC, and Integrated Completed Likelihood values (Fig. 2).

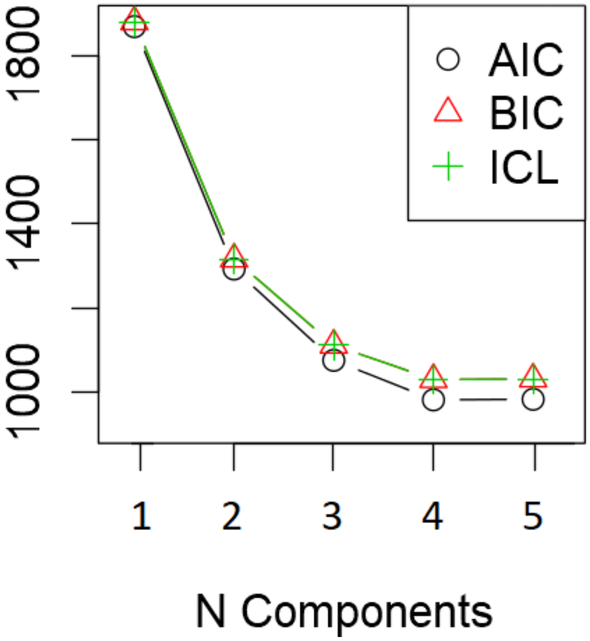

Fig. 2 Scree plot for cluster analysis, indicating that the participant sample was best described as four distinct groups

The final four clusters are depicted in Fig. 3. In describing these clusters, terms such as “average”, “higher”, or “lower” refer to the value relative to the sample mean and do not reflect any normative values reported in other studies.

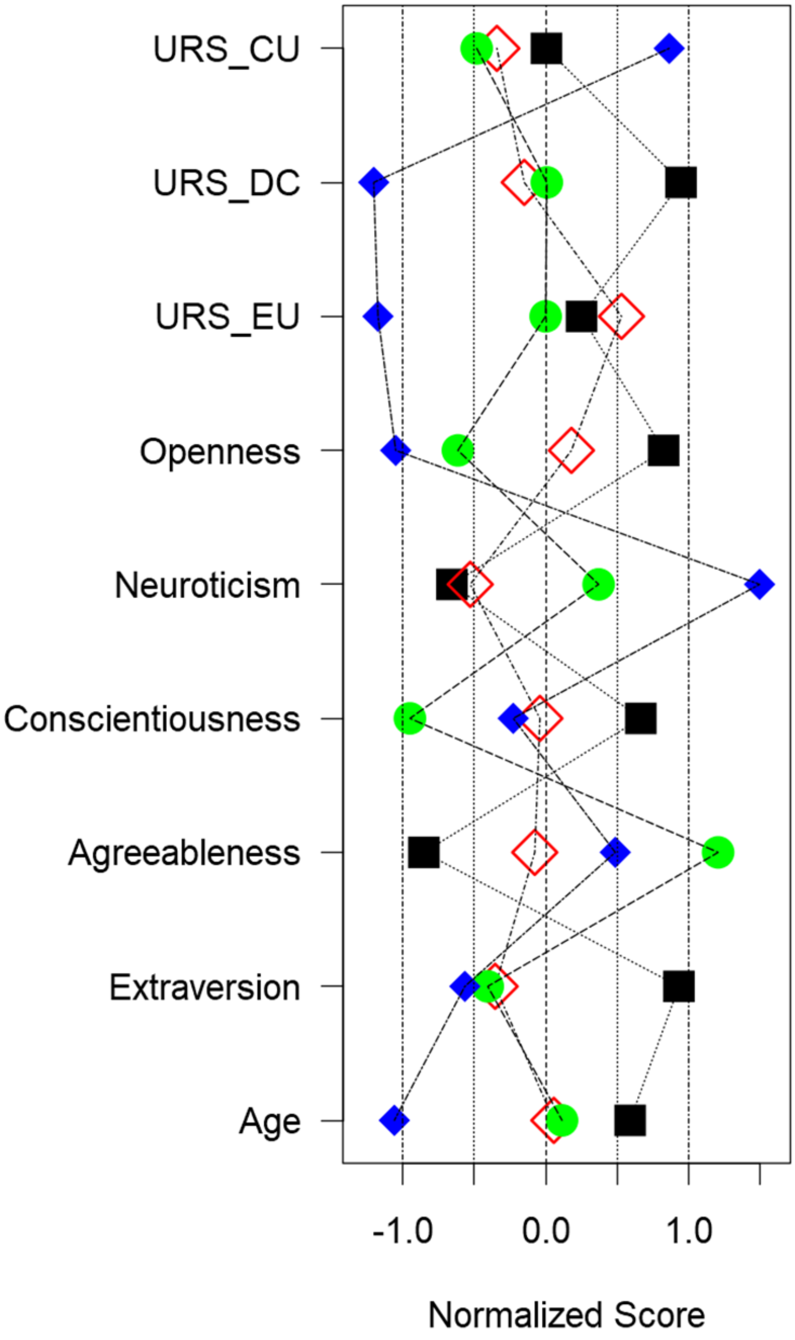

Fig. 3 Participants’ Z-scores for various characteristic traits, averaged by cluster

Cluster 1 (black squares) was representative of the oldest participants in the sample (though these participants were still relatively young relative to traditional age-related trust effects) with a high DFC, high openness, extraversion, and conscientiousness (N = 6). Tied with their low neuroticism scores, we expect this group to be novelty-seeking, be less impacted by stress or workload, and thus be more willing to accept and trust automation. When identifying trust calibration metrics, we expect members of this group to use the automation and be willing to hand off and take away control, but they may be prone to overtrust.

Cluster 2 (red diamonds) was relatively average on nearly all of the dimensions in the analysis (N = 6). However, this group did exhibit the highest EU in the sample, indicating a potential for maladaptive emotional and anxious responses to uncertainty. Therefore, we expect to see higher anxiety-based ratings in the facial data. For trust calibration metrics, we expect to see a greater negative trust response when the reliability of the automation is low.

Cluster 3 (green circles) was relatively average across most dimensions (N = 3). However, this group reported extremely low CU and conscientiousness but had high agreeableness suggesting a high preference for predictable, planned behavior but some willingness to give automation a chance. Based on this clustering, we would expect this group to exhibit more stress and workload with bad automation and thus lower trust, but less stress and workload with good automation and thus higher trust.

Cluster 4 (blue solid diamonds) was the youngest in the sample and reported extremely polarized scores on several key scales (N = 4). This group reported the lowest DC and EU scores, indicating that they do not seek novelty and would not respond emotionally to uncertainty. However, they reported the highest CU, indicating that they prefer predictability and structure in uncertain conditions. This coincided with this cluster's neuroticism scores, which were the highest in the sample. We expect this group to have higher stress and workload while interacting with automation and to exhibit a general negative response to automation.

For illustrative purposes of our data analysis, in Figs. 4–10 we have tried to depict differences among clusters according to their color grouping classification (e.g., Cluster 1 [Black], Cluster 2 [Red], Cluster 3 [Green], and Cluster 4 [Blue]).

4.2 Effect of Trust, Stress, and Workload

The mixed effect models described in this section were conducted in R (R Core Team 2016) using the lme4 package (Bates et al. 2015). Both trust measures (Muir and Moray 1996; Jian and Bisantz 1998) were analyzed and showed similar patterns of predicted changes in trust from the base condition across the type and reliability of the automation for each cluster (Fig. 4).

