Dynamical systems modeling of day-to-day signal-based patterns of emotional self-regulation and stress spillover in highly-demanding health professions

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***Abstract*— As hospital workers face a growing number of patients and have to meet increasingly rigorous standards of care, their ability to successfully modulate their emotional reactions and flexibly handle stress presents a significant challenge. This paper examines a multimodal signal-driven way to quantify emotion self-regulation and stress spillover through a dynamical systems model (DSM). The proposed DSM models day-to-day changes of emotional arousal, captured through speech, physiology, and daily activity measures, and its interplay with daily stress. The parameters of the DSM quantify the degree of self-regulation and stress spillover, and are associated with work performance and cognitive ability in a multimodal dataset of 130 full-time hospital workers recorded over a 10-week period. Linear regression experiments indicate the effectiveness of the proposed features to reliably estimate individuals' work performance and cognitive ability, providing significantly higher Pearson's correlations compared to aggregate measures of emotional arousal. Results from this study demonstrate the importance of quantifying oscillatory behaviors from longitudinal ambulatory signals and can potentially deepen our understanding of emotion self-regulation and stress spillover using signal-driven measurements, which complement self-reports and provide estimates of the psychological constructs of interest in a fine-grained time resolution.**

***Index Terms*— Dynamical systems, speech, physiology, emotional arousal, stress**

I. INTRODUCTION

Hospital workers are often exposed to high physical, mental, and emotional workload, having to face complex work environments with extensive responsibilities and limited latitude, which can often drain their mental and emotional resources. In order to cope with the demands and challenges of the profession, the ability of hospital workers to regulate their emotions can help prevent negative outcomes related to counter-productive work behaviors, cognitive decline, and stress-related symptoms [1].

Emotion regulation refers to one's flexibility to permit or delay emotional spontaneous reactions as needed in order to ensure daily functioning and obey social rules [2]. Increased emotion regulation has been linked to effective cognitive processing and high social competence, and varies from person to person under different conditions [3]. It is associated with reduced emotional exhaustion, which is likely to lead to less work-related burnout and increased work performance [4]. Prior work indicates that individuals' ability to carry out successful emotion regulation strategies depends on their cognitive resources [5]. Individuals with maladaptive emotion regulation tend to report more enduring negative emotions, which are likely caused by stressful events carrying over from previous days over a prolonged period of time [6]. Such stress spillover can hinder individuals' cognitive capacities and work performance [7].

The majority of existing studies capture emotion regulation and stress spillover through questionnaires, which produce a one-time snapshot of the constructs of interest, while heavily relying on individuals' potentially biased and subjective self-assessment reports [4], [6], [7]. On the other hand, changes in acoustic and physiological channels can be measured through a range of sensors [8] and do not suffer from subjective biases. Emotional arousal, manifested via these signals is related to emotion regulation through individual's conscious or unconscious efforts to control it [9]. In this paper, we quantify day-do-day emotion regulation and stress spillover of hospital workers using signal-based indices of speech, physiology, and daily activities. We further examine the extent to which the signal-driven measures of emotion regulation and stress spillover are associated with individuals' work performance and cognitive characteristics.

Dynamical systems models (DSM) describe the time dependence of a point in a feature space and can model oscillatory patterns of signals [10]. In human-related applications, DSMs have been employed to capture the amount of self-reported affect regulation [11] and physiological interrelation between partners [12], model the interplay between interlocutors in dyadic conversations [13]. DSM's properties render it ideal for our case, since we are interested in modeling the day-to-day oscillatory behavior of emotional arousal related to individuals' speech, physiology, and daily activities. In addition to modeling the trajectories of a given feature space, DSM can further represent the perturbation of the feature space in the presence of an input signal. We use individuals' self-reported stress as that input signal to the proposed DSM, in order to quantify the spillover of

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previous day's stress to the next day's emotional arousal. The parameters of the DSM, estimated through system identification techniques, can embody an individual's day-to-day self-regulation and stress spillover. The proposed model is evaluated using data from 130 full-time hospital workers over a 10-week period. Our results obtained through statistical analysis and machine learning experiments indicate that workers' self-regulation, as estimated from the DSM, is significantly associated with work performance ($r = 0.25$, $p < 0.01$) and cognitive ability ($r = 0.19$, $p = 0.05$). Our findings lay the foundation toward designing signal-driven models of emotional arousal for better understanding self-regulation, and promoting cognitive ability and work performance.

