Multimodal sensor-based identification of stress and compulsive actions in children with obsessive-compulsive disorder for telemedical treatment

Annika Thierfelder[1], Jonas Primbs[2], Björn Severitt[3], Carolin S. Hohnecker[4], Jan Kühnhausen[4], Annika K. Alt[4], Anja Pascher[4], Ursula Wörz[5], Helene Passon[6], Jens Seemann[1], Christian Ernst[6], Heinrich Lautenbacher[5], Martin Holderried[7], Enkelejda Kasneci[3], Martin A. Giese[1], Andreas Bulling[8], Michael Menth[2], Gottfried M. Barth[4], Winfried Ilg[1], Karsten Hollmann[4] and Tobias J. Renner[4]

Abstract— **In modern psychotherapy, digital health technology offers advanced and personalized therapy options, increasing availability as well as ecological validity. These aspects have proven to be highly relevant for children and adolescents with obsessive-compulsive disorder (OCD). Exposure and Response Prevention therapy, which is the state-of-the-art treatment for OCD, builds on the reconstruction of everyday life exposure to anxious situations. However, while compulsive behavior predominantly occurs in home environments, exposure situations during therapy are limited to clinical settings. Telemedical treatment allows to shift from this limited exposure reconstruction to exposure situations in real life.**

In the SSTeP KiZ study (smart sensor technology in telepsychotherapy for children and adolescents with OCD), we combine video therapy with wearable sensors delivering physiological and behavioral measures to objectively determine the stress level of patients. The setup allows to gain information from exposure to stress in a realistic environment both during and outside of therapy sessions.

In a first pilot study, we explored the sensitivity of individual sensor modalities to different levels of stress and anxiety. For this, we captured the obsessive-compulsive behavior of five adolescents with an ECG chest belt, inertial sensors capturing hand movements, and an eye tracker.

Despite their prototypical nature, our results deliver strong evidence that the examined sensor modalities yield biomarkers allowing for personalized detection and quantification of stress and anxiety. This opens up future possibilities to evaluate the severity of individual compulsive behavior based on multivariate state classification in real-life situations.

Clinical relevance— **Our results demonstrate the potential for efficient personalized psychotherapy by monitoring physiological and behavioral changes with multiple sensor modalities in ecologically valid real-life scenarios.**

*This work is funded by the Bundesministerium für Gesundheit (BMG) project SSTeP KiZ (2520DAT700)

[1]Hertie Institute for Clinical Brain Research, Section for Theoretical Sensorimotor Control, University of Tübingen, Germany, annika.thierfelder@uni-tuebingen.de

[2]Department of Computer Science, Communication Networks, University of Tübingen, Germany

[3]Department of Computer Science, Human-Computer Interaction, University of Tübingen, Germany

[4]Psychiatry, Psychosomatics and Psychotherapy in Childhood and Adolescence, University Hospital Tübingen, Germany

[5]Section for Information Technology, University Hospital Tübingen, Tübingen, Germany

[6]Institute for Healthcare and Public Management, University of Hohenheim, Stuttgart, Germany

[7]Department of Strategic Medical Development and Quality Management, University of Tübingen, Germany

[8]Institute for Visualisation and Interactive Systems, University of Stuttgart, Germany

I. INTRODUCTION

Obsessive-compulsive disorder (OCD) is a psychological disorder that mostly manifests in a combination of obsessions and compulsive behavior [1], [2]. Obsessions are defined as "repeated thoughts, urges, or mental images that cause anxiety" [3]. Common contents are fear of contamination, of infection, or of a bad incidence happening to oneself or other people. Compulsions are defined as "repetitive behaviors that a person with OCD feels the urge to do in response to an obsessive thought" [3]. This can include excessive and ritualized hand washing and showering, repeatedly checking that everything is secure (e.g., doors and windows locked, cooker turned off), or arranging objects symmetrically. In most cases, the action is performed until it feels "just right".

OCD affects around 0.5 - 4 % of children and adolescents [4], [5]. Especially young patients carry a high risk to develop chronic symptoms if they remain untreated [6]. State-of-the-art treatment for OCD is Cognitive Behavioral Therapy (CBT) based on Exposure and Response Prevention (E/RP) [2], [7]. During E/RP sessions, patients are explicitly exposed to their obsessions while asked to refrain from their usual response and to instead endure the discomfort caused by anxiety or disgust until it subsides on its own.

Most symptoms of OCD manifest stronger in patients' home environments, and are directly linked to specific objects or places, which cannot be reproduced in clinical settings. Telemedical therapy opens up the possibility to carry out the treatment in a natural home-based setting which benefits treatment outcomes [8].

Delivering CBT via telemedical approaches has proven to be beneficial for treating anxiety [9]. Often, telemedical treatment is provided through video-based therapy sessions [10], [11]. Despite latest advances in video call systems, therapists are still limited to the patient's webcam, which has so far allowed the situation to be assessed solely on the basis of verbal communication and facial expressions. Furthermore, video call situations require permanent interaction through an electronic device, limiting the realistic setting of E/RP sessions.

