Digital Twin - A Machine Learning Approach to Predict Individual Stress Levels in Extreme Environments

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Abstract

Remote Health Monitoring (RHM) has the potential to increase operational safety in extreme environments. Negative stress exposure influences mission success or the short- and long-term health conditions of deployed personnel. To quantify negative stress, we introduce a washable smart textile with integrated sensors. Analyzing the transmitted sensor values, medical advisors monitor up to 72 sensor values in parallel in case of an average group size of eight people. In order to aggregate the amount of data, we propose a stress level scale that includes stress trends. To predict individual stress levels based on sensor data, environmental quantities and the individual physiological fingerprint, we train different machine learning models. To evaluate such models, we implement a data acquisition environment to label data snapshots. Therefore, we do not need to collect in-field data and expose humans to negative stress. Moreover, we can mock sensor failures and rare, but relevant, sensor value combinations that are difficult to acquire in real-world scenarios. Our evaluation environment identifies Random Forest Regressor from a set of 25 models to perform best to predict individual stress levels. This model performs 23.19 times better than a zero rule classifier to distinguish among nine stress levels for mission goal health condition and 10.50 times better for mission goal mission success. Finally, we present our current RHM user interface design. It addresses issues such as information overload, avatar sympathy and unnecessary navigation paths.

UbiComp/ISWC '20 Adjunct, September 12–16, 2020, Virtual Event, Mexico

ACM ISBN 978-1-4503-8076-8/20/09…$15.00
https://doi.org/10.1145/3410530.3414316

ACM Reference Format:
Constantin Scheuermann, Thomas Binderberger, Nadine von Frankenberg, and Andreas Werner. 2020. Digital Twin - A Machine Learning Approach to Predict Individual Stress Levels in Extreme Environments. In *Adjunct Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers (UbiComp/ISWC '20 Adjunct), September 12–16, 2020, Virtual Event, Mexico.* ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3410530.3414316

1 Introduction

For the last five years we have been working in an interdisciplinary team of chemists, electrical engineers, medical practitioners, textile designers and software engineers. Our goal is to offer an end-to-end user journey to increase operational safety in extreme and remote environments.

We started with the first smart textile prototypes, user interfaces and scenario descriptions in 2015 [1]. We used and evaluated commercial products and partnered with startups such as ambiotex to accelerate the prototyping phase. We have explored how user interfaces and system architectures should look like and evaluated them [1], [2], [3]. In this publication we demonstrate our entire system design, covering our smart textile design, our current status on stress level prediction and our user interface.

Our motivation is to quantify negative stress exposures of deployed personnel such as firefighters or first responders in extreme, dangerous or hazardous environments. Our goal is to automatically predict stress exposures in almost real-time during deployments. We build a RHM system that consists of a smart textile, a prediction system to analyze the transmitted sensor data and a user interface to monitor deployed personnel. With a smart textile we facilitate the process of medical valid sensor application to form a body sensor network. Using our prediction model, we facilitate the aggregation of sensor values, the environmental context and the physiological fingerprint to one quantity. The proposed user interface visualizes relevant data in a meaningful way to medical trained personnel.

We transfer the concept of a digital twin, which is a common research topic in the domain of manufacturing to the domain of health monitoring. In manufacturing the digital twin enables the digital transformation towards data driven enterprises and creates a digital representation of physical objects. Within our research we create a digital representation of humans focusing on their vital quantities as well as the surrounding environment. We form a digital representation to train machine learning models with the goal to facilitate data analysis.

We first provide related work in Section 2. Then we explain the underlying problems of our proposed RHM system for the smart textile, the stress prediction and the user interface in Section 3. Concerning the smart textile we briefly describe the iterative process of sensor location, miniaturization and integration in Section 4. In detail we present our results of stress level prediction process in Section 5. Section 6 describes our latest user interface design and Section 7 concludes our publication.