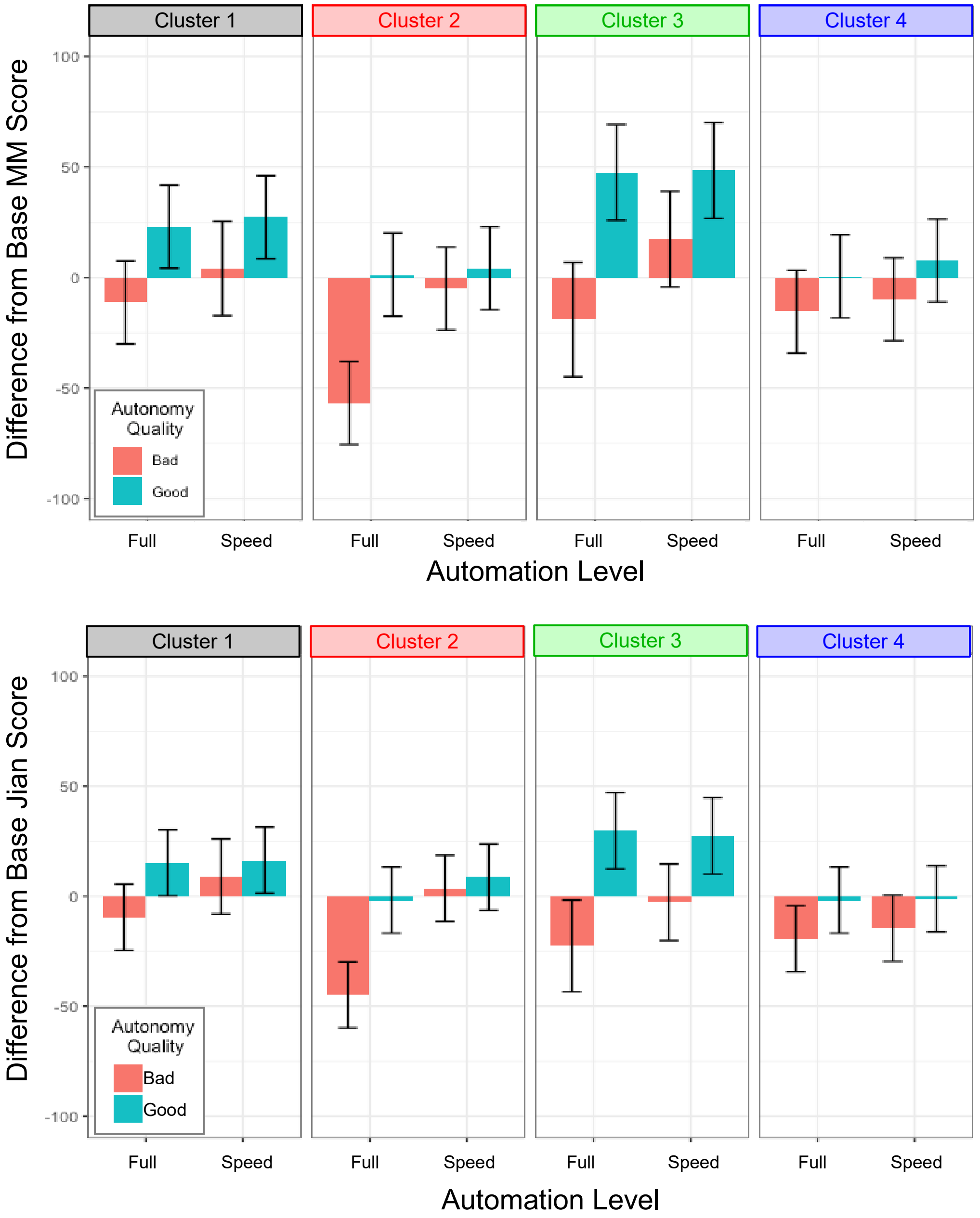

Fig. 4 Differences from baseline trust as a function of cluster, automation level, and automation reliability using the Muir and Moray trust questionnaire (top) and the Checklist for Trust in Automation (bottom). Error bars are 95% confidence intervals.

For both trust scales, automation reliability was a significant predictor of change in reported trust, χ^2 (1) = 9.37, p = 0.002 (Muir and Moray 1996), and χ^2 (1) = 7.08, p = 0.008 (Checklist), whereby the mean difference from baseline trust improved with good automation and decreased with bad automation. When analyzing the clusters, the Muir and Moray trust scale showed a significant interaction between automation reliability and cluster, χ^2 (3) = 10.73, p = 0.013 and automation level and cluster, χ^2 (3) = 9./84, p = 0.020. The checklist also showed a significant interaction between automation level and cluster, χ^2 (3) = 11.67, p = 0.009, but only a borderline significant interaction between automation reliability and cluster, χ^2 (3) = 7.28, p = 0.064. All other predictors were nonsignificant, p's > .10.

Follow-up analyses were conducted to determine specific differences between the clusters. Cluster 1 showed higher trust in good automation but had less negative response to bad automation. Cluster 2 had a stronger negative trust reaction to bad automation, especially when in the full automation condition, which identifies maladaptive anxiety responses to uncertainty. The patterns in trust-based response for Cluster 3 resulted in higher trust with good automation, but the results also show a trust degradation when the pattern of behavior becomes less predictable, as in the bad full automation condition. Finally, Cluster 4 showed an impact of bad automation on trust degradation, which corresponds with the high CU and neuroticism scores and general negative response to automation.

We then examined whether cluster (1–4), automation level (Speed, Full), and automation reliability (Good, Bad) predicted changes in stress from the baseline condition using the SVAS questionnaire. The best-fitting model included a fixed effect for cluster, automation level, and automation reliability and a random effect for participants, as shown in Fig. 5. However, the only significant predictor was the cluster, χ^2 (3) = 9.67, p = 0.022. Overall, the patterns suggest that for that individuals in Cluster 2, stress increased with the presence of automation. In contrast, for Cluster 3, stress generally decreased with automation. There was not a significant change in stress for Clusters 1 and 4.

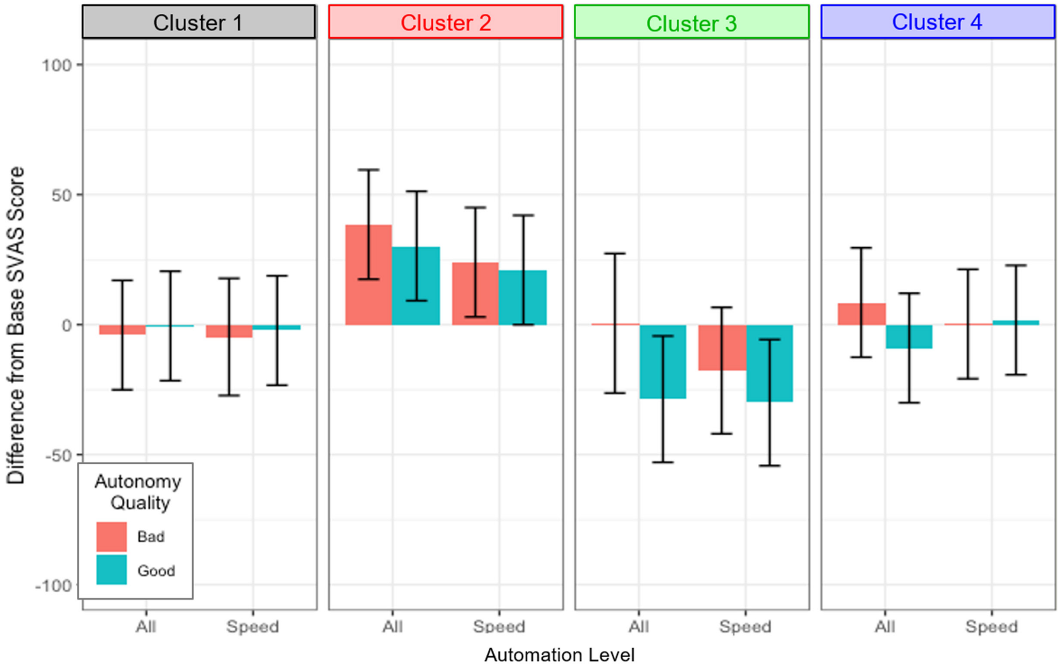

Fig. 5 Differences from baseline stress using the SVAS questionnaire as a function of cluster, automation level, and automation reliability. Error bars are 95% confidence intervals.