In the SSTeP KiZ study, we overcome these problems by combining video-based therapy with a multimodal wearable sensor setup. The setup includes the recording of physiological signals (ECG and pupillometry) to identify direct effects of anxiety, movement patterns (inertial sensors) to capture compulsive behavior and effects of increased stress levels, and gaze information (eye tracker) to follow the focus of attention.

Here, in this pilot study, we demonstrate that the examined sensor modalities capture essential features of stress reactions, compulsive behavior and the relief from anxiety, while focusing not only on exposure situations in artificial E/RP sessions, but also on different activities close to everyday life. With these findings, we lay the groundwork for the multivariate analysis of sensor modalities to detect obsessive-compulsive behavior in real-life settings.

II. METHODS

We recorded five subjects (four male, one female) between 13 and 17 years (mean: 15.2) with obsessive-compulsive disorder that were recruited via the child and adolescent psychiatry Tübingen. All patients and their parents gave consent prior to the study. The experimental procedure was approved by the local ethics committee (877/2020BO1).

A. Study Protocol

Each patient conducted one recording led by a psychotherapist that lasted 20 to 40 minutes. The sessions were structured into several parts with increasing stress level. During the baseline (BL), the patients performed only activities of daily living. In the Exposure and Response part (E/R), they were confronted with triggers of their obsession, but allowed to respond with their usual compulsive behavior. In the following Exposure and Response Prevention parts (E/RP), the patients were exposed to triggers but asked to refrain from their usual response and thereby endure the tension either for a defined time interval (*Variant A*) or completely (*Variant B*). If possible, the exposure was intensified over the E/RP sessions. Two exemplary session structures showing Variants A and B can be found in Figure 1.

During each part, the patients performed a sequence of daily activities that were not connoted with their OCD. The activities included walking on plain ground and up- and downstairs, washing their hands and a glass, sorting pencils, switching lights on and off, opening and closing doors, and shifting chairs.

B. Data Labeling

We used the NOVA software to both display and label the data in a synchronized way [12]. Labels were introduced on two levels of abstraction. On the high abstraction level, labels divided the recording into sequences of daily activities (ACT), sequences where patients discussed and prepared the upcoming exposure (COG), sequences where patients were exposed to situations triggering negative emotions like anxiety or disgust (EXPO), and sequences of relief through compulsive behavior (RESP). Labels on the low abstraction level described the single actions in the ACT sequences (common across patients) and during EXPO and RESP parts (personalized for each patient).

C. Individual Cases

Due to individual differences in the manifestation of symptoms, it was not possible to maintain strictly equal recording protocols for all subjects. Additional to individual exposure sessions, the sequence of events in the ER/P sessions had to be adapted to the nature of the compulsive behavior (cf. Figure 1). If it was possible to decouple the compulsive response from the exposure, *Variant A* was applied. In the E/RP session of Variant A, the urge for the compulsive response had to be endured for the duration of the ACT sequence, but the response was executed afterwards. If the

