Dynamic systems modeling of pre-schoolers' response to an emotionally stressful event

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***Abstract*—This paper presents preliminary results for using dynamic systems models to describe physiological and behavioral responses (cortisol and activity) to emotionally stressful events. Linear discrete-time models are used to approximate the nonlinear model of the LHPA axis around an assumed nominal operating condition. Measurements are taken of cortisol (from saliva) and activity (with an accelerometer). These two measurements are considered as either inputs or outputs of the model. Modeling choices are discussed in detail. Results are presented that indicate activity is better interpreted as an input and cortisol as an output. In addition, the paper discusses briefly how the resulting dynamic systems models can be used for statistical analysis, as well as for integrating across multiple levels of stress responses.**

I. Introduction

This paper presents preliminary results of a larger project with the goal of describing and examining the processes involved in regulation of systems inherent to emotional expression as observed in preschool-aged boys and girls. Data was collected over three days in three different domains: physiologic reactivity (salivary cortisol); behavioral reactivity (as indexed by motor activity and facial expressions of emotional behavior); and moderating factors (child gender, temperament, inhibition and executive functioning; parent emotionality and emotion socialization; and culture). This paper develops dynamic systems models to describe individual children's trajectories of either behavioral reactivity (amount of motor activity) or physiological reactivity (salivary cortisol levels), with an emotional "impulse" input. Moderating factors are not included in this analysis.

Section II, gives some background on the importance of emotion regulation processes and the roles played by cortisol and activity. The design of the study that generated the data we use herein for modeling is also presented. Section III describes the types of models that we have built for the different responses. Finally, Section IV discusses our findings thus far, and outlines our future work.

II. Background

A. Emotion regulation

Over the past two decades, developmental studies on emotion regulation have found that infants and toddlers manifest clear individual differences in their responses to environmental stressors and in their abilities to regulate strong negative emotions [1], [2], [3]. During the preschool years, children begin to develop additional inhibitory abilities to more finely regulate their emotional states and develop greater control over their emotional expressions [4]. These early-established patterns of regulatory competence are predictive of both biological and behavioral adjustment throughout the lifespan [5], [6]. Children who do not learn to regulate their emotional states and behaviors during the preschool period are at high risk of psychopathology and numerous problems later in life [7], [8].

Despite its obvious importance, the study of emotion regulation has been difficult because it involves coordination across behavioral, psychological, and neuroendocrine subsystems that develop over time. Research into the development of each of these subsystems has made significant progress in the past decade, but the regulation of this system as a whole is not well understood. Moreover, cultural differences in behavioral factors related to regulation have been found, but their relationships to physiological substrates have not been examined. The present study uses a dynamic systems approach to examine children's responses to an emotional challenge task by examining the role of the emotional "impulse" in response to the challenge. Motor behaviors that occur in conjunction with this task and the production of cortisol, a major stress-related hormone produced by the adrenal gland, are densely sampled, and can be considered as either inputs or outputs in the modeling approach.

B. Cortisol and activity

The LHPA axis plays an important role in modulating our physiological and behavioral reactions to stress. Cortisol is the end-product of LHPA activation, can be reliably measured in saliva, and can serve both as a regulator and an indicator of a stress response. Following the onset of a stressor such as an emotional challenge or exercise, the LHPA axis first triggers an autonomic response, such as an increase in heart rate, and later triggers the release of cortisol. It may take anywhere from 15 to 30 or more minutes for cortisol levels to increase, with both the peak levels and time to peak highly variable across individuals, situations, and type of stressor [9].