2 Related Work

Walter B. Cannon was the first to investigate on stress and the reaction to stress resulting in a *fight-or-flight response* [4]. His research focused on animals facing a post-traumatic stress disorder after threatening situations. Such threatening situations change the homeostasis and the maintenance of an internal equilibrium. To quantify this homeostasis, vital quantities such as blood sugar, oxygen saturation and core temperature were measured. Such imbalances increase the risk of long- and short term health conditions.

In this paper we focus on negative stress called distress, which deployed personnel such as firefighters or first responders typically face. Negative stressors, factors that influence stress perception, are perceived as unpleasant or unwanted experience [5]. Typical examples of distress are physiological strain, heat stress [6] and threats during deployment itself. Such exposure can lead to a decreased attention span or a decline in performance. Burnout seems to be connected to personal distress, including physical exhaustion, insomnia, increased use of alcohol and drugs, marital and family problems [7]. We want to quantify distress exposures with the goal to minimize the risk of burnout or similar negative health effects.

To quantify stress, scales are necessary. Several stress scales exists such as Effort-Reward Imbalance Scale (ERI), a scale for recording social stressors at the workplace [8], the Social Readjustment Rating Scale (SRRS) [9], Stress-Reactivity-Scale (SRS) [10], Trier Inventory for Chronic Stress (TICS) [11] and the Perceived Stress Questionnaire (PSQ) [12]. Those stress scales are mostly based on questionnaires and are not applicable for sensor data-driven health monitoring, so that we propose our own stress scale.

Data acquisition, data storage, data access, medical data analysis and the visualization are critical components of RHM [13]. In medicine, mock systems are used to gather knowledge about human cardiovascular systems [14]. Software engineers use mock patterns to mock data. We generate sensor data and apply those patterns to train models for stress level predictions.

RHM using wearables and smart textiles can be applied in modern battlefield environments [15] as well as for patient monitoring [13]. Very limited experience, with sensorized garments in space or military applications exists [16]. Batdok[1] is a RHM system that can be used during deployment scenarios. Batdok addresses similar problems as we do, but we do not have insights in their stress prediction mechanism. Other systems exist such as the Equivital EQ02 LifeMonitor and Equivital Black Ghost[2], Zephyr PSM Responder[3], Firstbeat[4], e-Health Sensor Platform V2.0[5], Ambiotex[6] or QUS[7]. An overview on current wearable sensors and RHMs can be found in [17]. Following the proposed taxonomy in [18] our RHM system is server-based. We are building a system to quantify stress exposures, prioritize mission actions and (in extreme cases) conduct a triage. To the best of our knowledge, a mission goal dependent prediction system for RHM including a completely integrated sensor application does currently not exist.

3 Problem

In this section we map problems of the problem domain to system components of the solution domain. We discuss the *smart textile*, the *data processing* and the *visualization* components.

Smart Textile — Sensor Position & Connectors: Sensors need to be attached to medically valid positions at the human body. Typically, medically trained personnel applies such sensors with tape directly to the skin. Such a process is time consuming before and after the deployment, and stresses the skin.

Connectors are necessary to modularize the smart textile. We propose a washable smart textile with removable subsystems such as the power supply and the embedded system.

[1]https://rhsusa.com/batdok
[2]https://www.equivital.com/
[3]https://senlab.io/
[4]urlhttps://www.firstbeat.com
[5]https://www.cooking-hacks.com/
[6]https://www.ambiotex.com/
[7]https://www.qus-sports.com

Figure 1: Smart Textile Prototype: Smart textile prototype of WIWeB (Erding) 2019 with a temperature and humidity sensor (1), built-in breathing frequency measurement (resistive) and a connector button for ECG (2). (3) shows the central aggregation and communication unit for all sensor data, limb temperature sensors for wrists and ankles (4) and the slave unit to collect and transmit ankle temperatures to the central aggregation and communication unit (5).