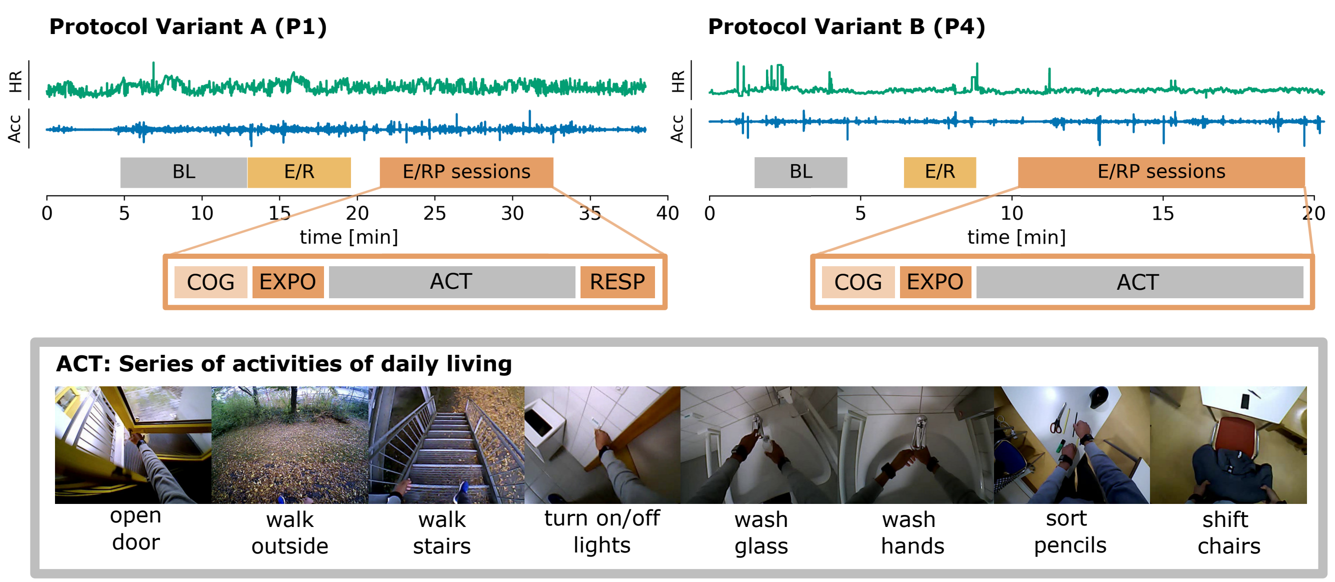

Fig. 1. Schematic overview of the study protocol. Each recording consisted of a baseline (BL), a part where exposure was followed by response (E/R), and several Exposure and Response (E/RP) sessions. The **upper panel** shows the difference between the E/RP variants that were chosen based on the individual manifestation of OCD: in **Variant A**, the patient endured the anxiety of exposure for the duration of the ACT sequence until the compulsive behavior was executed; in **Variant B**, the patient completely refrained from the response. The **lower panel** shows an example series of daily activities performed during the ACT sequences.

decoupling of exposure and response was not possible, we used *Variant B*. Here, the patients had to endure the urge to execute the compulsive action after the exposure completely.

In the following, we describe the manifestations for the single patients along with the design choice of Variant A or Variant B.

- Patient 1 (P1) presented with the reoccurring urge to check the contents of his bag. Since it was possible to separate the bag checking behavior from the exposure, we applied Variant A.
- Patient 2 (P2) presented with the obsession to search for his own name in the internet before passing on the phone to someone else. Since there was only the option of either searching the name or refraining from the urge completely, Variant B was be applied.
- Patient 3 (P3) presented with fear of contamination and the urge to perform actions in a certain way. For our recording session, he agreed to the exposures to not count the steps when walking stairs, to walk across the hallway while not following lines on the floor and to approach a public bathroom. Since the compulsions were intrinsically triggered, a separation of exposure and response was impossible (Variant B).
- Patient 4 (P4) presented with the urge to repeat actions until they felt "just right", but not exhibiting a prespecified amount of repetitions. As exposure, the actions were performed without repetition, including pouring water into a glass, switching on the light, and opening a window and a door. Since the compulsive repetitions could not be decoupled from the action itself, Variant B was applied.
- Patient 5 (P5) presented with the compulsion to arrange objects in a specific way, to turn a glass upside down before filling and drinking, and with the urge to wash hands excessively. He agreed to exposure to wrongly arranged pencils, drinking from a glass without turning it and touching equipment in a public bathroom. Both variants A and B were applied, depending on the compulsion.

For P3 and P4, actions that would trigger obsessive thoughts were removed from the daily activities performed in the ACT sequence.

D. Aggregation of Sensor Modalities

The complete equipment as worn by the participants is shown in Figure 2. Behavior and physiology of the patients were recorded with several sensor modalities: (i) an ECG chest belt (Suunto Movesense, Suunto, Vantaa, Finland) measuring the time between the R-peaks of consecutive heart beats (RR intervals); (ii) inertial motion sensors (Opal, APDM Inc., Portland, OR) attached to both wrists using Velcro bands synchronously recording acceleration at 128 Hz; and (iii) the *Look!* head-mounted device for eye tracking including a scene camera with a resolution of 640×480 px and two eye cameras with 320×240 px, all recording at 30 Hz [13]. The recording was controlled and sensor data was aggregated on a Windows 10 Tablet (Surface Pro 7 i7/16GB/256GB, Microsoft Corporation, Redmond, WA). During the recordings, the tablet was carried inside a small backpack. Overall, the equipment was light ($<$ 1 kg), thus not hindering the patients during the recordings.

Fig. 2. Equipment as worn by the patients. Sensors include an eye tracking device, an ECG chest belt, and inertial sensors on each wrist. Additionally, participants carried a backpack with a tablet for data collection.

To collect data and synchronize timestamps of the different sensor modalities in a uniform data format, we used a custom *Aggregator Software* developed as part of the SSTeP KiZ telemedical infrastructure. During the recording, the software cached the data in full resolution for the subsequent upload, but it also prepared the sensor data in a reduced resolution for the potential streaming to a therapist. For the patients, the *Aggregator Software* provided a Graphical User Interface to connect, control and record the sensors.

E. Heart Rate Variability

Crucial means to identify stressful events are heart rate (HR) and heart rate variability (HRV). Since HRV measures reflect autonomic balance [14], increased stress presents not only with an elevated HR, but predominantly with a decreased HRV [15], [16].

The established standard for short-term HRV computations uses recording lengths of 5 minutes, which does not allow for the analysis of immediate reactions to a stress trigger [17]. However, recent studies have proven that ultra-short-term HRV computations are representative for different age cohorts [17], [18]. For detecting a difference between stressful and baseline recordings, a minimum HRV window of 30 s has been reported [19].

