Automated Stress Recognition Using Supervised Learning Classifiers by Interactive Virtual Reality Scenes

Kuan Tao, Yuhan Huang, Yanfei Shen, and Lixin Sun

***Abstract*— Virtual reality (VR) technology offers a great opportunity to explore stress disorder therapies. We created a VR stress training system, which incorporates three highly interactive stressful scenes to elicit stress, and demonstrate the concurrent variations between physiological data (heart rate, electrodermal activity and eye-blink rate) and self-reported stress ratings through a self-designed customized perceived stress questionnaire (SSAI) and wearable devices. Several supervised learning models were rigorously applied to automate stress recognition. Our findings include the evaluations of the VR system by computing Cronbach's alpha (α=0.72) and Kaiser-Meyer-Olkin (KMO) coefficient (η=0.78) through a retrospective survey, which were subsequently confirmed as reliable on four aspects (sense of presence, sense of space, sense of immersion and sense of reality) via factor analysis. Additionally, we demonstrate the effectiveness of physiology-based stress level classification (no stress, low stress and high stress) and continuous SSAI score prediction, with accuracy reaching 0.742 by bagging ensemble learning model and goodness-of-fit reaching 0.44 via multivariate stepwise regression. This study provides detailed insight regarding the effect of objective physiological measures on the validation of subjective self-ratings under a novel complex VR stress training system, which stimulates the further investigations of stress disorder recognition and treatment.**

***Index Terms*— Computational physiology, stress, supervised learning classifiers, virtual reality.**

I. Introduction

STRESS, seen as a consequence of modern life [1], has become a pervasive phenomenon that confronts individuals daily. Psychological stress is often described as a state of mental or emotional strain and pressure [2] which can influence several fundamental biopsychological functions, that is, attention [3], decision making [4], and cognitive development [5], [6]. Stress is commonly elicited through internal or external stimuli, and is assessed using subjective and objective measurements. Traditionally, subjective methods determine the stress level of a person through questionnaires and answers rated on a stress scale. These measures are known to provide highly reliable data reflective of perceived emotions [7], with widely accepted approaches including the Profile of Mood States [8], General Health Questionnaire [9], Perceived Stress Scale [10], and Stress Response Inventory [11]. However, extensive research has elucidated on objective measures of stress as body functions are affected when a person experiences stress, which fails to be interpreted through conceptual data in a subjective manner. Body functions, primarily regarded as physiological responses, such as electrodermal activity (EDA), heart rate, blood pressure and eye-blink rate, are observed using wearable sensors [7], [12]–[14]. Objective measures completely eradicate the possibility of user intervention and falsification, and hereby stress levels can be automatically predicted using fused measurements. Both subjective and objective scenarios are complementary for automated stress recognition, hence a novel stress procedure that overcame practical challenges by combining physiological measures and subjective validations was proposed in the case study of simple singing tests [2].

Over the past two decades, cognitive behavioral therapy (CBT) [15], [16] has served as the most conventional technique to detect and treat stress disorders. CBT involves patients visualizing cognitive patterns when imposed with stressors, and can be conducted either *in vitro*, referring to stress caused by internal fears, or *in vivo*, referring to when it is induced through external stimuli [17], [18]. CBT is being increasingly delivered over the Internet (iCBT) [19], as such psychological interventions can be handled with or without therapeutic support [20]. Other extensions of CBT, such as the generic cognitive model (GCM) [21] and acceptance and commitment therapy (ACT) [22], also produce beneficial outcomes for stress detection and management. While GCM integrates early detection and orientation of external stimuli with information processing through specialized primal schemas, ACT examines the principles of stress management intervention. These exposure therapies are regarded as the gold standard in clinical trials to identify and cure stress disorders, though setting up controlled environments for feared stimuli could be very costly [18]. Meanwhile, the replication of reusable and interactive 3D environments is challenging [23].