Type	Sensor Range	Relevant Range	Frequency (Hz)	Variance
Core Body Temperature (°C)	0 – 50	32 – 42	2	± [0–0.35]
Humidity (%)	0 – 100	0 – 100	1	± [0–2]
Heart Rate (bpm)	30 – 300	40 – 220	1	± [0–20]
Heart Rate Variability (RMSSD in ms)	15 – 39	15 – 39	1	± [0–6]
Limb Skin Temperature Wrist (°C)	-40 – 125	27 – 39	10	± [0–0.2]
Limb Skin Temperature Ankles (°C)	-40 – 125	25 – 39	10	± [0–0.2]
Breathing Frequency (Breaths per Minute)	Based on resistance	6 – 35	1	± [0–6]

Table 1: Sensor Selection: Based on our structured interview, we identified relevant sensors to estimate stress levels. For our data acquisition environment we define the frequency and the variance close to the selected real-world scenario.

Data Processing — Stress Aggregation with Tendencies & Sensor Selection: Current health monitoring systems do aggregate measured quantities to estimate a stress level but the process of how such systems work is unknown. Therefore, an evaluation and comparison is hard to achieve. Our machine learning models rely on data snapshots to predict the current stress level of the deployed person. Therefore, we are able to provide a tendency indicator, which contributes to increase operational safety of deployed personnel and facilitates the observation of the entire group.

Data Processing — Data Acquisition: Health-data acquisition is a problem as we are facing data privacy issues, especially with medical relevant and personal information. Additionally, one would have to expose humans to extreme situations to acquire data, which is ethically problematic. Moreover, the amount of health-data necessary to train machine learning models is high and therefore, the acquisition is time consuming. We claim that each combiation of sensor values are important to identify, as they might also appear in real world scenarios. Sensors might malfunction and result in various combinations that on a first glance might be unrealistic. We propose a data acquisition environment to train machine learning models without the need to collect in-field data of deployed personnel. The environment allows us to label such data and use it to train our models.

Data processing — Data aggregation: A typical group size that a medical advisor monitors during deployment scenarios, is eight. Within our deployment scenario, each person of the group is equipped with nine sensors that are measuring relevant stress indicators. A total of 72 quantities have to be observed to estimate a stress level during a deployment scenario. A medical advisor has to analyze this amount of data in nearly real-time. Our earlier studies show that such an amount of data is difficult to analyze and causes stress to the medical advisor. In this publication we aggregate the sensor data automatically using our proposed stress scale, including stress tendencies for each deployed person.

Data Processing — Under- & Overprediction: Within extreme deployment scenarios, medical advisors might distinguish between two mission goals, ensuring health condition of deployed personnel or mission success. During evaluation of trained machine learning models, under- and overpredictions are problematic depending on the mission goal. Depending on the mission goal, trained machine learning models have to be evaluated differently. We define a formula using weights to evaluate prediction quality for health condition and for mission success each.

Data Processing — Bottleneck Medical Advisor: Medical advisors that monitor a deployed group to estimate stress levels are experienced experts in their field. There is a limited amount of experts available. Our motivation is to increase the number of experts using trained machine learning models.

Visualization — Sympathy, Dashboard & Usability: Based on our earlier user interface evaluation we identified the problem of avatar sympathy. An avatar is a digital representation, for example a picture, of a deployed person of the group. If a medical advisor sympathizes with a certain avatar, it will result in a higher probability that it receives more attention. Pictures and geometric shapes are not suited as they trigger sympathy. We propose a user interface design that aggregates information and offers an improved usability compared to our first designs.

4 Smart Textile Prototype

Our goal is to offer an end-to-end user journey to increase operational safety in extreme and remote environments.
We started with the first smart textile prototypes, user interfaces and first scenario descriptions in [1]. We have used and evaluated of-the-shelf products and partnered with startups such as ambiotex to accelerate the prototyping phase [2]. We demonstrate the latest, easy to apply, rugged and washable smart textile that measures vital quantities from our research partner - the Bundeswehr Research Institute for Materials, Fuels and Lubricants (WIWeB) (see Figure 1).

, Ml, Mm, Mh, Mx, Hl, Hm, Hh, Hx, Xl, Xm, Xh and Xx.