The HR is commonly measured in beats per minute (BPM). To achieve comparable time series of HR and HRV, we averaged the BPM over 30 s windows. The average HR of N_{30} RR intervals within a 30 s window is defined by Equation 1. RR intervals were given in ms.

$$\mathrm{BPM}_{30} = \frac{1}{N_{30}} \sum_{n=1}^{N_{30}} \frac{60{,}000 \text{ ms}}{\mathrm{RR}_n} \quad (1)$$

We used the root mean square of successive differences (RMSSD) as a measure for HRV. While the RMSSD is a simple but well-established parameter [17], it is also suitable to identify stressful periods in short windows [19]. Equation 2 shows how the RMSSD is calculated for N_{30} RR intervals corresponding to a 30 s window.

$$\mathrm{RMSSD}_{30} = \sqrt{\frac{1}{N_{30}-1}\sum_{n=2}^{N_{30}}(RR_n - RR_{n-1})^2} \quad (2)$$

After calculating BPM_{30} and RMSSD_{30} for every data point in the RR interval sequence, the data were synchronized to the video timestamps (recorded with 30 Hz). For upsampling, the most recent BPM_{30} or RMSSD_{30} value was replicated for every video timestamp. For better comparability across patients, we also z-scored both the BPM_{30} and RMSSD_{30} sequences, which will in the following be referenced as nBPM_{30} and nRMSSD_{30}, respectively.

Additionally to the ultra-short-term analysis, we calculated average BPM and RMSSD on the ACT sequences that were performed for every stress level. Since the RMSSD is sensitive to the size of the calculation window, the length of the shortest ACT sequence throughout the recording was chosen as window size to gain comparability within patients.

F. Movement Analysis

Before computing measures on the acceleration of the inertial sensors, the data was reoriented to a global reference frame using the orientation estimates provided by the APDM system [20] and the gravitational component was removed.

As a general movement parameter, we computed the energy of the three-axial accelerometer for single actions. Equation 3 shows the computation of movement energy for an action of sample length N_{act}, where $acc_{d,n}$ describes the acceleration of the sensor along dimension d at sample n.

$$\mathrm{energy}_{acc} = \frac{1}{N_{\mathrm{act}}}\sum_{n=1}^{N_{\mathrm{act}}}\sqrt{acc_{x,n}^2 + acc_{y,n}^2 + acc_{z,n}^2} \quad (3)$$

To analyze compulsive actions more specifically, we looked at the frequency content in the acceleration of both hands. Compulsive actions are often repetitive behaviors that are associated with a specific movement pattern [7], either due to an inherently repetitive movement like hand washing, or caused by a specific ritual or amount of repetitions to reduce the discomfort.

We computed the frequency spectrum separately for each spatial dimension of the signal using a Fast Fourier Transform [21]. To obtain a combined single value across all spatial dimensions for each frequency component, the frequency spectra were then averaged.

G. Gaze Analysis

Eye tracking devices commonly provide both information about the gaze of the patient as well as about the physiological state through pupillometry. In this study, however, we focused only on the information derived from gaze fixations.

Gaze was estimated with a convolutional neural network based on a method robust to small changes in positioning of the device for reliable calibration across subsequent sessions [22]. We analyzed gaze data using gaze density maps on images of distinct view points taken from the egocentric video. Gaze density was computed by counting the amount of fixations to the local surrounding of a pixel (11 px), smoothing the result matrix with a Gaussian kernel and scaling it to a density distribution.

H. Data Exclusion Criteria

Since the ECG chest belt for P3 did not stay in place, we had to exclude P3 from the ECG analysis. For similar reasons, we had to exclude the first half of the BL of P2 from the ECG analysis. Since P5 did not report a consistent subjective increase in stress over the course of the recording, we excluded the data of P5 from the computation of general trends over stress levels.

III. RESULTS

In this section, we will look at the effects of increasing stress level on HRV and movement energy, and show approaches for the location of stressful events using ECG. Moreover, we demonstrate the possibility to identify compulsions with inertial sensors as well as triggers of stress using gaze information.

A. Effect of increased stress on HR and HRV

To investigate the effect of rising stress in the ECG, we calculated RMSSD and average BPM for ACT sequences in all stress levels. As expected, the results depicted in Figure 3A+B show a decrease in RMSSD for all patients, while we can observe either an increase or a stable level of average BPM. For P1, the difference mainly emerges between E/R and E/RP levels, while for P2 the biggest change can be observed from BL to E/R. For P4, we removed the baseline recording from the trend computation due to an unusually high HR during that period. Apart from the baseline level, P4 shows an overall decrease in RMSSD accompanied by a stable heart rate level.

B. HR and HRV during stress reactions and their relief

In Figure 3C, we show examples for the progression of nRMSSD_{30} and nBPM_{30} in each patient's last E/RP session. We chose the last E/RP session for demonstration since it presented the most stressful situation for all patients. The upper panels show a stress reaction on the left and a period of relief on the right. The lower panels each show one instance that includes both the stress reaction and the subsequent relief.