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Advances in virtual reality (VR) technology present new opportunities for stress recognition [18], [24]and other behavior research [25], and help overcome the weaknesses present in CBT. VR systems let participants experience immersive visual stimuli through vivid computer-generated 3D environments that correspond to normal physical Cartesian space, but do not need to obey the Newtonian mechanics [26]. Additionally, VR systems support interactions with virtual objects under the precise kinematics of motion in response to visual stimuli, to simulate the naturalistic way objects appear to move [25]. Due to the notable improvements in VR techniques, virtual reality exposure therapy (VRET) is considered an efficient tool for stress recognition. VRET assumes the possibility that participants feel real-life stressful situations in a similar magnitude in VR, and a recent survey study showed that it can be equally effective as *in vivo* exposure therapy and have a lower dropout rate [27], [28]. More importantly, VRET systems succeed in tracking physiological signals [29], [30] and recognize affective stress states, which provides a method of linking subjective and objective measures of stress recognition. Note that VR devices should avoid causing additional discomfort, hence wristband-based biofeedback sensors are preferable, with physiological signals such as EDA and heart rate being collected [31], [32].

Physiological signals exhibit unique characteristics during stress, hence the extraction of features and classification of stress levels from signals are gaining enormous popularity and importance currently. Sharma and Gedeon [13] investigated the binary classification of stress based on EDA signals via an artificial neural network (ANN) model, with a similar modeling structure implemented using EDA, ECG and respiration rate as parameters for ANN input [33]. Machine learning algorithms are also developed with automatic feature selection procedures to recognize complex patterns behind physiological signals [34]. Support Vector Machines (SVMs) with non-linear kernels in combination with physiological signals identify emotional states in emotional rooms [35], museums [36]and racing games [37] via VR techniques. Other classifiers, such as k-Nearest Neighbor (kNN), Random Forest (RF) and Linear Discriminant Analysis (LDA) are also applied to detect stress levels, through either binary classification or multi-class classification [13], [31], [38], [39].

This study aims to create a novel complex VR stress training system, which incorporates highly interactive stressful scenes to elicit stress, and demonstrate the relation between physiological data (heart rate, EDA and eye-blink rate) and self-reported stress ratings through a self-designed customized perceived stress questionnaire and wearable devices. The main contributions are twofold. First, we realize the automation of stress recognition using several supervised learning algorithms. Second, this study provides detailed insight regarding the effect of objective physiological measures on the validation of subjective self-ratings, which stimulates the further investigations of stress disorder treatment.

II. METHOD

A. Participants

A mixture of 57 undergraduate and graduate students (19 males and 38 females) from Beijing Sport University, with an average age of 20.9 (SD = ±1.9), volunteered to participate in the study. Notably, 15 student athletes, certified as second-level national athletes (or above) by authorized sports administrations in China, were included as participants. This research was approved by the Ethic Committee from Beijing Sport University (2022146H), which was complied with the Declaration of Helsinki, and all participants signed consent forms at enrollment.

B. Self-Designed Stressful VR Scenes

We created a highly-interactive VR stress training system using 3DMAX and Unity engine, using C# as the main programming language. Unity has well-developed systems for detailed graphics and naturalistic physic simulations, but does not contain any features for human behavior research [26]. The system comprises three major scenes, namely *Snow Valley Adventure*, *Scary Monsters* and *Enemy Shooting*, with each containing two subscenes divided into low-stress mode and high-stress mode.

Snow Valley Adventure presents a highly disturbing scenario through a dual-task model. The main task involves skiing on a specified directional track at specified speeds. Participants must focus on controlling their speed and trajectory to avoid getting injured virtually. The sub-tasks include six random events (tree falling to the ground, birds attacking, beasts threatening, incorrect road sign, Flanker task and Stroop task) during skiing, which deliberately interfere with participants by causing additional stress. Participants could ski freely along the track in low-stress mode, while they had to complete both main and sub-tasks in high-stress mode.

Scary Monsters creates monster characters to elicit internal stress in participants under a tense experience. Participants are instructed to use handheld wireless controllers (presented as laser weapons VR) to defeat three different types of monsters. In the low-stress mode, participants need to eliminate the least scary monster, which is incapable of attacking, while they need to eliminate all kinds of monsters with attacking ability in high stress mode.

Enemy Shooting involves three sequential missions (from easy to hard), namely hostage rescue, bomb removal and enemy elimination under intense first-person shooter conditions. Participants receive a medal if one mission is completed and are subject to sudden white noise at 110 dB for 5 seconds as punishment for a failed mission. The hostage rescue and enemy elimination missions direct participants to defeat all enemies without a time limit, while the bomb removal mission requires completion in 10 seconds. Participants used one remote controller as a pistol, firing at targets as instructed. The two modes differed with high-stress mode offering a limited number of bullets and reducing participants' health point recovery.