5 Stress Level Prediction

To predict a stress level we first define a scenario independent stress level scale, then the scenario and the necessary vital quantities to measure. We have conducted a structured interview with Dr. Andreas Werner to gather necessary information. Dr. Andreas Werner is an expert in physiology and has years of experience in this field.

Stress Level Scale

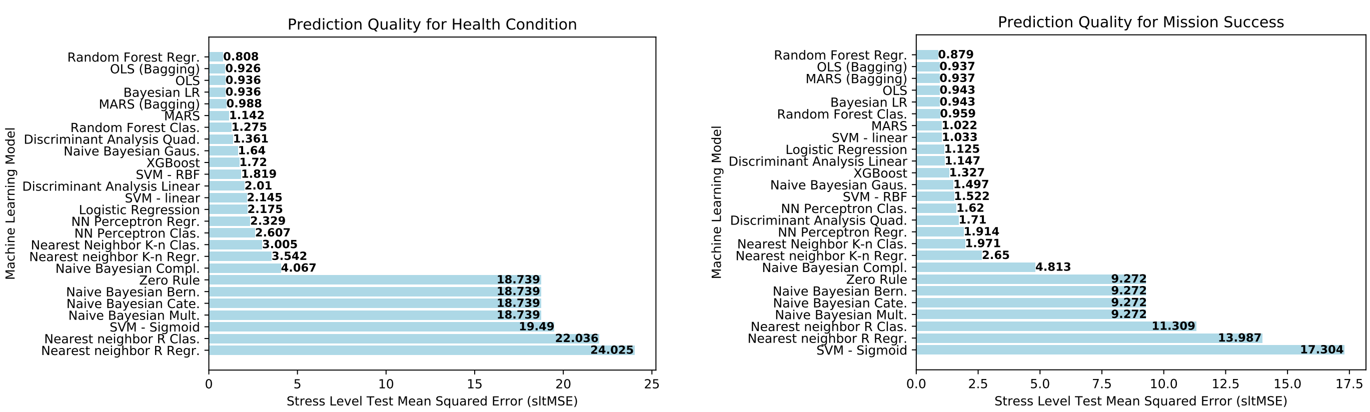
The stress level definition helps medical advisors to assign behavior of a person and appearance to a certain stress level. We define five stress levels categories: minimum, low, medium, high and maximum. For each of the stress level categories we provide a short definition.
During *minimum stress* exposure the person is smiling, emotionally caring and is still in a state of mindfulness. The facial expression is relaxed and body motions are smooth. The person is accepting and processing information easily. Parallel task execution is possible and compared to normal daily routine.
We assign a person to the *low stress* level in case physical strains trigger happiness and a positive stress (eustress) is present during task execution. Task execution correlates with trained situations and feels familiar. The person is able to compensate physiological strains after the deployment. This compensation depends on the training level, health condition, psychological status, sleep quality and sleep hygiene of the person.
We characterize *medium stress* as follows. The maximum amount of executable tasks has been reached and the person is in the highest state of attention. The person is focused on executing tasks which results in a reduced capability of information processing. The state is defined as submaximum physiological breaking point. Person can hold this state for a medium time period. Long exposure to this stress level can cause insomnia.
Non-responsive persons are assigned to *high stress*. The following two physiological reactions: stop muscle tremor due to hypothermia and sweating due to overheating. Humans show the lowest Heart-Rate-Variance (HRV) or hyperventilation including tetanie and fear. Humans in this stage are mentally unstable.
Maximum stress is the highest category and includes reactions such as the reduction to fight for survival, no possibilities to react or even coma.
This scale is the basis to label our data snapshots. Experts use our definitions of stress level categories as an orientation.