For P1, P5 and P2, the left dashed line represents the end of the exposure, after which they refrained from executing the response. Immediately after the exposure, we can see the drop in HRV (nRMSSD_{30}) and the parallel increase in HR (nBPM_{30}).

In P4, the two dashed lines show the beginning and end of the exposure, where P4 performed two different actions without the compulsive repetition. We can see a dominant stress increase during the exposure, shown by a peak in HR

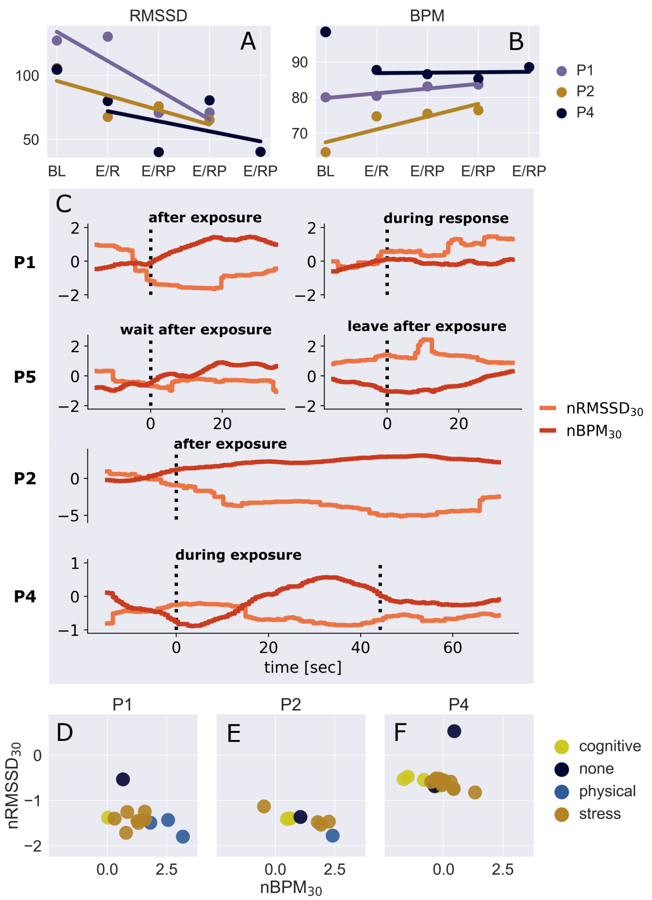

Fig. 3. Stress reactions in heart rate and heart rate variability. Figures **A** and **B** show the RMSSD and average BPM for the different stress levels (baseline (BL), exposure and response (E/R), and several E/RP sessions). Figure **C** shows examples of immediate stress reactions and the relief from the associated discomfort in z-scored HR ($nBPM_{30}$) and HRV ($nRMSSD_{30}$) for every patient during their last E/RP session. From top to bottom: **P1**, left panel: refraining from usual response after exposure; right panel: performing the compulsive action. **P5**, left panel: staying in public bathroom after exposure there, right panel: leaving the room after same exposure. **P2**: refraining from the usual response after exposure while performing daily activities. **P4**: executing two exposure actions and performing daily activities afterwards. Figures **D-F** depict the relationship between the average of $nBPM_{30}$ and $nRMSSD_{30}$ over 5 s for identified stress events. Stress events were defined crossings of the $RMSSD_{30}$ under the lower boundary of the $RMSSD_{30}$ normal range calculated during the baseline.

and low HRV. Although the HR peak diminishes with the end of the exposure, showing some immediate relief, the HR stays on a higher and HRV on a lower level. A similar pattern of relief can be seen in P2, where the stress response diminishes after around 60 s where the patient performed activities of daily living unrelated to his compulsions.

For P1 and P5, situations of relief from anxiety are depicted in the right panels, where we can see the increase in HRV accompanied by a stable or decreased HR. For P1, anxiety is relieved through the compulsive behavior that he refrained from before. For P5, both panels show the time after he was exposed to touching equipment around a public bathroom followed by a period where he refrained from executing his compulsion. However, in the left panel, he was asked to stay in the bathroom and endure the anxiety, while in the right panel, he left the bathroom after the exposure to perform other activities. Here, we can see that leaving the scene of exposure can relief the stress even without executing the compulsive action.

C. HRV for the identification of stressful events

Since the most dominant feature of stress is the drop in HRV, we identified all periods for each patient in which the $RMSSD_{30}$ dropped below the normal range to identify stressful events. The normal range was defined as one standard deviation around the mean $RMSSD_{30}$ computed during the BL. Each event was assigned to the following categories: "cognitive": anticipation of an exposure; "stress": during an E/RP session or as communicated by the patient; "physical": during physical activity; "none": events that fit into neither category. Ambiguous events were not included due to the lack of interpretability.

For each event, we calculated the mean $nRMSSD_{30}$ and $nBPM_{30}$ over the following 5 s. The length of the window was chosen as a trade-off between capturing the severity of the reaction while not being influenced by subsequent changes. The relationships between $nRMSSD_{30}$ and $nBPM_{30}$ for the different categories are shown in Figures 3D-F. In D and F, "none" events prove distinct from both "cognitive" and "stress" labels. The two "none" events in E and F falling within the "cognitive" and "stress" cluster could either be falsely identified or caused by a stressful trigger that was not communicated by the patient.