Finally, we examined whether corresponding changes from the baseline condition would be found in participants' self-reported workload using the NASA-TLX questionnaire. As with the SVAS models, the best-fitting model included a fixed effect for cluster, automation level, automation reliability, and a random effect for participants, as shown in Fig. 6. Automation reliability was a borderline significant predictor of change in workload, χ^2 (1) = 2.91, p = 0.09. Perceived workload tended to decrease with good automation and increase with bad automation, although the changes were small.

There was also a significant interaction between automation level and cluster, χ^2 (3) = 12.37, p = 0.006. Although the change in workload from baseline did not significantly differ based on automation level for any of the clusters, Cluster 2 participants reported an increase in workload for the FB condition that is significantly greater than zero. This fits with previous findings that Cluster 2 had maladaptive responses to emotional uncertainty, resulting in lower trust, higher stress, and higher workload.

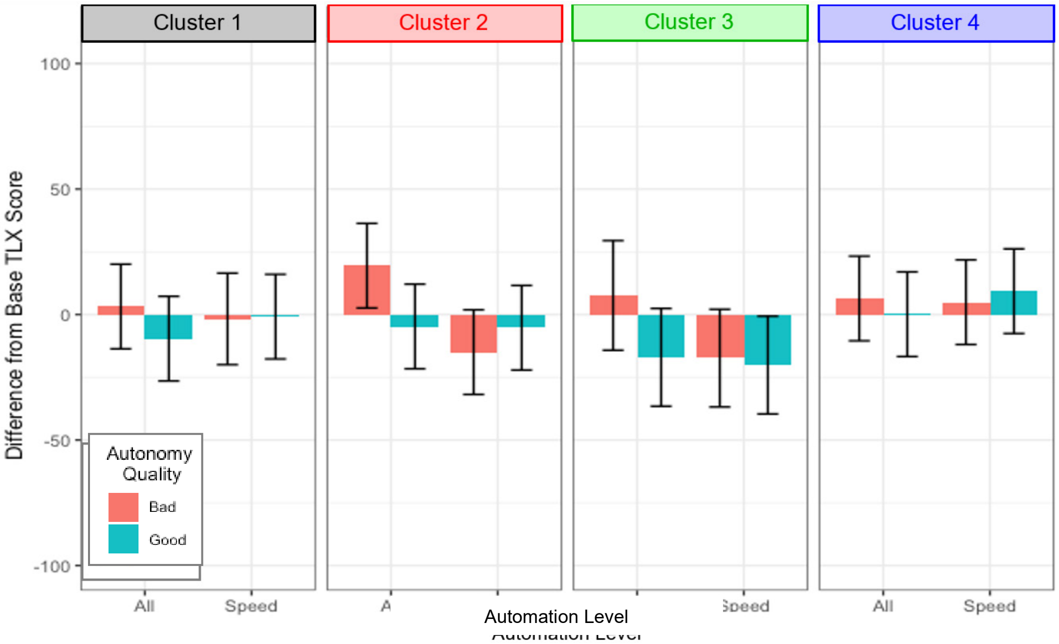

Fig. 6 Differences from baseline workload using the TLX questionnaire as a function of cluster, automation level, and automation reliability. Error bars are 95% confidence intervals.

Overall, there is a relationship between trust, stress, and workload within human-autonomy teams. Previous research tends show an increase in trust when stress and workload decrease. The patterns in our analyses provide a more in-depth understanding into this relationship. It is clear that the relationship is not a one-to-one correspondence, but rather a more complex interaction that can be more prominent in certain people and not others. In particular, more extreme changes in trust, stress, and workload are identified in Clusters 2 and 3. For Cluster 2, results showed that adding any type of automation led to an increase in stress, but also that a degradation of trust and increase in workload were only significant in the full automation, bad condition. These findings directly correspond to maladaptive anxiety responses to uncertainty. For Cluster 3, results showed that adding any type of automation reduced stress. There were also patterns of lower workload and higher trust, except for the full, bad automation condition. Results are in line with the cluster analysis that suggests a high preference for predictable, planned behavior but some willingness to give automation a chance.

4.3 Analysis of Facial Expressivity

Our last analysis focused on analyzing mean facial expressivity as a function of group clustering, automation type, and reliability. In the previous section, results of the subjective trust showed different patterns of trust for each of the four clusters, while stress and workload data indicated differences in responses for participants in Clusters 2 and 3. In regard to our analysis of differences in facial expressivity, results of interest point to differences in Clusters 1 and 3 (Fig. 7). Here, participants in Cluster 1 had higher average expression values than all other clusters, with significantly higher values of happiness and contempt than all other clusters, which was likely due to their having the highest extraversion scores and generally positive subjective response to automation (with the exception of the FB driving condition). Members of Cluster 3 yielded generally lower mean expression values than other clusters, with significant differences in mean values of anger, fear, and surprise than all other clusters, which concurs with their low conscientiousness and high agreeableness scores and higher trust with good automation reliability ratings. While no significant trend was found between the mean expressivity values and driving condition, it can be posited that the increases in anger, fear, and surprise were correlated with deviations from predictable, planned behavior of the automation.