C. Customized Perceived Stress Questionnaires

Two customized questionnaires were prepared to assess perceived stress states. First, an *Experience Evaluation of Virtual Reality Scenes* survey was proposed to evaluate whether the self-designed VR scenes were adequate for participants to experience stressful situations in the virtual environment. This questionnaire refers to the iGroup Presence Questionnaire [40],

[41], and has four types of questions (14 items in total), which correspond to the sense of presence, sense of space, sense of immersion and sense of reality. For instance, "*To what degree do you feel the external world (sounds, room temperature, etc.)?*", "*To what degree do you feel the authenticity of the virtual environment?*" and "*To what degree do you feel being absorbed in the virtual space other than playing video games?*". Participants rate answers on a 7-point Likert scale ranging from "strongly agree" (-3) to "strongly disagree" (3).

The other questionnaire administered was the Short State Anxiety Inventory (SSAI), which is a validated stress inventory [42] and is widely applied in research on stress recognition. The SSAI encompasses stress presence and absence types, with each having 3 items scored on a 4-point scale, ranging from "not at all" (point 1) to "almost always" (point 4) for stress presence type, with a reversed scale for stress absence type.

D. Procedure

The illustrations of the experimental procedure and timeline, which are categorized into three distinctive stages, are presented in Fig. 1. Before the experiment, participants were informed of the procedure in detail, and then asked to provide written consent and take the SSAI to assess benchmark stress states subjectively. Subsequently, with the experimenters' assistance, participants put on a heart rate belt and EDA monitoring devices (a chest-strap belt and wristband, manufactured by BodyPlus Co., Ltd and B4RealTime Co., respectively), a VR head-mounted display (HMD) (Vive Pro, manufactured by HTC Co.) and a full set of motion capture equipment (PN PRO, manufactured by Noitom Co.), which offers acceleration information measured through knee angle changes for skiing in *Snow Valley Adventure.* After adjusting equipment, subjects were asked to log into the self-designed VR stress training system and sit at ease on a chair for 3 min to dispel any other man-made distractions. During this, benchmark values of EDA, heart rate and eye-blink rate were recorded, indicating the baseline values of behavior arousal on affective response. Participants then entered the three VR scenes in a random order. Participants experienced each mode from all three scenes for at least 1 min, which enabled the biophysiological sensors to correctly record data every second. Participants were asked to complete the SSAI after the low-stress or high-stress mode of each scene was completed. The procedure lasted for approximately 30 minutes per participant. A retrospective survey on the *Experience Evaluation of Virtual Reality Scenes* was completed immediately upon completion to acquire the psychometric quality of the VR stress training system.

E. Physiology-Based Stress Classification and Prediction

This study measured EDA, heart rate and eye-blink rate using biofeedback sensors as subtle physiological cues are known to indicate a change in stress states [13]. EDA data was collected through the monitoring device, and heart rate was recorded through the chest-strap monitor. Meanwhile, eye-blink rates were measured through the VR HMD since the headsets tracked head position and orientation in 3D Cartesian coordinates and displayed stereoscopic images with a resolution of 2160×1200 per eye (refresh rate $= 90$ Hz). Since each participant experienced both modes in all VR scenes, a total of 342 physiology-based data records were included in analysis.

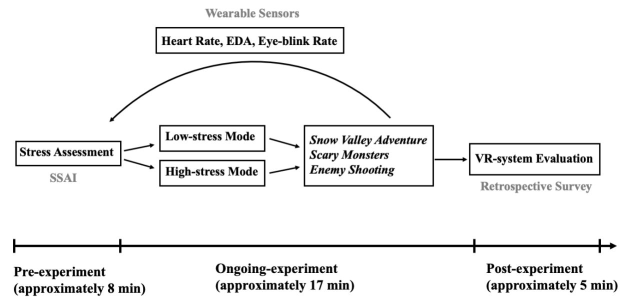

Fig. 1. Schematics of experimental procedure and timeline. Pre-experiment (approx. 8 minutes) includes the benchmark stress assessment. Ongoing-experiment (approx. 17 minutes) includes the modes selection and VR scenes experience, during which physiological data was collected through wearable sensors, and self-rated stress was assessed by SSAI. Post-experiment (approx. 5 minutes) indicates the VR-system evaluation, and the retrospective survey refers to *Experience Evaluation of Virtual Reality Scenes*.