II. Data Description

Our data includes 213 full time hospital workers at the University of Southern California's Keck Hospital in Los Angeles, CA, USA, aged between 21-65 years, who participated in the study over a 10-week period [14]. Participants engaged in their typical daily activities during the data collection period. At the same time, they were equipped with ambulatory wearable devices through out their entire work shift (each day for 10 weeks), and were asked to complete several self-assessment questionnaires prior to the study and on a daily basis. The data used in our experiments include 130 participants, who completed on average 70.15 ($\pm$5.39) days of the study.

As part of the self-reported questionnaires, an Initial Ground Truth Battery (IGTB) and a daily Mobile Ground Truth (MGT) assessment were collected from each participant. Participants completed the IGTB in the beginning of the study. Among the various IGTB scores that were recorded, in this paper we capture task performance assessed through the In-Role Behavior (IRB) [15] and the Individual Task Proficiency (ITP) [16] questionnaires. We further measured participants' general cognitive ability through the Shipley Vocabulary test [17]. Following the Experience Sampling Methodology (ESM) framework, participants completed the MGT surveys daily and the scores from participants' daily stress levels are taken into account in this paper. Each participant reported their perceived stress by rating it from 1 ("No stress at all") to 5 ("A great deal of stress").

Participants were further equipped with a variety of sensors to capture acoustic and physiological signals. The Fitbit Charge 2 was used to measure participants' sleep activity and exercise, and was worn throughout the entire day. During work time, participants also wore the OMsignal garment, which collected their heart rate and breathing rate. Finally, the Unihertz Jelly Pro smartphone, a tiny and lightweight phone worn on the lapel, was programmed to obtain acoustic measures from audio recordings (notably speech activity and ambient audio from an "egocentric perspective") [18].

III. Methodology

A. *Signal-based features of emotional arousal*

At the beginning, we compute daily features of emotional arousal related to speech, physiology, and daily activity, comprising the points of a time-series spanning the entire length of data collection period. Missing points are accounted for by linear interpolation method. Following previous work [19], [13], we quantify prosodic changes in speech by extracting the fundamental frequency (F0), jitter, and shimmer. Fundamental frequency (F0) has been extensively associated with emotional arousal [19], [13], while jitter and shimmer reflect the variability of F0 in terms of amplitude and time, and have also been affiliated with changes in emotional arousal [19]. Similarly, in terms of physiological features, we compute the heart rate and breathing rate from the OMsignal garment. Emotional arousal is also quantified in terms of daily activity features as the number of steps and sleep efficiency (in units of time), both are computed using the proprietary algorithms built-in on the Fitbit device.

B. *Dynamical systems model (DSM)*

We use a first-order coupled linear oscillator that incorporates signal-based features of emotional arousal(subsection: III-A) and the effect of an individual's self-reported stress on a given day to predict changes in emotional arousal on the following day. Let $x(t)$ be the signal-driven emotional arousal and $m(t)$ be the self reported stress on day t (Section II). The change in emotional arousal $\frac{dx(t)}{dt}$ from day t to day $t+1$ can be written as:

$$\frac{d}{dt}x(t) = \alpha \cdot x(t) + \beta \cdot m(t) \qquad (1)$$

Variable α in (1) captures the degree of day-to-day change over each of the acoustic, physiological and daily activity features. Positive values of α indicate high correlation between $x(t+1)$ and $x(t)$, therefore low changes in emotional arousal across consecutive days, and potentially high degree of self-regulation. In contrast, negative values of α indicate low correlation, and therefore lower degree of self-regulation, between emotional arousal across consecutive days. Similarly, variable β is associated with stress spillover across consecutive days. High value of β indicates increased correlation between stress $m(t)$ at the current day and emotional arousal $x(t+1)$ at the next day, and therefore high spillover. The opposite holds for low values of β, which indicate low spillover across consecutive days.

Parameter estimation is performed through the System Identification Toolbox in MATLAB®, which uses an iterative gradient descent algorithm to solve the corresponding optimization problem. A DSM is fit for each of the signal-based measures of emotional arousal (i.e., F0, jitter, shimmer, heart rate, breathing rate, number of steps, sleep efficiency), yielding a different estimate of α and β for each of these measures.