Scenario, Physiological Fingerprint & Sensor Selection

For our stress prediction we focus on one specific scenario. It is important to know the deployment scenario as it influences the selection of necessary sensors as well as the prediction of the stress level. We selected a mountain seek and rescue scenario with a group size of eight people. The environmental quantities are: Weather conditions that are cold and windy, the outer temperature ranges from -10°C down to -25°C.
The physiological fingerprint contains all the static health information of an individual, such as gender, blood type,

Stress Level Assessment Category	**S. Level**	**Stress Level Category**	**Definition**
Low (L)	0	Minimum	Stress levels in this stress category have the same level of criticality for health condition or mission success. Covers prediction distributions: Ll, Lm, Lh and Lx.
	1 (-)	Low	
	2 (0)		
	3 (+)		
Mid (M)	4 (-) 5 (0) 6 (+)	Medium	Stress levels in this category are optimal for mission success. Covers prediction distributions: Ml, Mm, Mh and Mx.
High (H)	7 (-) 8 (0)	High	All stress levels above describe a physical state, where deployed personnel is in risk of life. Covers prediction distributions: Hl, Hm, Hh and Hx.
Max (X)	9 (+)		Deployed personnel within this category is in risk of life. Covers prediction distributions: Xl, Xm, Xh and Xx.
	10	Maximum	

Table 2: Stress Level Assessment Categories and their relation to Stress Level Categories: Next to the stress levels, we show stress level tendencies in brackets. We marked the stress levels (grey background) that we do not include during our label process.



(a) Prediction Quality for Health Condition **(b) Prediction Quality for Mission Success**

Figure 2: Prediction Quality for Health Condition and Mission Success (rounded): Random Forest Regressor performs best for health condition with a sltMSE of 0.808, which is 23.19 times better than the sltMSE of the zero rule. Random Forest Regressor performs best for mission success with a sltMSE of 0.879, which is 10.50 times better than the sltMSE of zero rule.

allergies or resting heart-rate. To train our models we define a male person with an age of 28 and a resting heart-rate of 60bpm.
To predict the stress level of the person we have identified the following sensors based on the experience of our expert Dr. Andreas Werner. Based on our interview we selected the most important sensors as shown in Table 1 to estimate the stress level for this scenario. We define the *Sensor Range* and the (medical) *Relevant Range*. For our data acquisition environment we define an update*Frequency* (Hz) as well as a variance. We are able to configure the environment for any scenario and any sensor distribution. In this publication we

focus on one scenario and one person to predict the stress levels.

Data Acquisition Environment

To collect a labeled data basis and to not expose humans to negative stress, we developed a data acquisition environment. This environment enables an expert to generate labeled mock data. We generated 1027 labeled data snapshots that consist of sensor value combinations that are inside the *Relevant Range* of our sensors (see Table 1) and corresponding stress level labels from -1 to 8. Minus one describes not plausible or not assessable data snapshots. The stress level distribution is as follows: 26x (-1), 31x (0), 23x (1), 97x (2)s, 308x (3), 200x (4), 180x (5), 49x (6), 93x (7) and 20x (8).

Evaluation

For evaluation of stress level prediction models, we define under- and overpredictions, mission goals, criticality, stress level assessment categories, and introduce our developed evaluation environment.

Definition Under- & Overprediction: During evaluation of trained machine learning algorithms we face under- and overpredictions. An underprediction is a stress prediction, where the predicted stress level is lower than the true stress level that we know from the labeled data basis. Overpredictions have a higher predicted stress level than the true stress level.

Definition Mission Goals: Medical advisors make decisions based on stress levels and based on their desired mission goal. Mission goals are ensuring the health condition of deployed personnel or mission success. Deployed Personnel will most likely not suffer from health conditions in stress levels from zero to three. Keeping them at these stress levels contributes to mission goal health condition. Deployed Personnel are best operating in a stress level from four to six. Keeping them at these stress levels contributes to mission goal mission success.

Definition Criticality & Stress Level Assessment Categories: Prediction errors influence missions goals health condition of deployed personnel or mission success. Therefore, we define criticality to describe risk. Risk is the likelihood to not achieve a mission goal. Based on criticality and mission goals we assume the following: 1) Stress levels inside category minimum and low stress are not critical for health condition and critical on the same level for mission success. 2) Stress levels inside medium stress are not critical for mission success. 3) Stress levels above eight means risk of life for deployed personnel. To evaluate machine learning models we derive stress level assessment categories, based on our assumptions (see Table 2).