The authors developed stress-level classification model incorporating logistic regression (LR), SVM, RF, kNN, and ensemble learning approaches to automate stress recognition. These algorithms were applied to the leave-one-out validation scheme, with sample size ratio of training and validation sets equaling to 8:2. Stress levels were labeled as "no stress", "low stress" and "high stress" based on the score intervals from SSAI (no stress within points 1 to 2, low stress within points 2 to 3, high stress for points larger than 3). Moreover, the statistics (mean, median, standard deviation, maxima and minima) of EDA, heart rate, and eye-blink rate per participant (real-time measurements during experiments minus benchmark values at rest state) were calculated as eleven-element feature vectors to feed into the machine learning models. A multivariate stepwise regression model was established based on these calculated statistics to predict continuous SSAI scores.

The hyperparameters for each supervised classifier were finely attuned. All data processing were performed using Python 3.7, Matlab 2017b and SPSS on Windows 10, with an Intel i7-9700 6.00 GHz CPU and NVDIA RTX 2080 GPU.

III. Results

A. Evaluation of VR Stress Training System

The reliability of the VR stress recognition system was rigorously evaluated through the *Experience Evaluation of Virtual Reality Scenes* questionnaire. This evaluation was based on subjective feedback from participants, which demonstrated the novel concept of how laboratory experiments with costly settings could effectively and efficiently be replaced with non-laboratory settings. Validity and reliability tests were performed by computing Cronbach's alpha ($\alpha = 0.72$) and Kaiser-Meyer-Olkin (KMO) coefficient ($\eta = 0.78$), which indicated a strong internal consistency for the whole scale and a small partial correlation relative to the original correlations,

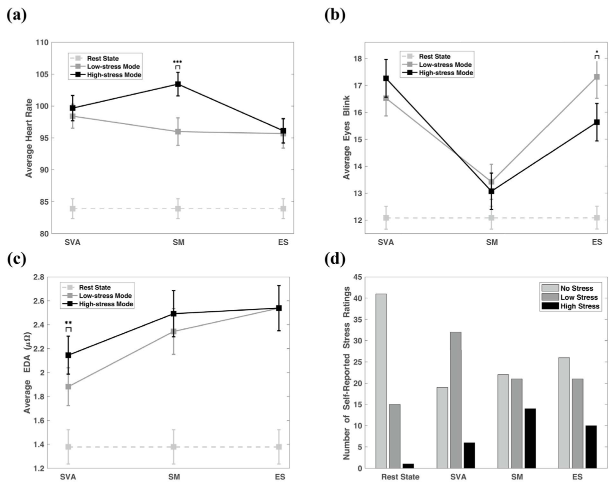

Fig. 2. Descriptive statistics of physiological data and self-rated perceived stress. SVA, SM and ES represent *Snow Valley Adventure, Scary Monsters* and *Enemy Shooting* VR scenes, respectively. Error bar stands for sample errors. *p<0.05, **p<0.005 and ***p<0.001. (a-c) Average heart rate, eye-blink rate and EDA during VR experiments for both low and high-stress mode, with benchmarks at the rest state displayed. (d) Number of self-reported stress ratings at every scene. Rest state stands for the benchmark stress prior to the onset of experiment.

which meant that the dimensions of the questionnaire (four aspects to evaluate sense of presence, sense of space, sense of immersion, and sense of reality for VR system) were reliably dependent on the 14 designed items, confirmed through factor analysis. Consequently, four aspects took up 64.2% of the accumulated accountability through factoring, with the scores (from 7-point Likert scale) for sense of presence ($M = 3.17, SD = 1.46$), sense of space ($M = 3.5, SD = 1.43$), sense of immersion ($M = 2.53, SD = 1.48$), and sense of reality ($M = 1.51, SD = 1.53$) demonstrating that the designed VR stress training system was effective.