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In addition to emotionally "stressful" responses, motor activity is highly related to changes in cortisol and other aspects of the autonomic nervous system [10], but these changes are not straightforward. Some work has examined the relationship between cortisol and activity in the form of exercise. Cortisol levels have been found to remain constant or slightly decrease at low levels of exercise intensity for healthy adult males, but after 15 or more minutes of high intensity exercise (anywhere from 60-100% of a participant's maximal oxygen uptake), they have been found to increase anywhere from 35% to 85% above resting levels [11], [12]. Similar results have been found for children around 10 years of age [13]. However, few studies have been done on the effects of exercise on cortisol levels in healthy children younger than 10 years of age. Furthermore, there is a lack of studies relating cortisol levels to regular physical activity. Although a positive correlation has been found between cortisol levels and accelerometer activity counts in women with anorexia nervosa [14], no studies have been carried out on other groups. It is therefore of interest to investigate this relationship further, especially in children, whose HPA stress response is particularly sensitive to seemingly small variations among stressors [9].

C. Study description

112 four-year-old children attending preschool participated in the study: 53 in Ann Arbor, USA and 59 in Beijing, China. The children participated over three consecutive days, for approximately two hours each day. On each day, they arrived at the same time of day (although the time could be different for each participant). The arrival time is denoted by $t = -30$. After 30 minutes of quiet play with a research assistant (experimenter), they were engaged in a planned stressful task that started at $t = 0$ and lasted approximately 2–5 minutes. After this stressful task, some simple behavioral tasks and videos occupied the rest of the two hour sampling period without intending to induce additional stress responses. Cortisol was sampled densely over the two hour period (approximately every 10 minutes, as discussed below). Activity was measured in counts, sampled at 32Hz and logged over 15-second epochs for the two-hour period. We used an omnidirectional accelerometer (Actical, Mini Mitter Co.) that attached snugly to the child's waist via an adjustable elastic strap. It produced time-stamped output that was referenced to cortisol sampling times.

On the first day, participants were asked to help the experimenter stuff envelopes. While this was not supposed to be stressful, and was intended as a baseline, the experimenter did leave the child alone in the room for three minutes (180 seconds). We refer to the day one task as the envelope task. The other two tasks were designed to elicit strong emotions from the pre-school children. Half of the participants did task two on day two and the other half did task two on day three. In the prize task (task two), participants were asked to choose among several objects (e.g., toy truck, bubbles, broken comb, paper clip) which one they like best, second best, and so forth, up to their least preferred. The experimenter left the room, and another experimenter came in and gave the child their least preferred prize, remained in the room, unresponsive, for one minute, then left. After the child was left alone for one more minute with the bad prize, the original experimenter returned, exclaimed that there was a mistake, and gave the child their favorite prize. In the computer task (task three), the child played a simple computer game with the objective of helping a farmer get his cows into the barn (by "lassoing" them as they strayed off the path). The practice version was always successful. The child was then left alone to play the real game and told that if they won they would get a prize. However, the real game was impossible to win, and the child remained alone for one more minute after he/she lost the game. When the experimenter returned, he or she noted that the game was broken, and gave the child a prize anyway.

III. Descriptive modeling

In this section, we describe dynamic systems models that are fit to the cortisol and activity data, and discuss the choices that we made in the modeling. While the LHPA axis is multivariable and nonlinear, here we consider a linear discrete-time model as a linear approximation to the system around an operating condition [15], [16]. We have measurements of two "outputs" of the system: cortisol (as measured from saliva samples) and activity (from the Actical accelerometers). While we cannot determine the causal relationship between these two variables from our data, we can fit mathematical models that consider both of them as inputs and outputs, and see how well these input-output models describe the observed data. We also consider the stressful task, modeled as an impulse, as an input to the system. Thus, we use single-input and multi-input linear models, with a single output.

A. Cortisol data

1) Data availability: Although there were originally 112 participants in the study, this paper focuses on a subset of 59 of these participants (32 from China and 27 from the US) for which we have complete cortisol and Actical data. Although there are well-developed techniques for imputing missing samples [17], and we have extensive notes available for correcting the Actical logs, the analysis of this more complete data set is left for future work.