Evaluation Environment: We train and evaluate machine learning models within our developed evaluation environment. We define a measure, the stress-level-test-mean-squared-error (sltMSE), to compare machine learning models. We evaluate them for both defined mission goals. We use the true stress level assessment category taken from our labeled data to validate the predicted value. Four stress level assessment categories (see Table 2) result in 16 possible prediction distributions that consist of predicted and true categories, Ll, Lm, Lh, Lx, Ml, Mm, Mh, Mx, Hl, Hm, Hh, Hx, Xl, Xm, Xh and Xx. Capital letters of a prediction distribution describe the true and small letters the predicted stress level assessment category. Prediction distributions influence decision making of medical advisors to different extends. We map prediction distributions to their criticality for both mission goals and assign them to categories and corresponding weigths. Therefore, we define five criticality categories: *none* 0% rounded likelihood of negatively affecting mission goal with weight 0, *unlikely* 1%-30% rounded likelihood of negatively affecting mission goal with weight 0.15, *mediocre* 31%-70% rounded likelihood of negatively affecting mission goal with weight 0.5, *likely* 71%-95% rounded likelihood of negatively affecting mission goal with weight 0.825 and *very-likely* 96%-100% rounded likelihood of negatively affecting mission goal with weight 0.975.

The formulas for sltMSE consist of total members that describe prediction distributions. The total members follow the structure:

$$sltMSE_{Tp} = \frac{1}{Tt + Tp} \sum_{i=1}^{|Tp|} (y_i - \hat{f}(x_i))^2 \tag{1}$$

Tp describes the actual prediction distribution, Tt the corresponding prediction distribution, where true category and predicted category are the same. y_i is the true stress level and $\hat{f}(x_i)$ is the predicted stress level. We derive this formula from the mean squared error. We add all total members for all prediction distributions and multiply them with the assigned weights. Therefore, we derive the following formulas.

The formula for health condition:

$$sltMSE_{healthCon} = 0.5 \cdot sltMSE_{Ml} + 0.975 \cdot sltMSE_{Hl} + 0.825 \cdot sltMSE_{Hm} + 0.975 \cdot sltMSE_{Xl} + 0.825 \cdot sltMSE_{Xm} \tag{2}$$

The formula for mission success:

$$sltMSE_{missionSuc} = 0.5 \cdot sltMSE_{Lm} + 0.825 \cdot sltMSE_{Lh} + 0.975 \cdot sltMSE_{Lx} + 0.15 \cdot sltMSE_{Ml} + 0.825 \cdot sltMSE_{Mh} + 0.975 \cdot sltMSE_{Mx} + 0.5 \cdot sltMSE_{Hl} + 0.5 \cdot sltMSE_{Hm} + 0.825 \cdot sltMSE_{Hx} + 0.975 \cdot sltMSE_{Xl} + 0.975 \cdot sltMSE_{Xm} + 0.825 \cdot sltMSE_{Xh} \quad (3)$$

6 User Interface

Figure 3 shows our proposed design for the mission overview screen. The user interface is divided into three different areas, the *Stress Overview* ①, the *Out* area ④ and the *Quick View* ⑥.
The *Stress Overview* area is subdivided into three stress level categories low ①, medium ③ and high ⑤. Each stress level category possesses eight buckets (grey background) that represent placeholders for eight deployed humans. Each colored circle represents a deployed participant. We neither use avatars nor shapes to represent the participants to avoid an avatar sympathy bias. The circles illustrate the stress tendency with the three symbols -/0/+ (see Section 2). ① shows a selected participant expressed with a blue line at the bottom of the bucket. A click on the corresponding circle will trigger the *Quick View* ⑥. An icon indicates a connection problem between the transmitting smart textile and the receiving unit ③. A notification indicator close to the circles sums the number of thresholds exceeds of any measured vital parameter that has not been checked yet ①. At ② the overall deployment time is displayed, whereas ④ represents the drop out area. A message to the corresponding human will be triggerd if a circle is dragged to the drop out area. This user interface design aggregates information to stress levels and addresses the problem of avatar sympathy.