C. *Evaluation and comparison to baseline*

Motivated by findings from psychological science [4], [6], [7], we examine the association between the estimated DSM parameters of day-to-day self-regulation α and stress spillover β (Section III-B) with individuals' general task performance and cognitive ability scores, as measured by IGTB self-reports obtained in the beginning of the study (Section II). We compare the proposed DSM parameters

TABLE I

PEARSON'S CORRELATION COEFFICIENT BETWEEN TASK PERFORMANCE AND COGNITIVE ABILITY WITH THE SELF REGULATION α QUANTIFIED USING ACOUSTIC, PHYSIOLOGICAL, AND DAILY ACTIVITY MEASURES BASED ON THE PROPOSED DYNAMICAL SYSTEMS (DSM) MODEL.

Performance & Cognitive Measures	Speech			Physiology		Daily activity	
	F0	Jitter	Shimmer	Breathing rate	Heart rate	Number of steps	Sleep efficiency
Individual task proficiency (ITP)	**0.22***	0.18	**0.25****	-0.04	0.03	0	-0.17
In-role behavior (IRB)	0.07	0.16	0.18	0.06	0.09	0.02	-0.01
Shipley vocabulary	0.16	0.19 †	0.15	0.08	0.13	-0.06	0.03

*: p <0.05 ; **: p <0.01

TABLE II

PEARSON'S CORRELATION COEFFICIENT BETWEEN ACTUAL AND PREDICTED VALUES OF TASK PERFORMANCE AND COGNITIVE ABILITY USING LINEAR REGRESSION WITH THE PROPOSED SELF-REGULATION α AND SPILLOVER β FEATURES AND THE BASELINE SIGNAL AVERAGE MEASURES.

Performance & Cognitive Measures	Baseline	Speech			Physiology		Daily activity	
		F0	Jitter	Shimmer	Breathing Rate	Resting Heart Rate	Number of steps	Sleep Efficiency
Individual task proficiency (ITP)	0.06	0.19*	0.17	0.19*	0.07	0.12	0.03	0.07
In-role behavior (IRB)	0.01	-0.12	-0.01	-0.02	-0.09	-0.12	-0.13	-0.16
Shipley vocabulary	0.12	0.12	0.18*	0.13	0.09	0.11	**0.26****	0.12

*: p <0.05 ; **: p <0.01

against a baseline, that consists of the aggregate acoustic and physiological arousal values averaged for each participant over all days. Despite the effectiveness of such measures in capturing general trends in similar studies [20], they do not incorporate oscillatory signal behaviors, which are modeled by the DSM.

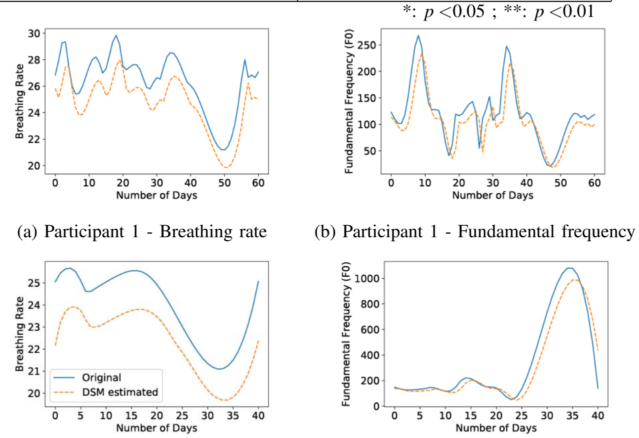
We first measure Pearson's correlation between the self-regulation and stress spillover parameters extracted from DSM model with the self-reported IGTB measures of task performance (IRB and ITP) and cognitive ability (Shipley vocabulary test). We then evaluate the predictive ability of the proposed DSM features to estimate individuals' IGTB characteristics using a linear regression model in a 10-fold cross-validation framework. We note that there is no contamination of samples from the same participant between the train and test set in this 10-fold cross-validation framework, since each participant was represented by one sample only extracted from the proposed DSM model. The features of the linear regression first included the combination of DSM-based self-regulation α, DSM-based stress spillover β, and average for each of the signal-based measures of emotional arousal, resulting in a 3-dimensional feature. We further combined the aforementioned features by grouping the acoustic measures of F0, jitter, and shimmer (i.e., 9-dimensional vector), the physiological measures of heart rate and breathing rate (i.e., 6-dimensional feature), and the daily activity measures of number of steps and sleep efficiency (i.e., 6-dimensional feature). The predicted value from each linear regression model was compared with the actual IGTB value using Pearson's correlation coefficient.