For all three patients, anticipatory cognitive stress tends to present with a lower heart rate than stress during an E/RP session. However, this effect could be partially caused by physical activity, since the patients were often sitting or standing during cognitive preparation and walking during the E/RP sessions.

We also observe that a drop in $nRMSSD_{30}$ due to physical activity is accompanied with a more elevated HR than in stressful events, demonstrating the ability to distinguish these two categories. Note that P4 did not perform actions involving physical activity.

D. Movement energy increases with stress

As for the ECG data, we first analyzed the impact of the rising stress level on the accelerometer data. We found that movement energy of repetitive movements increased with higher stress levels as shown in Figure 4.

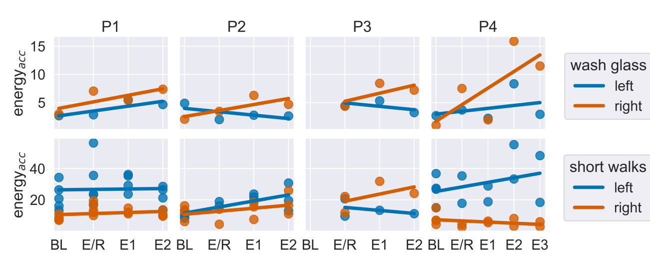

Fig. 4. Increase of movement energy in the acceleration of both hand sensors during the two repetitive actions washing and walking across the different stress levels: baseline (BL), exposure and response (E/R), and E/RP sessions (E1 - E3).

The upper panel shows the movement energy of left and right hand sensors for washing a glass, while the lower panel shows it for short walks of approximately 5-10 m. In both panels, we can see the increase in movement energy over time. While washing the glass, patients held the glass in the left hand while washing it with the right hand, therefore the energy increase is unilateral. While walking, P1 and P4 were holding the glass in their right hand during some or all of the walks, accounting for the lower energy in this hand.

E. Unique movement patterns during compulsive behavior

Only P1 presented with a repetitive compulsive behavior suitable for an analysis with inertial sensors. Figure 5 depicts the difference of the right and left hand power spectra for the repetitive opening and closing of the bag in comparison to other repetitive but non-compulsive actions.

In Figure 5, we can see that the compulsive action is asymmetric, dominated by the right hand, with a unique power distribution that peaks between 2 and 3.5 Hz. Actions with high power in a similar range, like walking, are rather symmetric and therefore do not show extreme values in the difference of frequency spectra. Other actions with strong unilateral frequencies are washing a cup (washing with the right hand) and washing hands (getting soap with the left hand). Compared to the compulsive action, they present with similarly high power but in a different frequency range or dominated by the other hand. The distinct power distribution of the compulsive behavior underlines the role of inertial sensors for detecting and quantifying compulsions.

F. Gaze fixations

To demonstrate the effect of exposure to stress on the gaze data, we selected the last E/RP session of P5. The exposure consisted of touching equipment within a public bathroom. Afterwards, the patient was asked to stay in the bathroom while refraining from the urge to wash hands. Figure 6 shows the three predominant view points of the egocentric video with gaze density maps to show the patient's attention.

In total, the three analyzed view points made up over 50% of the total head poses during the scene. To ensure precise overlay of the gaze densities, we did not take view points into account that were directed at the same object in a different angle. Within the three view points, P5 focused twice as often on the equipment around the public toilet (59%) than on the floor (27%). Fixations on the sink made up 14%.

The distribution of fixations complements the progression of HR and HRV shown in Figure 3C, which indicated that staying in the public bathroom induced high stress, while leaving the room relieved the anxiety. The intense gaze focus on the equipment around the toilet underlines the importance of gaze information for identifying locations that likely trigger stress reactions.

IV. DISCUSSION

In this study, we recorded five adolescents with OCD using multiple sensor modalities. Participants performed several E/RP sessions of increasing stress levels intertwined with sequences of daily activities.

The effect of rising stress was detectable both within the ECG and the inertial sensors. ECG analysis showed an increasing HR and a decreasing HRV, which are known effects of mental stress [15], [16]. In the inertial wrist sensors, we observed an increase in the energy of repetitive movements like washing or walking. These findings lay the groundwork for estimating patients' overall stress level with respect to their individual baseline.

On a smaller scale, HR and HRV calculated on 30 s windows showed distinctive patterns both for immediate stress reactions to exposure as well as for the relief from associated discomfort through compulsive behavior. Although these reactions were rather individual, we were able to apply their common pattern to identify stressful events. These stress events clustered into cognitive stress, actual E/RP episodes and physical activity. The distinction between stress and physical activity is an important aspect of stress detection in real-life environments. While ECG measures may not be powerful enough alone, these results underline that the distinction can be accomplished with a combination of HRV and movement measures.