B. Physiological Data and Self-Rated Perceived Stress

The variations in physiological data (heart rate, EDA, and eye-blink rate) in response to stress during different immersive VR scenes are presented in Fig. 2. Unsurprisingly, rest-state values for all collected data were significantly lower than those in stress modes, which meant that both modes elicited stress for the subjects. Average heart rate and EDA were higher in the high-stress mode than the low-stress mode (Fig. 2 a and Fig. 2 c), indicating that physiological responses of greater intensity were activated when facing circumstances eliciting higher stress. However, eye-blink rate showed a different picture. The rate obtained in low-stress mode in *Snow Valley Adventure* was higher than that obtained in the same mode in *Scary Monsters* and *Enemy Shooting* (Fig. 2 b) because subjects were distracted by dodging unexpected obstacles in the *Snow Valley Adventure* sub-task, which increased the eye-blink rate. Meanwhile, due to limited health points and bullets, participants had to be highly attentive to avoid mission failure which led to a lower rate of eye-blink in the other scenes. Meanwhile, the dynamical evolutions of physiological data in all the immersive VR scenes were presented in Appendix. As for the self-reported stress ratings, all three

TABLE I
PERFORMANCE COMPARISONS OF DIFFERENT SUPERVISED LEARNING CLASSIFIERS

	Accuracy $\frac{TP+TN}{TP+TN+FP+FN}$	Recall $\frac{TP}{TP+FN}$	Precision $\frac{TP}{TP+FP}$	F1-score $2\times\frac{Precision\cdot Recall}{Precision+Recall}$
SVM	0.712	0.721	0.657	0.672
LR	0.636	0.595	0.645	0.555
RF	0.727	0.726	**0.714**	0.682
kNN	0.682	0.687	0.625	0.642
XGBoost	0.697	0.686	0.659	0.649
Bagging	**0.742**	**0.774**	0.687	**0.709**

Notes: (1) TP, TN, FP and FN stand for true positive, true negative, false positive and false negative samples, respectively. (2) Training and test dataset was randomly split under the same random seed in all of the supervised learning classifiers.

VR environments had largely reduced no-stress cases and increased low and high stress cases, respectively (Fig. 2 d).

C. Automated Stress Level Classification

Since subjective measures and objective stress ratings vary concurrently, the natural problem of automatically classifying stress levels arises. To address this concern, we applied supervised learning algorithms containing SVM, LR, RF, kNN, XGBoost, and Bagging. Performance metrics are listed in Table I. Bagging achieved the highest scores on accuracy (0.742), F1-score (0.709) and recall (0.774), while RF obtained the best performance on precision (0.714). Also, both ROC curves and AUC values (Fig. 3) indicated that the performance of these classifiers was robust. The LR algorithm performed slightly worse than others, possibly because the self-reported stress ratings were not functions of physiological data, and could not be logistically regressed. Though visualization of high-dimensional data was challenging, it can be inferred that the features of physiological data exhibit clustered or even multiple linear-separable patterns, and thus distance-based approaches (SVM, kNN, RF and Bagging) perform the stress classification task well.

D. SSAI Score Prediction

Additionally, the prediction of SSAI scores was investigated, which directly linked physiological responses to subjective stress ratings from a continuous perspective, to automate stress level classification. Multivariate regression was used on the whole dataset ($N = 342$) based on ordinary least

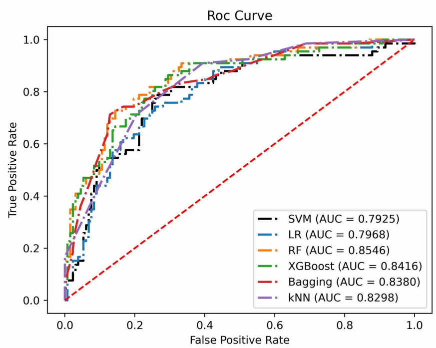

Fig. 3. Evaluations of automated stress classification models. The false positive rate versus true positive rate figure, also named as Receiver Operating Characteristic (ROC) curves, of the proposed supervised learning algorithms presented in Table I. Also, the area-under-curve (AUC) values were displayed accordingly. Red dashed line represents the benchmarks of classification algorithms.

square criteria by selecting features as inputs step-wise, with optimal feature combinations consisting of the mean, median, maximum, and minimum of heart rate and EDA, as well as the standard deviation of EDA and the maximum eye-blink rate. The goodness-of-fit $R^2 = 0.06$ ($p = 0.39$), which meant that SSAI score was barely related with the selected features.