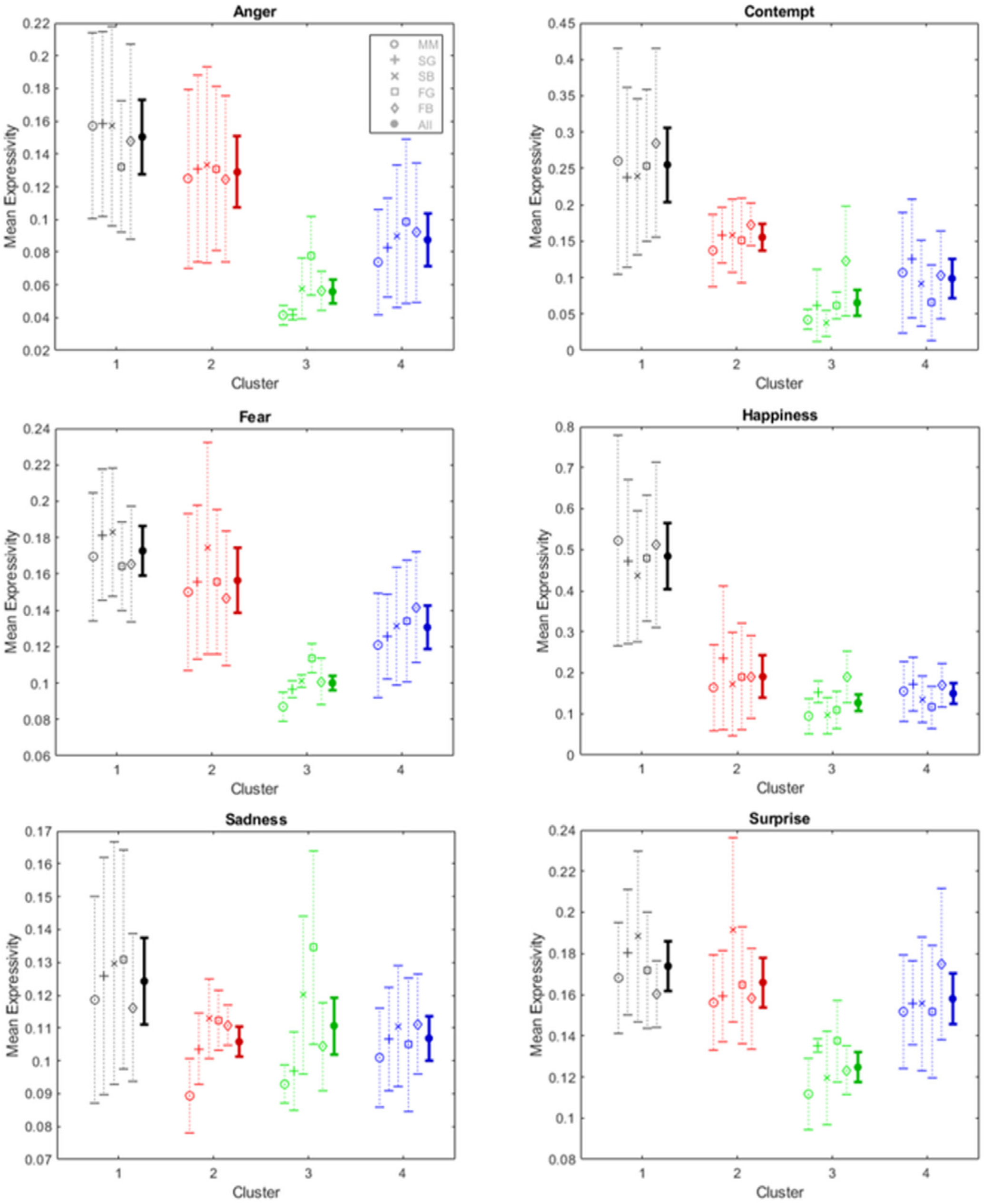

Fig. 7 Mean values are depicted for the six facial expressions calculated for the duration of the experimental drive within the four clusters. Values taken within each condition are shown in order of the MM, SG, SB, FG, and FB driving conditions. The rightmost (bold) values for each cluster correspond to the overall mean computed across conditions. Error bars are standard error.

Next, we looked at any differences between relative levels of facial expressivity that were exhibited during periods when participants were engaged in human (e.g., no automation) or automated driving (Fig. 8) and where participant driving violations occurred (Fig. 9). We refer to "driving violations" as any instance where points were deducted from the subject's score. Violations were labeled as "position violations” (i.e., deviations from the participant’s lane position and following distance tolerances lasting more than 3 s) as well as collisions with pedestrians or other vehicles. Additionally, when looking at the following figures, it is imperative to note that the distance of these mean values from the plot origin indicates the overall magnitude of the expression. In other words, the degree to which these values lie above or below the 45° line (dotted) indicates whether greater expressivity was seen during human (x-axis) or automated driving (y-axis), respectively.

We first separated our analysis to illustrate individual facial expression magnitude during human and automated driving for all driving conditions and across group cluster. From Fig. 8, it is evident that the positions of mean happiness and contempt for each cluster indicated relatively even expressivity between instances of human and automated driving, while the relative expressivity between human and automated driving appears to vary significantly among the clusters for the other expressions. Specifically, the expressions of anger and fear, for members of Cluster 1, are above the 45° line, indicating a relatively higher mean expressivity during human rather than automated driving. This conforms to expectations that Cluster 1 would be most willing to accept and trust automation, possibly to the point of overtrust, yielding relatively higher levels of anger and fear when in control of driving themselves than during automated driving.

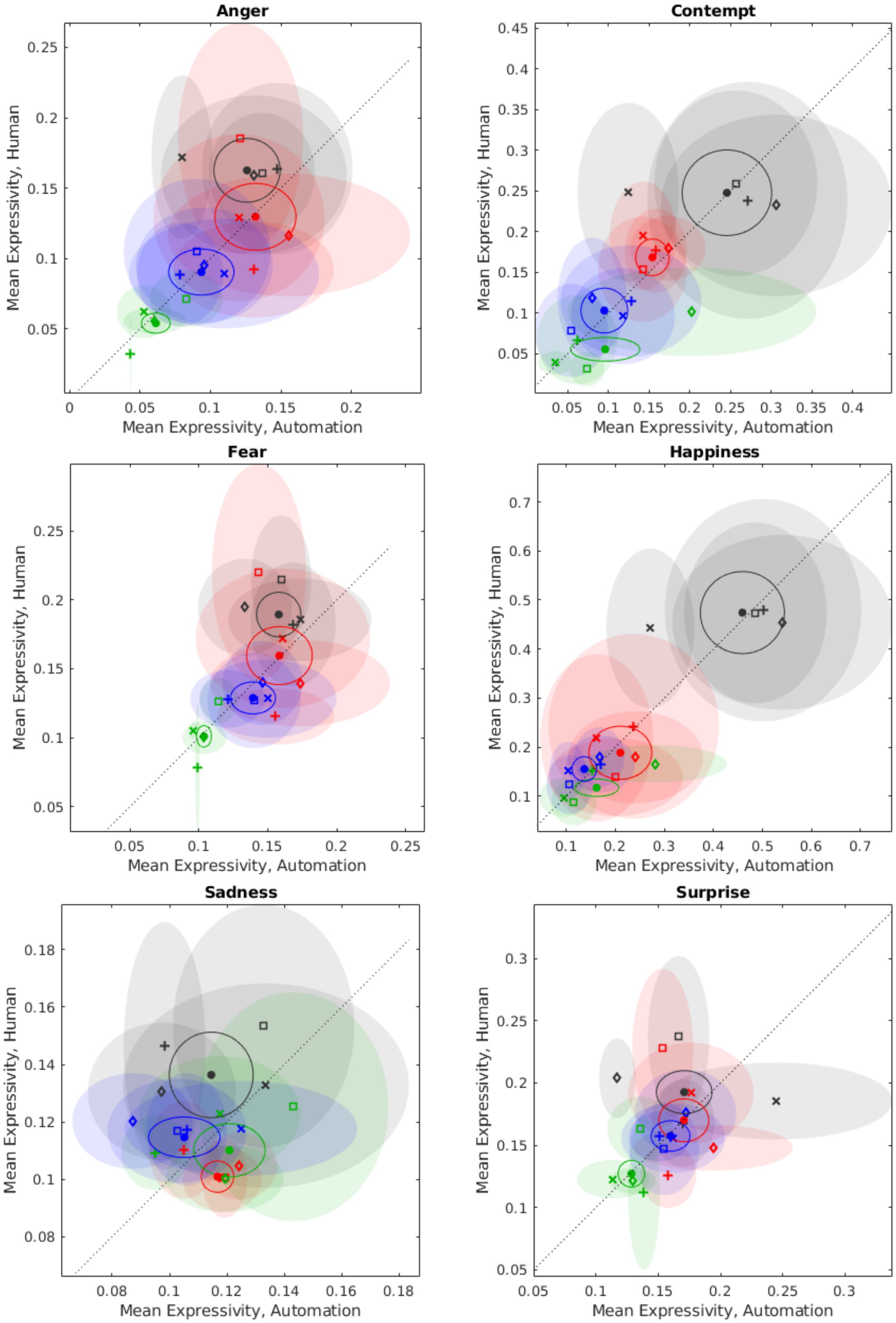

Fig. 8 Comparisons between the automation (x-axis) and human driving (y-axis) mean facial expression values within clusters. The distance of these mean values from the plot origin indicates the overall magnitude of expression. Mean values are shown within each condition and across all conditions by the respective markers. Major axes of the ellipses are respective standard errors for the mean within conditions (shaded) and across driving conditions (solid outline).