Our analysis of eye tracking data during exposure demonstrated how gaze predominantly rested on the object that triggered the stress reaction. Combining this information with object recognition opens up the possibility to identify

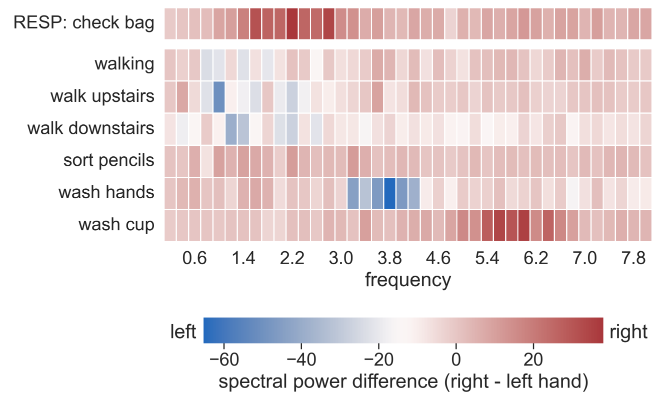

Fig. 5. Difference of the left and right hand frequency spectra for different repetitive actions. To facilitate comparison, frequencies were split into frequency bands in steps of 0.2 Hz. The upmost panel shows the compulsive action that we aim to identify (rhythmic opening and closing of the bag when checking its content). The rows below show other repetitive but non-compulsive actions.

Fig. 6. Illustration of P5's attention in the three most frequent view points of the egocentric video while waiting in the public bathroom after the exposure. In this scene, he is enduring the anxiety caused by refraining from the urge to wash hands after touching equipment in the public bathroom.

triggers, but also quantify how strongly the object is influencing the stress level.

In addition to stress reactions, we analyzed how relief from associated discomfort through compulsive behavior is reflected in the sensor signals. In the ECG, relief can be immediately detected by an increase in HRV and decrease in HR. The results suggest that also a change of environment (i.e., distance to the trigger) or simple distraction (i.e., performing other actions) can cause the anxiety to subside, depending on the individual condition of the patient.

The identification and quantification of repetitive compulsive behavior also benefits from adding inertial sensors. At the example of P1, we showed that unique frequency distributions of compulsive behavior can make movement sensors an essential tool in detecting compulsive actions, while changes of power in the typical frequency band could help to quantify the amount of preceding stress.

The main limitation of this pilot study is the restricted amount of available data. For a more detailed analysis, more patients need to be recorded to verify general parameters for stress detection. However, since manifestations of OCD are highly individual, also more sessions of the same patient are needed in order to adapt and develop personalized parameters and algorithms.

Despite these limitations, our study shows promising results for detecting stress and compulsive behavior with the different sensor modalities. In our future studies, we will consolidate stress detection by combining the sensor modalities in multi-variate classifiers to automatically detect stressful periods.

We will also focus on personalized algorithms for each patient to detect and quantify individual aspects of stress and compulsive behavior. This quantification constitutes valuable information for therapists to optimize the exposure strategy during remote therapy sessions. Moreover, stress can also be quantified during patients' everyday life, providing additional information about the manifestation of obsessive-compulsive behavior during non-artificial real-life situations.

ACKNOWLEDGEMENT

The authors thank the International Max Planck Research School for Intelligent Systems (IMPRS-IS) for supporting A.T. and J.S.. A.B. was funded by the European Research Council (ERC; grant agreement 801708). M.G. was funded by the European Research Council (ERC SYNERGY Grant RELEVANCE).

REFERENCES

[1] World Health Organization, "International classification of diseases for mortality and morbidity statistics (11th revision)," May 2021. [Online]. Available: https://icd.who.int/browse11/l-m/en

[2] J. S. Abramowitz, S. Taylor, and D. McKay, "Obsessive-compulsive disorder," *The Lancet*, vol. 374, no. 9688, pp. 491–499, 2009.

[3] National Institute of Mental Health, "Obsessive-Compulsive Disorder," Oct. 2019, retrieved January 11, 2022. [Online]. Available: https://www.nimh.nih.gov/health/topics/obsessive-compulsive-disorder-ocd

[4] I. Heyman, E. Fombonne, H. Simmons, T. Ford, H. Meltzer, and R. Goodman, "Prevalence of obsessive-compulsive disorder in the British nationwide survey of child mental health," *The British Journal of Psychiatry*, vol. 179, pp. 324–329, Oct. 2001.

[5] H. M. Douglass, T. E. Moffitt, R. Dar, R. McGEE, and P. Silva, "Obsessive-Compulsive Disorder in a Birth Cohort of 18-Year-Olds: Prevalence and Predictors," *J Am Acad Child Adolesc Psychiatry*, vol. 34, no. 11, pp. 1424–1431, Nov. 1995.

[6] S. E. Stewart, D. A. Geller, M. Jenike, D. Pauls, D. Shaw, B. Mullin, and S. V. Faraone, "Long-term outcome of pediatric obsessive–compulsive disorder: a meta-analysis and qualitative review of the literature," *Acta Psychiatrica Scandinavica*, vol. 110, no. 1, pp. 4–13, 2004.