The gathered physiological data were clustered, and hence it was inappropriate to treat them as a whole. To that end, the strategy was adjusted by assembling similar clusters preceding stepwise regression. The entire dataset was split into several subsets (with minimum inclusion $N = 96$ guaranteed), and this time the adjusted $R^2 = 0.44 \pm 0.002$ ($p = 0.05$), which was highly robust, significantly improved.

IV. Discussion

The findings of the current study were threefold. First, an interactive VR system was created to elicit stress, which was proven to be reliable and successful. Second, the concurrent variations of self-reported stress ratings and physiological data were demonstrated through the designed questionnaire and wearable devices. Third, automated stress recognition from discrete (stress level classification) and continuous (SSAI score prediction) scenarios was verified through several supervised learning algorithms and multivariate stepwise regression.

A. A Novel Complex VR Stress Training System

The VR stress recognition system developed in this study has advantages over existing VR environments. One salient characteristic is the complex human-computer interaction involved for participants in immersive scenes; for instance, inertial measurement units are used to control the speed of skiing in *Snow Valley Adventure*. In *Scary Monsters* and *Enemy Shooting*, participants should be prepared to wave handheld controllers to defeat monsters or shoot enemies coming from 360 degrees in corresponding missions. Existing research on stress recognition induced stress in new laboratory and portable settings using VR technology [25]. However, they provide little evidence on such interactions. Some studies were conducted to explore the effects of virtual reality natural scenic videos on stress detection [43] and reduction [44], [45], with additional tasks, that is, performing digits calculations [45], used to induce stress. Others presented more specific stressful scenarios using VRET, such as public speech anxiety [18], dental phobias in adults [46] and fear of heights [47], which were achievements of the immersion perceived from experiencing videos, images, and sounds in a VR world.

The software that encompassed diverse scenarios pertaining to different types of stressors took over a year to develop; the stressors include distraction-induced stress in *Snow Valley Adventure*, feared-stimuli-based stress in *Scary Monsters*, and bonus-penalty-stimuli-based *Enemy Shooting*, which promoted user feasibility and motivation during task completion. Such designs are in line with recent multidimensional evaluations of VR paradigms in behavior research [48].

B. Objective Measures on Subjective Validation

As noted earlier, this study is not the first to suggest linking objective measures to subjective validation by advancing knowledge about physiological stress responses to social-evaluative mechanisms. However, this framework is still worth in-depth investigation, since stress-related changes in human physiology are extremely subtle and comprehensive, such that even participants themselves lack awareness of the changes to truly report stress. Most existing studies focus on stress scales [2], [18], [49] (by rating a single level) to label stress levels after physiological data processing ranging from EDA, heart rate, skin temperature signals to salivary cortisol measures and MRI brain scanning, which are seemingly over-simplified.

The stress scale was extended to SSAI, which reflects the subjective ratings more fairly as it contains 14 meticulously designed items, and provides a plausible solution to multiple treatment sessions [18]. Several supervised learning models, besides the widely-used SVM and RF [13], and ensemble learning algorithms were used to classify stress levels. Multivariate stepwise regression was applied to predict SSAI scores, to find the mechanisms between objective measures and subjective validations.

It is noteworthy that features of physiological data, which constitute a high-dimensional vector, are hypothetically clustered, and must be treated separately. Unfortunately, no existing research considered separation. Lee *et al.* investigated the stress level and concentrations in urinary Hyp and Pro via stepwise multivariate regression, with the adjusted $R^2 = 0.05$ ($N = 97$) [50]. Another group regressed psychiatric characteristics and coronary angiograms (physiological traits for chest pain), with $R^2 = 0.29$ ($N = 139$) [51]. Others presented cross-sectional studies on regression between health factors and stress scales, with $R^2 < 0.20$ [52], [53]. Therefore, this study provides heuristics to researchers regarding splitting dataset before performing regression in order to increase the model's predictability.