Further, the position of the cluster means for expression shows generally greater similarity between Clusters 1 and 2 with higher expressivity, and greater similarity between Clusters 3 and 4 with lower expressivity. However, as shown in Fig. 9, the position of the cluster means for violation rates instead show similarity between Clusters 1 and 4 with more frequent violations, and similarity between Clusters 2 and 3 with less frequent violations. Additionally, Cluster 1 (black) displayed higher magnitudes of expressivity during these periods of driving than the members of the other clusters, generally consistent with the results from Fig. 7. This illustrates that expression responses are not directly tied to performance rates and are more likely moderated by subject characteristics captured in their questionnaire responses, which delineate them by cluster.

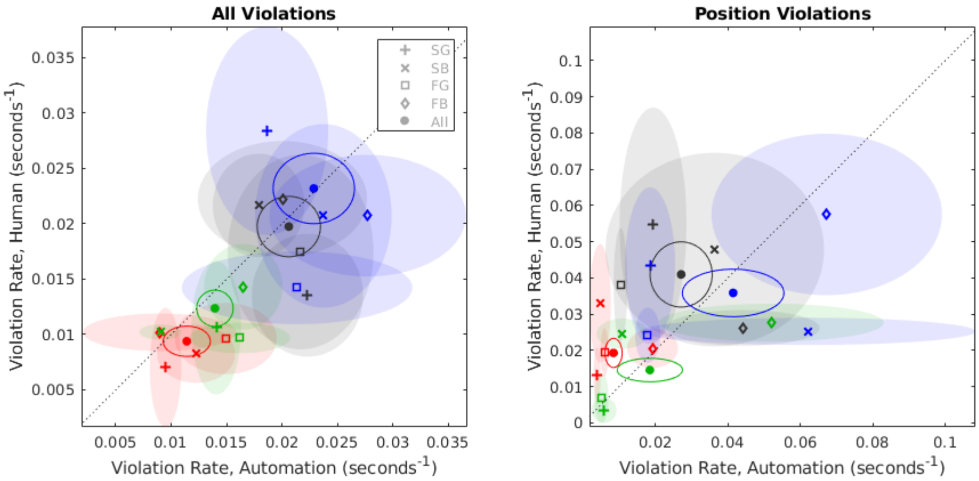

Fig. 9 Comparisons between the magnitudes of facial expressivity exhibited during periods of automation (x-axis) and human driving (y-axis) within clusters. The distance of these mean values from the plot origin indicates the overall magnitude of expression. Mean values are shown within each condition and across all conditions by the respective markers. Major axes of the ellipses are respective standard errors for the mean within conditions (shaded) and across driving conditions (solid outline).

Finally, we looked at time-dependent trends that differed between members of the four clusters (Fig. 10). More specifically, this figure illustrates emotional responses for a 10-s window around events of interest (i.e., violations and authority toggles, either hand-offs or takeaways), averaged across all instances exhibited by members within each cluster. From this figure it is most notable that Cluster 2 had the strongest expressive reactivity to violations, which aligns with our expectation to see maladaptive anxiety responses to uncertainty and greater negative trust response to instances of low reliability. Cluster 4 showed the most expression reactivity to toggles of driving authority to the automation (hand-offs) and from the automation (takeaways), which corresponds with expectations of higher stress and workload while interacting with, and greater negative response to, automation.

Finally, subjects in Cluster 3 demonstrated relatively low expressive reactions to either authority toggles or violations, which again concurs with their low conscientiousness and high agreeableness scores. Overall, these findings indicate that expressivity between human and automated driving varied significantly among the clusters for each expression, which has implications for individual trust calibration and appropriate intervention development.

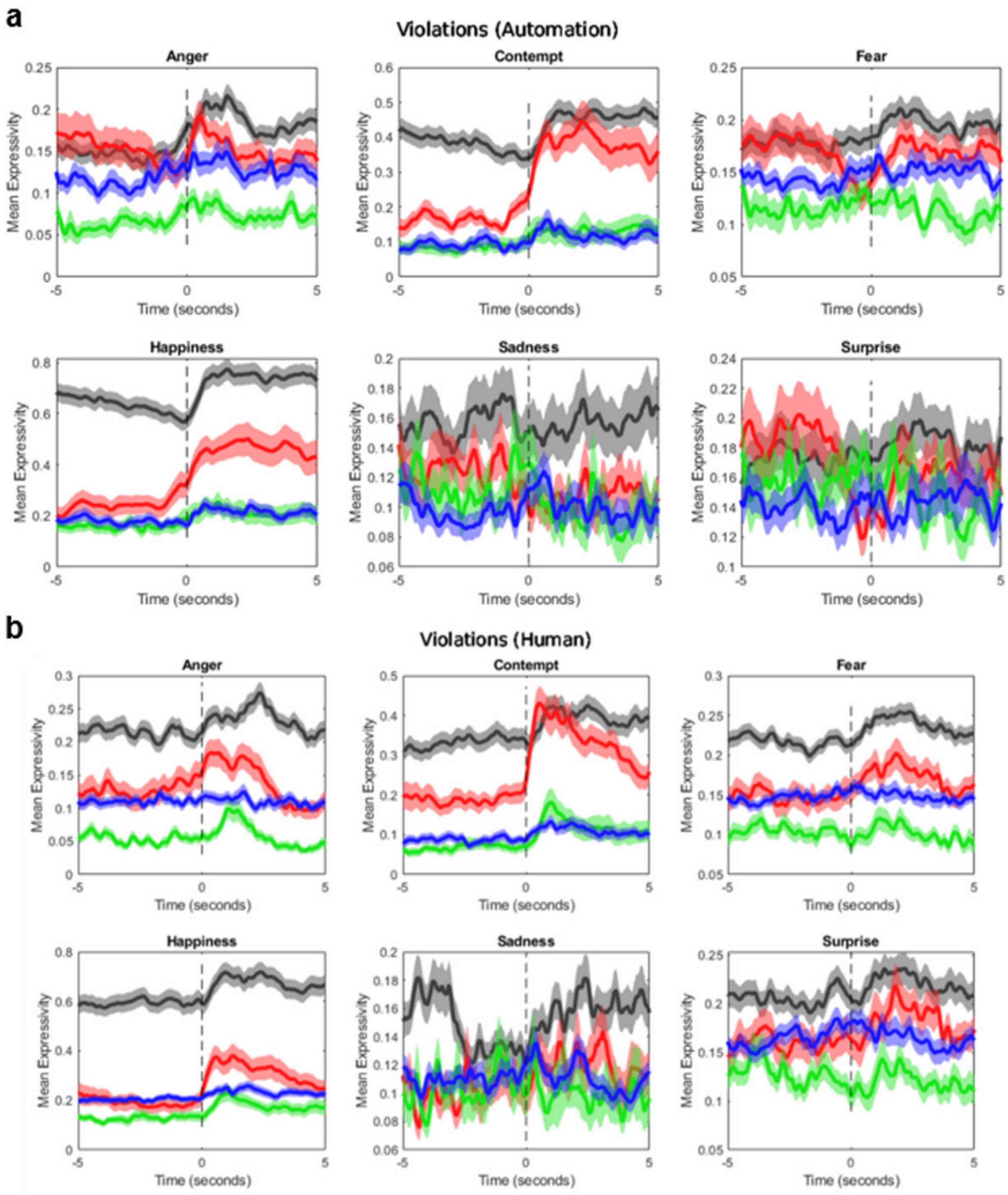

Fig. 10 Event-locked time histories for the six expressions in 10-s windows centered on instances of a) violations during automation driving, b) violations during human driving, c) hand-offs, and d) takeaways. Solid curves are averaged values across all conditions for subjects within the four clusters. Shaded bands are standard errors. The color of each time history corresponds, respectively, to Cluster 1 (black), Cluster 2 (red), Cluster 3 (green), and Cluster 4 (blue).