Recognizing that cortisol follows a circadian rhythm with highest values in the morning and lowest in the evening, morning and evening cortisol samples were taken for the participants and for their parents. In this paper, however, we do not consider this circadian rhythm and model only the cortisol reactivity in response to a stressful task. Cortisol samples are taken from the participants when they arrive in the lab (at time $t = -30$), just before the start of the stressful task ($t = 0$), every 10 minutes thereafter until $t = 60$, then at $t = 75$ and $t = 90$. We chose to replace the two $t = 70$ and $t = 80$ samples by a single sample at $t = 75$ so that all of the cortisol samples for a child (including the morning and evening samples) could fit on a single plate for analysis. Thus, there are 10 samples per participant per task. We denote these values by $c(-30), c(0), c(10), \ldots, c(60), c(75), c(90)$ where c indicates the raw cortisol value (in μg/dl).

While 10 samples seems like very few data points for system identification purposes, we note that the collection and processing of cortisol samples is relatively expensive, and represented a large portion of the budget for the project. The cost for each cortisol data point was approximately $15.

2) Interpolation: The dynamic systems models that we fit assume that the data is regularly sampled over the time period. To fill in the data where no samples were available, we use a linear interpolation. For example,

$$c(-20) = (2/3)c(-30) + (1/3)c(0) \tag{1}$$

$$c(-10) = (1/3)c(-30) + (2/3)c(0) \tag{2}$$

A similar interpolation is used to obtain $c(70)$ and $c(80)$. Thus, after interpolation, we have 14 data points, representing times from -30 to 90, every 10 minutes: $c(-30), c(-20), \ldots, c(90)$.

In [18], we considered only the cortisol response to a stressful input, modeled as an impulse (activity was not considered). We concluded that there were no statistical differences between the models fit with linear or logarithmic interpolation of the data points. Since there are only a few interpolated points, this conclusion is not surprising. Thus, we chose to use linear interpolations for simplicity.

3) Magnitudes and scaling: The dynamic systems models that we fit have an equilibrium point at 0, whereas the true equilibrium cortisol value in the saliva is nonzero. To account for this offset, we subtract from each time trace $c(t)$ the minimum value of the trace. Also, since we work in discrete time, we divide all of the time values by 10. Thus,

$$y(k) = c(10k) - \min_t c(t) \tag{3}$$

and all modeling is done with the time series $y(-3), y(-2), \ldots, y(9)$. All plots in this paper are for the actual cortisol values and actual time, in minutes.

B. Actical data

The Actical records the number of accelerations ("counts") in intervals of 15 seconds, whereas the cortisol data is discretized every 10 minutes. We aggregate the Actical input by summing up the counts in the 10-minute cortisol intervals, see Figure 1. We also divide this sum by 10,000 so that the order of magnitude of the Actical input is not significantly different than the impulse or the cortisol. The experimenter pushed an indicator button on the Actical sensor to mark the start and end of testing. In this paper, we assume that the start of testing is at the first marker press, and we just count forwards in intervals of 10 minutes. If the net elapsed time between the first and last button press in the Actical file was between 110–130 minutes, we accepted the data set. Ongoing work is developing better methods for qualifying and synchronizing the Actical data with the cortisol and other data.

We have considered relating the 10-minute interval either to the first or last minute of this interval, and have not found statistically significant differences in the two choices. In this paper, the results are presented using the sum of 10-minute Actical activity referred back to the beginning of the interval; the activity value at time $k = 3$ is the sum of the activity between $t \in [30, 40)$. Thus, the value of the activity at $k = 9$ ($t = 90$) is always zero. Since the minimum is zero, we do not subtract an offset.