V. Outlooks

This study has several limitations which can be addressed in future studies. First, the VR system could be modified to monitor real-time stress by incorporating the automated stress recognition results. Second, participants could be recruited

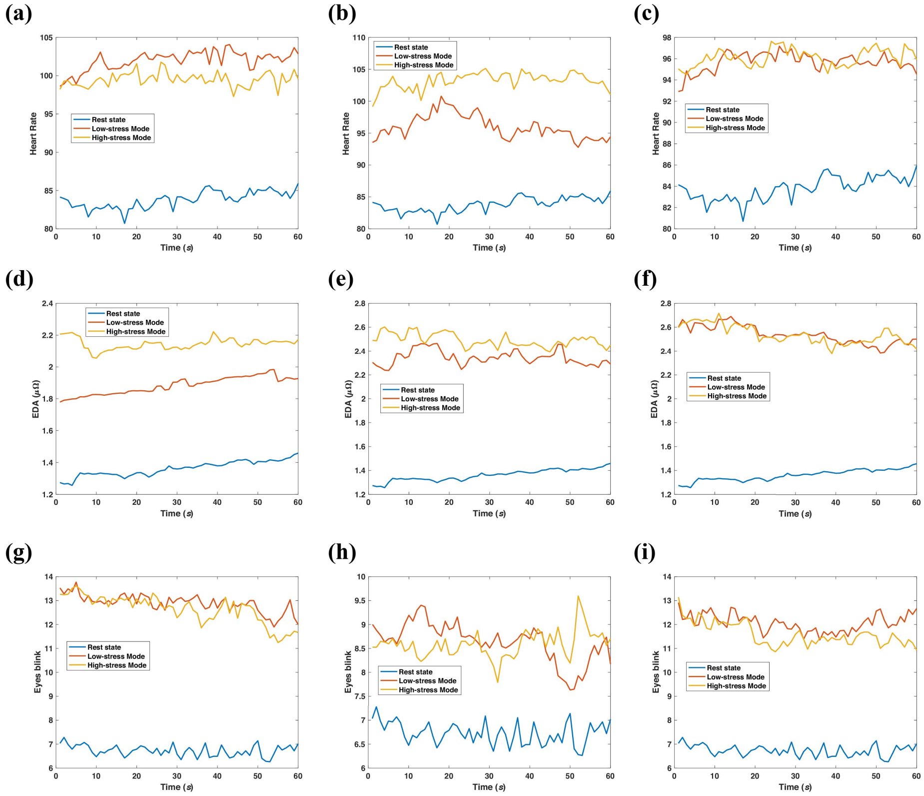

Fig. 4. Dynamical evolutions of physiological data in each immersive VR scene separately. (a-c) Variations of heart rate in *Snow Valley Adventure* (a), *Scary Monsters* (b) and *Enemy Shooting* (c), respectively. (d-f) Variations of EDA in *Snow Valley Adventure* (d), *Scary Monsters* (e) and *Enemy Shooting* (f), respectively. (g-i) Variations of heart rate in *Snow Valley Adventure* (g), *Scary Monsters* (h) and *Enemy Shooting* (i), respectively.

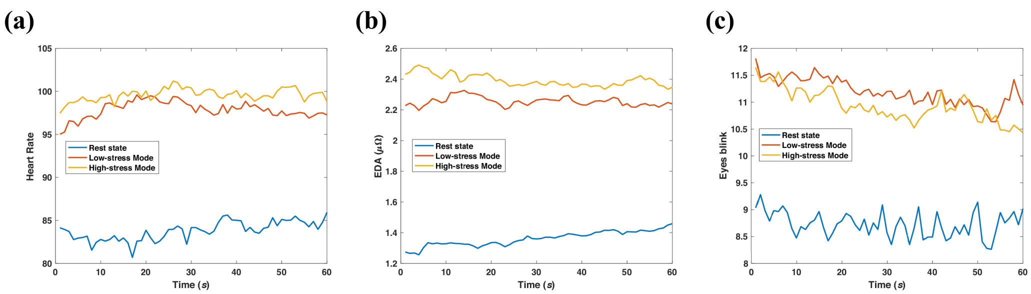

Fig. 5. Dynamical evolutions of physiological data in all VR scenes. (a-c) Variations of heart rate (a), EDA (b) and eye-blink rate (c), respectively.

from more diverse backgrounds (in terms of age and occupation), and the results obtained might increase the scale's effectiveness and robustness. Third, the transferability determined by high-quality immersive VR systems can be tested in clinical trials, which is an important application of behavior research. Finally, although the SSAI score prediction model is acceptable ($R^2 = 0.44$), it still has much room for improvement. Future research should delve into the internal connections between objective and subjective data and clarify the patterns they possess.

Appendix

See Figs. 4 and 5.

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