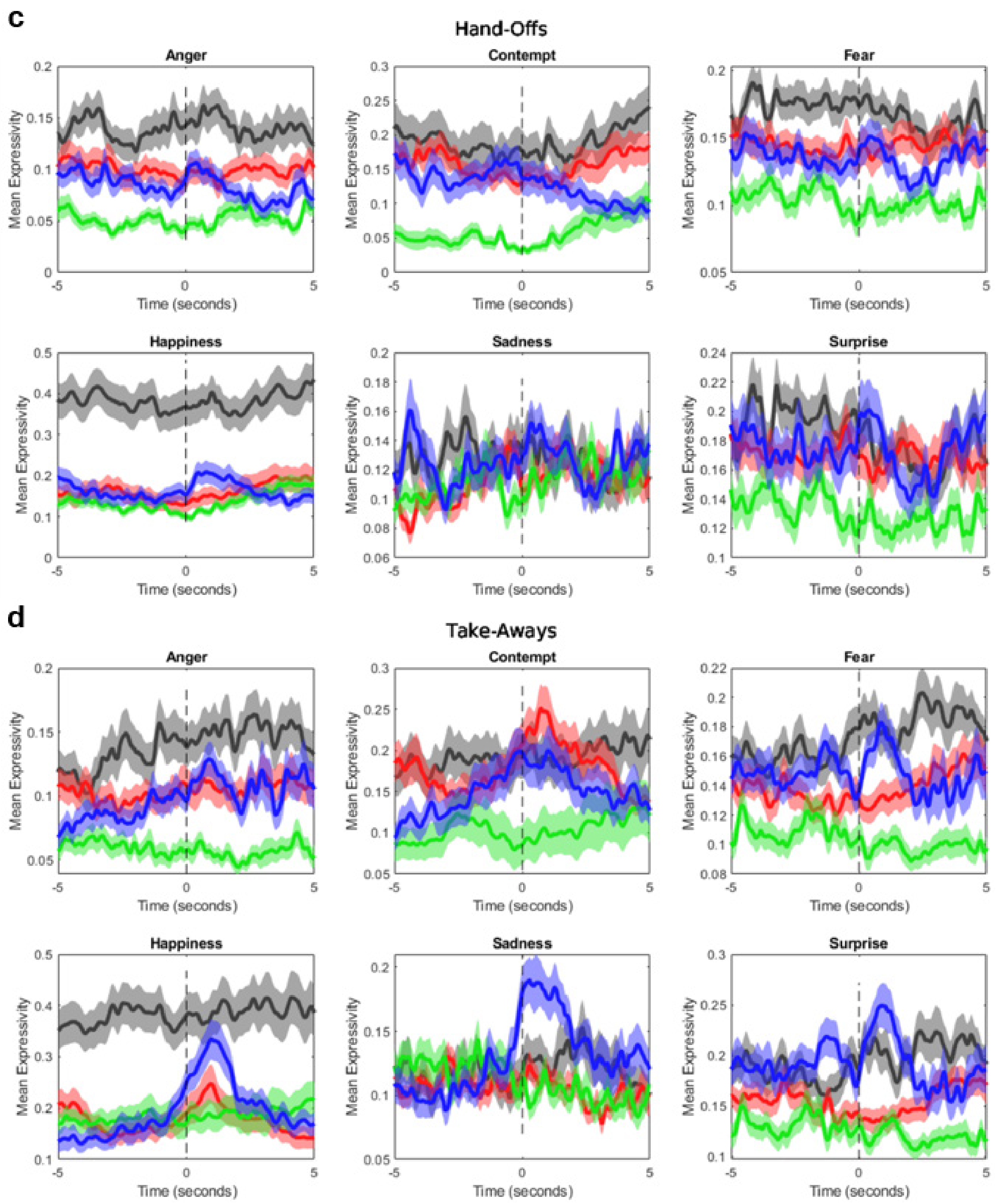

Fig. 10 Event-locked time histories for the six expressions in 10-s windows centered on instances of a) violations during automation driving, b) violations during human driving, c) hand-offs, and d) takeaways. Solid curves are averaged values across all conditions for subjects within the four clusters. Shaded bands are standard errors. The color of each time history corresponds, respectively, to Cluster 1 (black), Cluster 2 (red), Cluster 3 (green), and Cluster 4 (blue) (continued).

5. Conclusions

In this report we were interested in identifying possible assessment metrics for evaluating affect-based trust within human-autonomy teaming. Results of our clustering analysis indicated that the participant sample was best described by four distinct groups who varied in their level of subjective trust and facial expressivity across the different drives. Convergent results from the cluster analysis of the trust questionnaires and mean facial expressivity values showed that there are indeed different patterns of response by different groups of people. It is not enough to look at single individual difference ratings in isolation, but rather the variance is dependent on an interplay of multiple features. It is often stated that for appropriate trust to be developed and effectively calibrated, an individual's expectations need to match the system's actual behaviors. What this research shows is that calibration metrics will not be the same for all people. In these cases, certain groups may be more prone to overtrust in automation (as seen in Cluster 1's high levels of baseline trust) compared to a misaligned level of trust in automation from the start (as seen in Cluster 4's somewhat moderate to low levels of baseline trust). These findings may impact intervention plans for individuals who engage in human-autonomy teaming and should consider the following: 1) we should not expect the same results regarding individual propensities to trust, subjective response to automation interaction, and overt behavioral responses from all individuals, 2) multivariate methodologies focusing on grouping individuals can illuminate informative clusters of individuals, and 3) interventions that use these clustering methodologies will need to account for psychological dynamics and behavioral responses that vary qualitatively and quantitatively between individuals. For example, Cluster 1 interventions will require the expectation that these individuals may overtrust the automation, while also expressing strong outward changes in facial expressivity, while Cluster 4 interventions should account for a bias against automation to begin with and limited facial expressivity responses during an interaction with automation.

Additionally, significant differences were found regarding subjective responses for each group cluster and changes in facial expressivity. We will attempt to outline and summarize these differences according to the four clusters previously described.

Cluster 1: Tied with their low neuroticism, stress, and workload scores (i.e., no difference from baseline), we expected this group to be novelty-seeking and thus more willing to accept and trust the automation. When identifying trust calibration metrics, we expect members of this group to use the automation and be willing to hand off and take away control, but they may be prone to overtrust (as shown in their higher trust ratings during good automation reliability and less negative response to bad automation comparatively). This group also exhibited the highest levels of facial expressivity (e.g., specifically for expressions relating to happiness and contempt), which may be expected from their high extraversion scores. This shows some validation, or at least a plausible and consistent connection, between the questionnaire responses and the measurement of behavioral response. More specifically, inferences based on real-time measures can or should be calibrated to have expected ranges based on baseline questionnaire responses (i.e., evidence of high facial expressivity should not be solely dependent upon the task stimuli, particularly for a subject with high extraversion scores). Additionally, as outlined in Fig. 8, for the expressions relating to anger and fear, data for Cluster 1 are above the 45° line, indicating that these expressions were stronger or more frequent during instances of human driving than automated driving. Given proneness to reliance on the automation and a willingness to accept and trust autonomy, this result suggests trust for this cluster was miscalibrated in the direction of overtrusting the automation.