[7] G. Krebs and I. Heyman, "Obsessive-compulsive disorder in children and adolescents," *Arch Dis Child*, vol. 100, no. 5, pp. 495–9, 2015.

[8] R. R. Selles, Z. Naqqash, J. R. Best, D. Franco-Yamin, S. T. Qiu, J. S. Ferreira, X. Deng, D. K. Hannesdottir, C. Oberth, L. Belschner, J. Negreiros, L. J. Farrell, and S. E. Stewart, "Effects of treatment setting on outcomes of flexibly-dosed intensive cognitive behavioral therapy for pediatric ocd: A randomized controlled pilot trial," *Front Psychiatry*, vol. 12, p. 669494, May 2021.

[9] C. Hollis, C. J. Falconer, J. L. Martin, C. Whittington, S. Stockton, C. Glazebrook, and E. B. Davies, "Annual Research Review: Digital health interventions for children and young people with mental health problems – a systematic and meta-review," *J Child Psychol Psychiatry*, vol. 58, no. 4, pp. 474–503, Apr. 2017.

[10] K. Hollmann, K. Allgaier, C. S. Hohnecker, H. Lautenbacher, V. Bizu, M. Nickola, G. Wewetzer, C. Wewetzer, T. Ivarsson, N. Skokauskas, L. Wolters, G. Skarphedinsson, B. Weidle, E. de Haan, N. Torp, S. Compton, R. Calvo, S. Lera-Miguel, A. Haigis, T. J. Renner, and A. Conzelmann, "Internet-based cognitive behavioral therapy in children and adolescents with obsessive compulsive disorder: a feasibility study," *J Neural Transm*, vol. 128, no. 9, pp. 1445–1459, Sep. 2021.

[11] L. Babiano-Espinosa, L. H. Wolters, B. Weidle, S. N. Compton, S. Lydersen, and N. Skokauskas, "Acceptability and feasibility of enhanced cognitive behavioral therapy (eCBT) for children and adolescents with obsessive-compulsive disorder," *Child Adolesc Psychiatry Ment Health*, vol. 15, no. 1, p. 47, Sep. 2021.

[12] T. Baur, A. Heimerl, F. Lingenfelser, J. Wagner, M. F. Valstar, B. Schuller, and E. André, "eXplainable Cooperative Machine Learning with NOVA," *Künstliche Intelligenz*, vol. 34, no. 2, pp. 143–164, Jun. 2020.

[13] T. C. Kübler, "Look! Blickschulungsbrille: Technical specifications," Look! ET, Tech. Rep., Dec. 2021.

[14] Electrophysiology, Task Force of the European Society of Cardiology the North American Society of Pacing, "Heart rate variability: standards of measurement, physiological interpretation, and clinical use," *Circulation*, vol. 93, no. 5, pp. 1043–1065, Mar. 1996.

[15] R. Castaldo, P. Melillo, U. Bracale, M. Caserta, M. Triassi, and L. Pecchia, "Acute mental stress assessment via short term HRV analysis in healthy adults," *Biomedical Signal Processing and Control*, vol. 18, pp. 370–377, Apr. 2015.

[16] J. Taelman, S. Vandeput, A. Spaepen, and S. Van Huffel, "Influence of Mental Stress on Heart Rate and Heart Rate Variability," in *4th European Conference of the International Federation for Medical and Biological Engineering*. Springer, 2009, vol. 22, pp. 1366–1369.

[17] F. Shaffer and J. P. Ginsberg, "An Overview of Heart Rate Variability Metrics and Norms," *Front Public Health*, vol. 5, p. 258, Sep. 2017.

[18] H. Baek, C.-H. Cho, J. Cho, and J.-M. Woo, "Reliability of Ultra-Short-Term Analysis as a Surrogate of Standard 5-Min Analysis of Heart Rate Variability," *Telemed J E Health*, vol. 21, Mar. 2015.

[19] L. Salahuddin, J. Cho, M. G. Jeong, and D. Kim, "Ultra short term analysis of heart rate variability for monitoring mental stress in mobile settings," in *29th Annu Int Conf IEEE Eng Med Biol Soc. 2007*. IEEE, 2007, pp. 4656–4659.

[20] L. Holmstrom, "How is the orientation of an Opal estimated?" Apr. 2021, retrieved November 27, 2021. [Online]. Available: https://support.apdm.com/hc/en-us/articles/

[21] J. W. Cooley and J. W. Tukey, "An Algorithm for the Machine Calculation of Complex Fourier Series," *Mathematics of Computation*, vol. 19, no. 90, pp. 297–301, Apr. 1965.

[22] T. Santini, D. Niehorster, and E. Kasneci, "Get a grip: Slippage-robust and glint-free gaze estimation for real-time pervasive head-mounted eye tracking," in *Proceedings of the 2019 ACM Symposium on Eye Tracking Research & Applications (ETRA)*, Jun. 2019.