7 Conclusion and Future Work

In this publication we show our Remote Health Monitoring system that creates digital twins of humans deployed in extreme environments. We developed a modular, washable smart textile undergarment equipped with integrated sensors and a central processing and communication unit. With our smart textile we facilitate sensor application on the human skin at medical valid positions and allow a seamless health monitoring experience. We propose a stress level scale that distinguishes eleven stress levels. To estimate and predict stress levels we first focus on a mountain rescue scenario in an cold environment. We define the individual physiological fingerprint with static vital quantities and define sensors types necessary to estimate and predict stress levels in this environment.

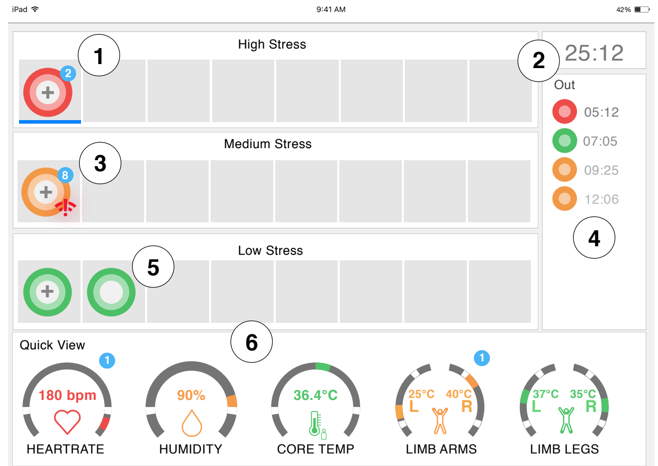


Figure 3: User Interface Design: The improved user interface design based on the proposed user interface composition in [1]. The figure shows the medical advisor overview and addresses all issues we faced during our evaluations.

Our data acquisition environment allows us to label generated data snapshots. Within the environment, the scenario, the physiological fingerprint as well as sensor value frequency and variance can be modified and we labeled 1027 data snapshots. The challenges of under- and overpredictions are dependent on the overall mission goals. Therefore, we define two possible mission goals, health condition and mission success and assigned criticality values, expressed in weights, for each stress level. We use this criticality values, to define the sltMSE, a measure to compare prediction quality. The evaluation environment compares 25 machine learning models on prediction quality for the mission goals health condition and mission success. Random Forest Regressor performs best for both mission goals. The model performs 23.19 times better than sltMSE of zero rule for health condition and 10.50 times better for mission success. Finally, we show our latest user interface design that visualizes the collected and aggregated data to medical trained experts. We show the overview screen that visualizes stress categories, stress tendencies and current vital quantities in a dashboard.
In our future work we want to develop a smart textile for different body shapes as well. We will focus on data acquisition for different scenarios and want to investigate how prediction models perform. Concerning the user interface we want to provide a detail view that shows the value history of each sensor as shown in our evaluation environment. Sometimes it is necessary to have a look at historical data to validate and make decisions.
With our RHM system design we improve the experience of the deployed person as well as the medical expert analyzing

real-time health-data. We want to further contribute to increase operational safety of humans operating in extreme, hazardous or dangerous environments.

Acknowledgments

We thank the Bundeswehr Research Institute for Materials Lubricants and Fuels (WIWeB) and the company Interactive Wear for the support and providing the smart textile. The Bundeswehr Research Institute for Protective Technologies and NBC Protection (WIS) conducted together with Dr. Andreas Werner the field trials, which were crucial for the further development of the smart textile.
We thank Michael Möhrle for his contribution to the questionnaire, the stress scale and the initial data acquisition environment.

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