Cluster 2: This group exhibited that highest EU in the sample, indicating a potential for maladaptive emotional and anxious responses to uncertainty. Therefore, we expected to see higher anxiety-based ratings in the facial data. For trust calibration metrics, we expected to see a greater negative trust response when the reliability of the automation was low. This was confirmed from Cluster 2's increase in subjective stress and workload and stronger negative trust reaction to full automation with bad reliability. This group also had the strongest expressive reactions to violations (e.g., specifically for emotions relating to anger, contempt, fear, and surprise), which is indicative of their potential for maladaptive anxiety responses to uncertainty. When compared with their relatively low rate of violations, these factors suggest that this cluster experienced miscalibrated trust in the form of undertrust.

Cluster 3: Reports of CU and conscientiousness were extremely low in Cluster 3; however, high agreeableness was also reported, suggesting a high preference for predictable, planned behavior but some willingness to give automation a chance. Based on this clustering, we expected this group to exhibit more stress and workload with bad automation and thus lower trust, but less stress and workload with good automation and thus higher trust, which was somewhat confirmed. Here, the patterns in trust-based response for Cluster 3 resulted in higher trust and lower workload with good automation, but the results also showed a trust degradation and increased workload when the pattern of behavior becomes less predictable, as in the bad, full automation condition. This group also exhibited relatively low expressive reactions to either authority toggles or violations, which in conjunction with their appropriately balanced evaluations of trust in the automation with respect to the level of reliability and their overall lower violation rate, suggest this group’s trust level was calibrated best relative to the other clusters.

Cluster 4: This group was the most polarized and reported the lowest DC and EU scores, indicating that they do not seek novelty and would not respond emotionally to uncertainty. However, they also reported the highest CU, indicating that they prefer predictability and structure in uncertain conditions. This coincided with this cluster's neuroticism scores, which were the highest in the sample. In fact, the subjective responses for Cluster 4 showed an impact of bad automation on trust degradation, which corresponds with the high CU and neuroticism scores and general negative response to automation. Cluster 4 also demonstrated the greatest changes in expressivity to toggles of driving authority away from the driving automation, which comports with their proneness to stronger negative trust-based reactions to bad automation and their relatively poor performance.

Outcomes from this work have shown that expressive response is not uniformly related to performance or even to interactions with the automation, even at granular, time-resolved scales, across all subjects. These responses instead form more consistent patterns when subjects are grouped based on their characteristic traits. Overall, we believe the current work extends the state of the art by explicitly evaluating facial expressions in response to level and degree of reliability of automation during a leader–follower driving task. Although more work is needed, we believe that the methods outlined here provide a way to systematically group, evaluate, and eventually predict individual behaviors relating to affect-based trust within human-autonomy teams.

6. References

Baltrušaitis T, Zadeh A, Lim YC, Morency L-P. OpenFace 2.0: facial behavior analysis toolkit. IEEE International Conference on Automatic Face and Gesture Recognition; 2018.

Bartlett MS, Littlewort G, Fasel I, Chenu J, Kanda T, Ishiguro H, Movellan JR. Towards social robots: automatic evaluation of human-robot interaction by face detection and expression classification. In Proc IEEE Int Conf Systems, Man, and Cybernetics; 2004. p. 592–597.

Bates D, Mächler M, Bolker B, Walker S. Fitting linear mixed-effects models using lme4. J Stat Soft. 2015;67:1–48.

Burke C, Sims DE, Lazzara EH, Salas E. Trust in leadership: a multi-level review and integration. Leadership Quarterly. 2007;18:606–632. doi:10.1016/j.leaqua.2007.09.006.

Desmond PA, Hancock PA. Active and passive fatigue states. In: Hancock PA, Desmond PA, editors. Stress, workload, and fatigue. Mahwah (NJ): Lawrence Erlbaum; 2001. p. 455–465.

Desmond PA, Hancock PA, Monette JL. Fatigue and automation-induced impairments in simulated driving performance. TRR. 1998;1628:8–14.

Desmond PA, Matthews G. Individual differences in stress and fatigue in two field studies of driving. Transp Res Part F. 2009;12:265–276.

Dong Y, Hu Z, Uchimura K, Murayama N. Driver inattention monitoring system for intelligent vehicles: a review. IEEE Trans Intell Transp Syst. 2011;12:596–614.

Drnec K, Metcalfe JS. Paradigm development for identifying and validating indicators of trust in automation in the operational environment of human automation integration. In: Schmorrow DD, Fidopiastis CM, editors. Foundations of augmented cognition 2016, lecture notes in computer science. 2016;9744:157–167.

Ekman P, Friesen W. Facial action coding system: a technique for the measurement of facial movement. Palo Alto (CA): Consulting Psychologists Press; 1978.

Freedy A, de Visser E, Weltman G, Coeyman N. Measurement of trust in human-robot collaboration. Proceedings of the 2007 IEEE International Conference on Collaborative Technologies and Systems. 2007; Orlando, FL.

Greco V, Roger D. Coping with uncertainty: the construction and validation of a new measure. J Pers Individ Differ. 2001;3:519–534.

Gremillion G, Metcalfe JS, Marathe AR, Paul VJ, Christensen J, Drnec K, Haynes B, Atwater C. Analysis of trust in autonomy for convoy operations. Proceedings of International Society for Optics and Photonics Defense+ Security; 2016.

Gruen B, Leisch F. Fitting finite mixture of generalized linear regressions in R. Comput Stat Data Anal. 2007;51:5247–5252.

Gu H, Ji Q. An automated face reader for fatigue detection. FGR 2004: Proceedings of the Sixth IEEE International Conference on Automatic Face and Gesture Recognition; 2004 May. p. 111–116.

Hancock PA, Verwey WB. Fatigue, workload and adaptive driver systems. Accident Anal Prevent. 1997;29:495–506.

Hart SG, Staveland LE. Development of NASA-TLX (Task Load Index): results of empirical and theoretical research. In: Hancock PA, Meshkati N, editors. Human mental workload. Amsterdam (Netherlands): North-Holland Press; 1988. p. 239–250.

Jian JY, Bisantz AM, Drury CG. Towards an empirically determined scale of trust in computerized systems: distinguishing concepts and types of trust. Proceedings of the 42nd Annual Meeting of the Human Factors and Ergonomics Society; 1998; Chicago, IL.

John OP, Donahue EM, Kentle RL. The big five inventory—versions 4a and 54. Berkeley (CA): University of California, Berkeley, Institute of Personality and Social Research; 1991.

John OP, Naumann LP, Soto CJ. Paradigm shift to the integrative big five trait taxonomy: history, measurement, and conceptual issues. In: John OP, Robins RW, Pervin LA, editors. Handbook of personality: theory and research. New York (NY): Guilford Press; 2008. p. 114–158

Leisch F. FlexMix: a general framework for finite mixture models and latent class regression in R. J Stat Soft. 2004;11:1–18.

Lisetti CL, Nasoz F. Affective intelligent car interfaces with emotion recognition. 11th International Conference on HCI; 2005 July; Las Vegas, NV.

Little C. The Intelligent vehicle initiative: advancing ‘human-centered’ smart vehicles. Public Roads. 1997 Sep/Oct;61(2). https://www.fhwa.dot.gov /publications/publicroads/97septoct /p97sept18.cfm.

Marathe AR, Metcalfe JS, Lance BJ, Lukos JR, Jangraw D, Lai KT, McDowell K. The privileged sensing framework: a principled approach to improved human-autonomy integration. TIES. 2018;19:283–320.

Matthews G, Desmond PA. Task-induced fatigue states and simulated driving performance. Q J Exp Psychol. 2002;55A:659–686.

