

APPLICATION: TRAUMA-RECOVERY

- 1. Each year, over 3 million people in the United States are affected by post-traumatic stress, a serious mental condition.
- 2. Mental trauma is often associated with symptoms like, avoidance of treatment, negative beliefs, hyper arousal, cognitive impairments etc.
- 3. Self-help web interventions for mental health effectively follow a one-size-fits-all approach.
- 4. Personalization and automated adaption in selfhelp websites can positively aid people with mental health issues.





WHY ENGAGEMENT AND SELF-EFFICACY?

- 1. Engagement is an indispensable part of user experience and interaction with applications.
- 2. Vision and learning based methods can provide a proactive, scalable and cost-effective web-based treatment for trauma recovery by analyzing webcam feeds.
- 3. Self-reported user efficacy has been found, in many psychology studies, to be highly correlated with outcomes.
- 4. Self-efficacy is a key component of social cognitive theory and refers to a perceived capability to cope with challenges and uncertainty in stressful situations.
- 5. The website and task can adapt to enhance or maintain engagement and recovery based on reliable and quantitative engagement and self-efficacy measurement.

EASE DATAS



Dataset Details

- 1. Web-intervention used for trauma-recovery : *http://ease.vast.uccs.edu/*.
- 2. Participants consisted of total 110 subjects with 88 Female, 17 Male, 5 did not specify in the age group of 18-79 years, with 80% being under the age of 46.
- 3. Study comprised of 3 Sessions using six Modules of trauma-recovery: Relaxation, Triggers, Social-Support, Self-Talk, Professional-Help, Unhelpful-Coping.
- 4. Face data, audio and sensory data (skin conductance, respiration, ECG) was captured from subjects while they were interacting with website while performing self-regulation exercises.
- 5. Self-Reports were collected from subjects about their engagement level, mood (Very Short Profile of Mood States (POMS) questionnaire) and self-efficacy measures.

Learning based Visual Engagement and Self-Efficacy

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Svati Dhamija

University of Colorado Colorado Springs

sdhamija@vast.uccs.edu



RESULTS AND PUBLICATIONS

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	RX - Test	TR - Test		
RX - Train	39.1 ± 8.8 %	$38.1 \pm 4.4\%$		
TR - Train	$36.7 \pm 3.3\%$	$50.7 \pm 11\%$		
(RX + TR) - Train	$39.5 \pm 6.1\%$	$49.1 \pm 7.6\%$		

Experiment Details

- regression for automated mood-predictors.

3. Learning Protocol for Contextual Engagement Models:

- mood disturbance estimates.

Related Publications

1. S.Dhamija, T. Boult, "Exploring contextual engagement for trauma-recovery" DALCOM-W, CVPR 2017 2. S.Dhamija, T. Boult "Automated Mood-aware Engagement Prediction" ACII 2017 Acknowledgements: The work support in part by NSF Research Grant SCH-INT 1418520



CONTRIBUTIONS

- 1. Demonstration of contextual engagement in two different tasks within the recovery regime: "Relaxation" and "Triggers".
- 2. Explored relationship of subject's mood as an initialization parameter for engagement estimation.
- 3. Developed automated mood predictors for mood sub-scales and total mood disturbance.
- 4. Automated mood-aware predictors outperform selfreported mood-aware predictors for engagement.

	RX	TR
TM Baseline	0.9989	0.7653
MS-aware LSTM	0.9493	0.6786

	Trigger	Relaxation
Engagement-baseline	$48.55 \pm 17.7 \%$	$42.04 \pm 11.7 \ \%$
Engagement-Mood Aware POMS-SR	$52.57 \pm 17.2\%$	43.88 ± 11.9 %
Engagement-Automated MA POMS-TMD	54.04 ± 18.14 %	46.14 ± 14.38 %
Engagement-Automated MA POMS-TMDS	55.54 ± 18.43 %	45.42 ± 12.99 %

1. Features: 20 AUs using OpenFace Framework each from 30 sec video segment (900 frames/segment).

2. Algorithms: Support Vector Classification and LSTM based classification for Engagement Prediction. LSTM based

• Training on Relaxation Module, Testing on Trigger Module & Relaxation Module

• Train on Trigger Module, Testing on Trigger Module & Relaxation Module

• Training on mixed (Relaxation & Trigger), testing on Trigger Module & Relaxation Module

4. Mood-Aware Engagement Prediction: Leave-One-Subject-Out methodology: Training on Relaxation Module & testing on Relaxation Module, Training of Trigger Module & Testing on Trigger Module

5. Comparison of self-reported mood to automated mood: 20-fold validation: Baseline is engagement prediction results without mood conditioning. Mood pre-conditioning performed with POMS self-reports & automated total