TABLE III

PEARSON'S CORRELATION COEFFICIENT BETWEEN ACTUAL AND PREDICTED VALUES OF TASK PERFORMANCE AND COGNITIVE ABILITY USING LINEAR REGRESSION WITH THE PROPOSED SELF-REGULATION α AND SPILLOVER β FEATURES GROUPED INTO DIFFERENT SIGNAL MODALITIES.

Performance & Cognitive Measures	Baseline	Speech	Physiology	Daily Activity
Individual task proficiency (ITP)	0.06	0.18	0.05	0.04
In-role behavior (IRB)	0.01	0.07	-0.11	-0.17
Shipley vocabulary	0.12	**0.24****	0.13	**0.23***

*: p <0.05 ; **: p <0.01



(a) Participant 1 - Breathing rate (b) Participant 1 - Fundamental frequency

(c) Participant 2 - Breathing rate (b) Participant 2 - Fundamental frequency

Fig. 1. Example plots of actual and predicted values–based on the dynamical systems model (DSM)–of day-to-day emotional arousal in terms of breathing rate and fundamental frequency.

IV. RESULTS

Example plots of day-to-day emotional arousal measures, as quantified by the breathing rate and F0, are shown for two participants (Fig. 1). The plots suggest a good fit of our data to the DSM model, as well as a high variability with respect to the daily emotional arousal patterns between different participants. Our results further indicate positive association between task proficiency and the proposed self-regulation measure α, as estimated based on F0 (r =0.22, p <0.05) and shimmer (r =0.25, p <0.05) (Table I). Similar associations approaching statistical significance were found between cognitive ability, measured through the Shipley index, and the self-regulation quantified from jitter (r =0.19, p =0.05) and shimmer (r =0.15, p =0.07) (Table I). Regarding the stress spillover β, our results further indicated that stress spillover quantified through F0 was significantly associated only with the Shipley verbal score (r =0.22, p <0.01). Similar results were found for the speech-based measures of self-regulation α and stress spillover β, when performing the linear regression experiments (Table II). Results with the proposed features capturing the oscillatory behavior of signals outperformed the baseline, which included the aggregate average scores from the seven emotional arousal measures. Specifically, the proposed features as quantified based on the number of steps were also able to reliably predict cognitive ability (r =0.26, p <0.01). Finally, combinations of the aforementioned signal-driven self-regulation and stress spillover measures also depicted significant correlations (Table III). Indicatively, cognitive ability was successfully predicted by speech-based indices (r =0.24, p <0.01) and daily activity features (r =0.23, p <0.05), which for the case of the acoustic measures exceeded the individual features (Table III). Combining all modalities did not improve the predictive ability of the system.

V. DISCUSSION

Our results indicate that the parameters of the proposed DSM are associated with work performance and cognitive ability, in accordance to previous studies [21]. Implications of these findings can result in designing objective measures for quantifying and predicting work performance, potentially leading to "task-readiness" measures and personalized in-the-moment interventions.

Despite the encouraging results, there are several limitations in the proposed framework. First, we used a hypothesis-driven approach and indirectly evaluated the ability of our model to capture emotional self-regulation by measuring how the signal-based self-regulation indices are associated with constructs of cognitive ability and work performance. As part of our future work, we will examine whether the signal-driven emotion regulation metrics are associated with constructs of psychological flexibility, which refers to how a person adapts to social demands, reconfigures mental resources, and shifts perspective [22]. Second, this paper has modeled the result of emotion regulation, as reflected on speech and physiology, and has considered emotional arousal irrespective of its positive or negative connotation. Previous work suggests that when comparing regulatory strategies, positive and negative affect reflect different functions [1]. Different strategies of emotion regulation, such as cognitive reappraisal and emotion suppression, have been shown to be more or less successful [1], but have not been taken into account by this approach. Therefore, as part of our future work, we will focus on integrating emotional valence into the existing model. Additional contextual information would shed light into the specific mechanisms that are being triggered to achieve emotion regulation. Finally, we would like to examine emotional arousal in a more fine-grained time resolution or in relation to specific events in the day instead of consecutive days.

VI. CONCLUSION

We proposed a DSM to capture day-to-day trajectories of emotional arousal and its interplay with stress. This work provides insights into ways to objectively quantify self-regulation in highly demanding work scenarios and lays a foundation toward ambulatory-based in-the-moment interventions for promoting productivity and general well-being in highly stressful and demanding professions.

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