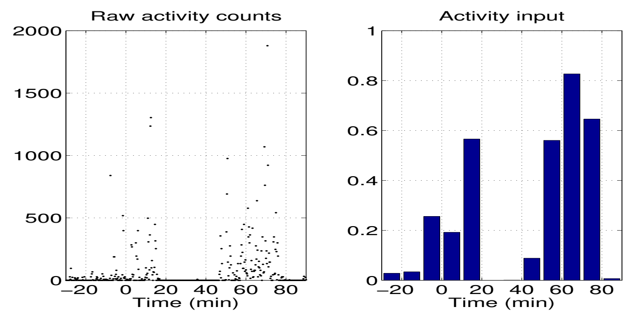


Fig. 1. Activity for participant C24, prize task. The raw Actical counts are shown on the left. The input that we use for the model is shown on the right, where the Actical counts have been summed over 10 minute intervals and divided by 10,000.

Since the 10-minute interval is much larger than the Actical resolution, and usually includes the entire emotional challenge period, we also analyzed this activity data on a finer time scale. We divided the data into the pre-challenge period (from the introduction of the task until until the experimenter leaves the room), the challenge period (while the child is alone), and the post-challenge or resolution period; these time points were identified from the videotapes. A repeated measure ANOVA using Proc Mixed in SAS showed no difference on activity counts per minute by task $F(2, 221) = .36, p = .697$ and no differences among the three periods, $F(2, 221) = .32, p = .728$. Also a test for interaction between tasks and periods was not statistically significant, $F(4, 221) = 1.69, p = .154$. The lack of difference between the activity counts over these periods does not imply that the emotional challenge has little effect on the amount of activity, since the children were asked to stay seated during this time.

C. Linear system models

We assume linear system models as approximations to the full nonlinear model around an operating condition. Using the cortisol and activity time traces as discussed above, we use standard system identification techniques to fit simple first, second, third, and fourth order ARMAX models for each child for each task. For example, the second-order model is:

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + b_1 u(k-1) + b_2 u(k-2) \tag{4}$$

In [18], we considered only the cortisol response to a stressful input, modeled as an impulse. The linear model of equation (4) was used. We demonstrated that, for the cortisol trace as output, an impulse input resulted in a better overall fit than no input. We also discussed the expected stability of the cortisol response, and chose to use only stable models as descriptors. In this paper, we also consider activity as another

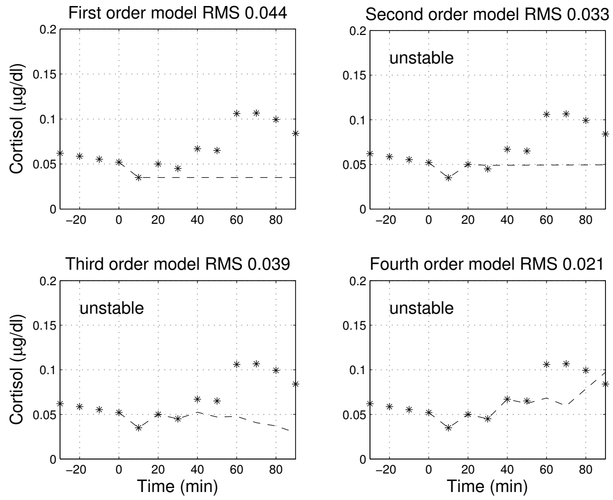


Fig. 2. Impulse input only: a "bad fit" for U15, computer task.

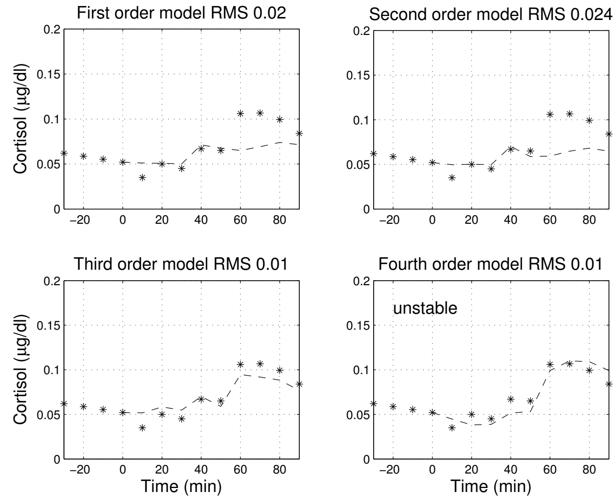


Fig. 3. Activity input only: third order is best for U15, computer task.