McAllister, D. Affect- and cognition-based trust as foundations for interpersonal cooperation in organizations. Academy of Management Journal. 1995;38:24–59. doi:10.2307/256727.

Metcalfe JS, Marathe AR, Haynes B, Paul VJ, Gremillion GM, Drnec K, Atwater C, Estepp JR, Lukos JR**,** Carter EC, et al. Building a framework to manage trust in automation. In: George T, Dutta AK, Islam MS, editors. Proceedings of SPIE 10194, Micro- and Nanotechnology Sensors, Systems, and Applications IX; 2017.

Muir BM, Moray N. Trust in automation part II. Experimental studies of trust and human intervention in a process control simulation. Ergonomics. 1996;39:429–460.

Nass C, Jonsson I-M, Harris H, Reaves B, Endo J, Brace S, Takayama L. Improving automotive safety by pairing driver emotion and car voice emotion. 11th International Conference on HCI; 2005 July; Las Vegas, NV.

National Center for Statistics and Analysis. Traffic safety fact crash stats: drowsy driving. Washington (DC): National Highway and Transportation Security Administration; 2011 Mar. Publication No.: DOT HS 811 449. www-nrd.nhtsa.dot.gov/pubs/811449.pdf.

Neubauer C, Gremillion G, Perelman B, La Fleur C, Metcalfe J, Schaefer-Lay K. How analysis of facial expressions explain affective state and trust-based decisions during interaction with autonomy aids. Proceedings of the 3rd International Conference on Intelligent Human Systems Integration: Integrating People and Intelligent Systems; 2020; Modena, Italy.

Neubauer C, Matthews G, Saxby DJ, Langheim LK. Simulator methodologies for investigating fatigue and stress in the automated vehicle. ATS. 2010 Special:7–18.

Neubauer C, Matthews G, Saxby DJ. The effects of cell phone use and automation on driver performance and subjective state in simulated driving. Proceedings of the 56th Annual Human Factors and Ergonomics Society; 2012; Boston, MA.

Neubauer C, Matthews G, Saxby DJ. Fatigue in the automated vehicle: do games and conversation distract or energize the driver? Proceedings of the 57th Annual Human Factors and Ergonomics Society; 2014; Chicago, IL.

Parasuraman R, Manzey DH. Complacency and bias in human use of automation: an attentional integration. HFES. 2010;52:381–410.

Perelman BS, Dorton S, Harper S. Identifying consensus in heterogeneous multidisciplinary professional teams. Proceedings of the 2019 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA); 2019; Las Vegas, NV.

Purtiman B. Preparing for future battlefields: the Next Generation Combat Vehicle. Army (US); 2018 Sep 17 [accessed 2020 Mar 30]. https://www.army.mil/article/211236/preparing_for_future_battlefields_the /next_generation_combat_vehicle.

R Core Team. R: a language and environment for statistical computing. Vienna (Austria): R Foundation for Statistical Computing; 2016.

Sarter NB, Woods DD, Billings CE. Automation surprises. In: Salvendy G, editor. Handbook of human factors and ergonomics. 2nd ed. New York (NY): Wiley; 1997. p. 1926–1943.

Saxby DJ, Matthews G, Warm JS, Hitchcock EM, Neubauer C. Active and passive fatigue in simulated driving: discriminating styles of workload regulation and their safety impacts. J Exp Psychol Applied. 2013;19:287–300.

Schaefer KE, Chen JYC, Szalma JL, Hancock PA. A meta-analysis of factors influencing the development of trust in automation: implications for understanding autonomy in future systems. Hum Fact. 2016;58:377–400.

Schaefer KE, Perelman BS, Gremillion GM, Marathe AR, Metcalfe JS. A roadmap for developing team trust metrics for human-autonomy teams. In: Nam CS, Lyons J, editors. Trust in Human-Robot Teaming. Amsterdam (Netherlands): Elsevier; Forthcoming 2020.

Schaefer KE, Scribner DR. Individual differences, trust, and vehicle autonomy a pilot study. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting; 2015. p. 786–790; Vol. 59.

Scheutz M, Dame N, Schermerhorn P, Kramer J. The utility of affect expression in natural language interactions in joint human-robot tasks. Proceedings of ACM SIGCHI/SIGART Conference on Human-Robot Interaction; 2006. p. 226–233.

Stanton NA, Young MS. Driver behaviour with adaptive cruise control. Ergonomics. 2005;48:1294−1313.

Tan YYS, Mueller ST. Adapting cultural mixture modeling for continuous measures of knowledge and memory fluency. Behav Res Methods. 2016;48:843–856.

Yagoda RE, Gillan DJ. You want me to trust a ROBOT? The development of a human–robot interaction trust scale. Int J Social Rob. 2012;4:235–248.

Young MS, Stanton NA. Malleable attentional resources theory: a new explanation for the effects of mental underload on performance. Hum Fact. 2002;44:365–375.

Young MS, Stanton NA. Back to the future: brake reaction times for manual and automated vehicles. Ergonomics. 2007;50:4658.

Zhang Z, Zhang J-S. Driver fatigue detection based intelligent vehicle control. In: ICPR ’06: Proceedings of the 18th International Conference on Pattern Recognition; 2006; Hong Kong, China; IEEE Computer Society. p. 1262–1265.

List of Symbols, Abbreviations, and Acronyms

AU	action unit
BFI	Big Five Inventory
BIC	Bayes Information Criterion
CCDC	US Army Combat Capabilities Development Command
CU	Cognitive Uncertainty
DFC	Desire for Change
E-M	expectation maximization
EU	Emotional Uncertainty
FB	full, bad
FG	full, good
FMM	flexible mixture modeling
NASA	National Aeronautics and Space Administration
NASA-TLX	NASA-Task Load Index
NGCV	Next Generation Combat Vehicle
SB	speed, bad
SG	speed, good
SVAS	Stress Visual Analogue Scale
URS	Uncertainty Response Scale

1 DEFENSE TECHNICAL
(PDF) INFORMATION CTR
DTIC OCA

1 CCDC ARL
(PDF) FCDD RLD CL
TECH LIB

1 CCDC ARL
(PDF) FCDD RLH B
T DAVIS
BLDG 5400 RM C242
REDSTONE ARSENAL AL
35898-7290

1 CCDC ARL
(PDF) FCDD HSI
J THOMAS
6662 GUNNER CIRCLE
ABERDEEN PROVING
GROUND MD
21005-5201

1 USAF 711 HPW
(PDF) 711 HPW/RH K GEISS
2698 G ST BLDG 190
WRIGHT PATTERSON AFB OH
45433-7604

1 USN ONR
(PDF) ONR CODE 341 J TANGNEY
875 N RANDOLPH STREET
BLDG 87
ARLINGTON VA 22203-1986

1 USA NSRDEC
(PDF) RDNS D D TAMILIO
10 GENERAL GREENE AVE
NATICK MA 01760-2642

1 OSD OUSD ATL
(PDF) HPT&B B PETRO
4800 MARK CENTER DRIVE
SUITE 17E08
ALEXANDRIA VA 22350

ABERDEEN PROVING GROUND

16 CCDC ARL
(PDF) FCDD RLH
J LANE
Y CHEN
P FRANASZCZUK
K MCDOWELL
K OIE
G GREMILLION
K E SCHAEFER
B S PERELMAN
J S METCALFE
FCDD RLH BD
D HEADLEY
FCDD RLH FA
A DECOSTANZA
C NEUBAUER
FCDD RLH FB
A EVANS
FCDD RLH FC
J GASTON
FCDD RLH FD
A MARATHE
C LA FLEUR