manifestation of emotional response. Since it is unknown whether activity "causes" cortisol to increase, or cortisol "causes" activity to increase, we consider activity, cortisol, and the stress impulse as different factors that can act in isolation or in tandem, to produce a response of either activity or cortisol. The time scales of the cortisol and activity response are quite different; cortisol has a much slower response and is sampled at 10-minute intervals; activity behavior reacts more quickly and is recorded every 15 seconds. The interplay between these two different time scales has been addressed at only a very basic level in this preliminary work. Cortisol and activity are possibly best regarded as two of several outputs of a complex dynamic system; the models that we build here can help address the question of the relative phase.

Thus, the possible choices for the model are:

1) A stress input happens at time $t = 0$, when the participants undergo the emotionally challenging task. Since we are unable to measure exactly what happens during the stressful event, we model the input as a unit, discrete impulse: $u(k) = 1$ for $k = 0$ and $u(k) = 0$ for other values of k. This model assumes that the stress is the same for all participants, although they may experience it differently. The output can be either cortisol or activity.
2) The input $u(k)$ is the activity as measured by the Actical accelerometer, and the output is cortisol.
3) The input $u(k)$ is the cortisol, and the output is activity.
4) There are two inputs, $u_1(k)$ and $u_2(k)$, corresponding to the stress and the activity (or stress and cortisol), with the output being cortisol (or activity). The single-input model of equation (4) can be extended in a straightforward manner to get the two-input model.

One consideration is that the impulse input may not be sufficiently rich to allow the system to be identified correctly [19], but we have been satisfied with the descriptive capabilities of even these simple models.

We have initial condition measurements at $t = -30$ and $t = 0$, and we expand these to get four initial conditions (every 10 minutes). Of course, these are not independent, but we use them as the initial conditions in the system identification algorithm. The expectation is that the cortisol values will decline towards the baseline as the child arrives at the lab and goes through the quieting activities during the first half-hour. Since an n^{th} order model requires n initial conditions, we can consider models up to fourth order.

The model-fitting is done as follows (for the second order model example). First, we write out all of the equations. The initial conditions will be $y(0)$ and $y(-1)$.

$$\begin{aligned} y(1) &= a_1 y(0) + a_2 y(-1) + b_1 u(0) + b_2 u(-1) \\ y(2) &= a_1 y(1) + a_2 y(0) + b_1 u(1) + b_2 u(0) \\ &\vdots \\ y(9) &= a_1 y(8) + a_2 y(7) + b_1 u(8) + b_2 u(7) \end{aligned}$$

Then, all the data are put together into a matrix as follows:

$$\begin{aligned} Y = \begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(9) \end{bmatrix} &= \begin{bmatrix} y(0) & y(-1) & u(0) & u(-1) \\ y(1) & y(0) & u(1) & u(0) \\ \vdots & & & \\ y(8) & y(7) & u(8) & u(7) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ b_1 \\ b_2 \end{bmatrix} \\ &= \Psi \Theta \end{aligned}$$

To solve for the unknowns in Θ, we simply take the pseudo-inverse of Ψ by multiplying both sides by Ψ^T, then inverting:

$$\begin{aligned} \Psi^T Y &= \Psi^T \Psi \Theta \\ (\Psi^T \Psi)^{-1} \Psi^T Y &= \Theta \end{aligned}$$

Once we have the parameters $\Theta = \begin{bmatrix} a_1 & a_2 & b_1 & b_2 \end{bmatrix}^T$, we can simulate the model of equation (4) to get y_{model}. By definition, the model will result in the smallest possible RMS error between the simulated data and the actual data in Y and Ψ, with the given input (either an impulse or the activity). Extending this analysis to the two-input case be done in a straightforward manner.

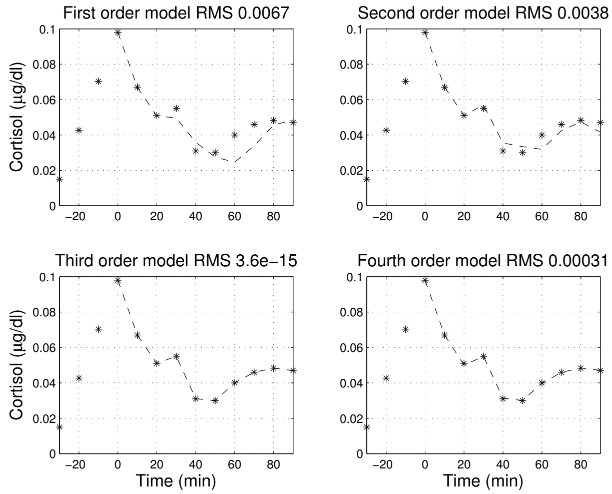
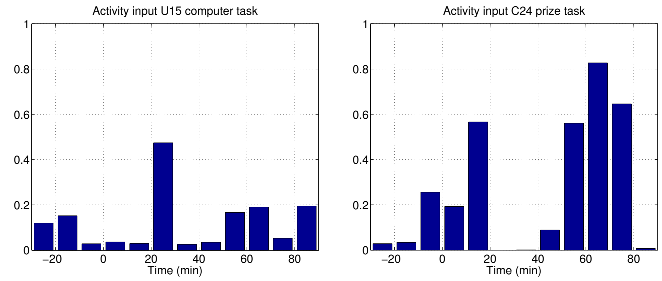


Fig. 4. Both inputs: second order is best for C24, prize task.



(a) U15 Computer (b) C24 Prize

Fig. 5. Activity input for (a) U15, computer task and (b) C24, prize task.

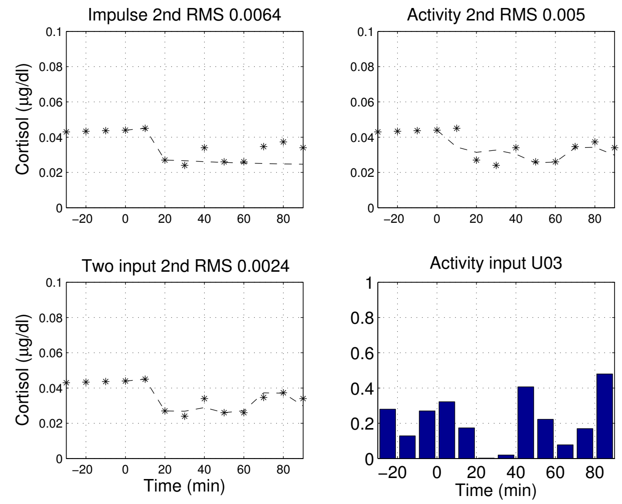


Fig. 6. For participant U03, envelope task, the best models for each input type are shown, along with their RMS errors.

D. Defining the "best" model fit

For each child, for each task, we fit first, second, third, and fourth order models to the data. By definition, the fourth order model should give the lowest RMS error, since the lower-order models are special cases of the fourth order. However, we would like to choose the "best" model as the simplest (e.g., lowest order) model that adequately captures the key features of the time response.

We have defined three cases for choosing the best model:

1) If all of the models are unstable, or the RMS error for every stable model is greater than 50% of the average output (cortisol or activity) value (for that data set), then we define a "bad fit."
2) If at least one of the models is stable, then we consider all of the stable models. If the minimum RMS error is greater than 0.005 but less than 50% of the average output value, then we choose the one that has the minimum RMS error.
3) If the minimum RMS error is less than 0.005, then we choose the smallest model order that has RMS error is less than 0.005.

The value 0.005 was chosen to reflect the fact that the cortisol measurements are only accurate to 5%; RMS errors that are smaller than the measurement error are not meaningful.

Case 1 is illustrated in Figure 2, for participant U15 with only the stress impulse input. The average cortisol value is 0.067 and the RMS error for the only stable model is greater than 50% of that. Case 2 is illustrated in Figure 3, also for participant U15, but with only Actical input (shown in Figure 5(a)). The first three models are stable, but none have an RMS error less than 0.005, so the stable model with the lowest error (third) is chosen. Case 3 is illustrated in Figure 4, where the activity input is shown in Figure 5(b). The second order model is chosen since the error is below the threshold.

Another example of comparing the different models is shown in Figure 6. All of the best-fit models are second order, as indicated in the title of each plot. The combination of the two inputs gives the overall lowest RMS error.

E. Summary of model fitting results

Table I shows a summary comparison of "best fit" models, with each combination of input and output and model orders. There are 59 participants over 3 days, thus 177 total models (for each input/output combination). The average RMS error does not include those designated as a "bad fit." From the table, it can be seen that cortisol is a better output than activity, and that assuming some input gives a better fit than assuming no input (a simple auto-regressive model).

TABLE I
SUMMARY COMPARISON OF THE DIFFERENT MODELING CHOICES.

Input	Output	1st	2nd	3rd	4th	Bad	RMS
None	Cort.	20	21	33	68	35	0.0155
Impulse	Cort.	28	34	44	48	23	0.00995
Act.	Cort.	32	37	62	30	16	0.0113
Act. and Imp.	Cort.	35	36	25	65	16	0.00322
None	Act.	5	1	2	9	160	0.0155
Impulse	Act.	9	1	12	41	114	0.00821
Cort.	Act.	7	5	13	34	118	0.0177
Cort. and Imp.	Act.	12	16	36	38	75	0.00602

Interestingly, despite the fact that the impulse model was an approximation of the emotional response to the stressful task and the activity was directly measured and scaled appropriately, there were no significant differences in the order of model needed to capture the data for these single input models. However, models with motor activity and combined models incorporating both an emotional impulse and measured motor activity resulted in more lower order models as "best fits" $\chi^2 = 22.5$, $p < .001$, with fewer unstable models (16 vs. 23 and 35 for impulse and no input models, respectively) and most 1st or 2nd order models (69 and 71 vs. 62 and 41) appearing as the "best fit" for the data.

IV. DISCUSSION AND FUTURE WORK

This paper represents an initial step towards building dynamic systems models of emotional reactivity and regulation. Linear systems models were used to represent the dynamic relationships between measured values of cortisol and activity response during and after a stressful task. We considered that cortisol and activity could be either inputs or outputs to the linear systems models, and showed that the better fits are obtained with a cortisol output than with an activity output. Our findings are novel in that they demonstrate a clear link between regular, daily motor activity and cortisol release in a normative pre-school sample. Moreover, the models that resulted from these analyses were better than those that only assumed an impulse input at the time of an emotion challenge task. Thus, our findings also suggest some straightforward directions in modeling the complexities inherent in stress responding and emotional reactivity more generally.

The dynamic systems model can represent the cortisol time trace in a compact fashion, and can be used to build statistical relationships between the model parameters and other variables of interest (such as survey responses). The model parameters can be used in addition to, or instead of, traditional cortisol indicators such as peak value, peak time, or area under the curve, and could be of particular use in predicting individual differences in emotional responding. These statistical uses will be examined in future work.

We are currently working on expanding our data set to include imputed data, extracting the activity data for all of the participants, and analyzing the predictive capabilities of the models. In parallel, we are coding the videotapes, and from these codes, extracting discrete event models of the exhibited emotional and behavioral activities. We plan to consider these discrete-event traces as additional inputs and/or outputs to/from the discrete-time models. Finally, statistical models are being built to relate the dynamic systems models, and summary measures of them, with more traditional measures of emotional regulation, to incorporate culture to the models, and to better understand the underlying physiological processes.

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