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Physical Activity Dynamics During a Digital Messaging Intervention Changed After the Pandemic Declaration

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Abstract

Background The COVID-19 pandemic adversely impacted physical activity, but little is known about how contextual changes following the pandemic declaration impacted either the dynamics of people's physical activity or their responses to micro-interventions for promoting physical activity.

Purpose This paper explored the effect of the COVID-19 pandemic on the dynamics of physical activity responses to digital message interventions.

Methods Insufficiently-active young adults (18–29 years; $N = 22$) were recruited from November 2019 to January 2020 and wore a Fitbit smartwatch for 6 months. They received 0–6 messages/day via smartphone app notifications, timed and selected at random from three content libraries (Move More, Sit Less, and Inspirational Quotes). System identification techniques from control systems engineering were used to identify person-specific dynamical models of physical activity in response to messages before and after the pandemic declaration on March 13, 2020.

Results Daily step counts decreased significantly following the pandemic declaration on weekdays (Cohen's $d = -1.40$) but not on weekends ($d = -0.26$). The mean overall speed of the response describing physical activity (dominant pole magnitude) did not change significantly on either weekdays ($d = -0.18$) or weekends ($d = -0.21$). In contrast, there was limited rank-order consistency in specific features of intervention responses from before to after the pandemic declaration.

Conclusions Generalizing models of behavioral dynamics across dramatically different environmental contexts (and participants) may lead to flawed decision rules for just-in-time physical activity interventions. Periodic model-based adaptations to person-specific decision rules (i.e., continuous tuning interventions) for digital messages are recommended when contexts change.

Lay Summary

Physical inactivity is recognized as one of the major risk factors for cardiovascular disease, diabetes, and many cancers. Most American adults fail to achieve recommended levels of physical activity. Interventions to promote physical activity in young adults are needed to reduce long-term chronic disease risk. The COVID-19 pandemic declaration abruptly changed many individuals' environments and lifestyles. These contextual changes adversely impacted physical activity levels but little is known about how these changes specifically impacted the dynamics of people's physical activity or responses to micro-interventions for promoting physical activity. Using data collected from Fitbit smartwatches before and after the pandemic declaration, we applied tools from control systems engineering to develop person-specific dynamic models of physical activity responses to messaging interventions, and investigated how physical activity dynamics changed from before to after the pandemic declaration. Step counts decreased significantly on weekdays. The average speed of participants' responses to intervention messages did not change significantly, but intervention response dynamics had limited consistency from before to after the pandemic declaration. In short, participants changed how they responded to interventions after the pandemic declaration but the magnitude and patterns of change varied across participants. Person-specific, adaptive interventions can be useful for promoting physical activity when behavioral systems are stimulated to reorganize by external factors.

Keywords COVID-19 · fitness trackers · exercise · patient-specific modeling · social environment · precision medicine

Introduction

Physical activity reduces risk for chronic disease and promotes well-being [1, 2]. The correlates and determinants of physical activity span many levels of influence and include biological, psychological, social, environmental, and policy-related factors [3, 4]. The COVID-19 pandemic declaration abruptly changed many individuals' environments via stay-at-home orders and remote work arrangements. These contextual changes adversely impacted physical activity but little is known about how these changes specifically impacted the dynamics of people's physical activity or responses to micro-interventions for promoting physical activity [5]. The stability of these models needs to be understood to inform decisions about whether it is necessary to adapt model-based decision rules in the face of dramatic contextual changes. The purpose of this paper is to compare how responses to digital messaging micro-interventions to promote physical activity changed from before to after the COVID-19 pandemic declaration.

Physical Activity Behavior

Physical activity contributes to numerous health benefits, with the most recent US guidelines showing that bouts of any length are beneficial to health [2]. Yet surveillance research reports only 24–65% of adults 18 and over in the US meet recommendations for aerobic activity [6, 7]. Aerobic activities can be tracked with wearable devices to provide behavioral feedback on physical activity. That feedback can also integrate with other widely-adopted mobile technologies, such as smartphones, to promote aerobic physical activity in the natural context of daily life.

A recent systematic review shows that digital messaging interventions for physical activity promotion are associated with small-to-medium sized increases in daily step counts (standardized mean difference = 0.38) [8]. These estimates are based on differences in aggregated physical activity levels between participants who receive digital messages and those who do not. They do not speak to the effects of individual messages on subsequent physical activity. This gap is important because physical activity is a dynamic process that varies over time within each person and understanding those dynamics can improve predictions about behavior change [9]. Accelerometer data from the NHANES dataset revealed normative differences in physical activity as a function of the time of day and day of week [10]. Based on this within-person variation, just-in-time interventions may be useful for providing support to regulate the dynamics of physical activity. To realize the potential for just-in-time interventions, it is important to understand whether (and how) the dynamics of physical activity are impacted by different contexts. That information will inform decisions about generalizing models across contexts and the value of adapting models based on accumulating information.

Digital Message Effects on the Dynamics of Momentary Physical Activity

Dynamical systems modeling can be used to predict future behavior based on current and recent behavior. In these models, systems refer to processes that connect past and present values of an input/stimulus (different types of messages) to an output/outcome (physical activity behavior/step count). System identification tools from the field of control systems engineering can be applied to characterize how physical activity changes following digital message delivery [11, 12]. For example, these models can regress physical activity during a fixed epoch (15 min) on physical activity during prior epochs and a series of binary variables indicating whether a person received a digital message during each of those epochs. These models can be expanded to include multiple series of binary variables, each representing a different type of intervention content, or to describe the dynamics of weekend and weekday activity separately [13]. Coefficients from these models are difficult to interpret by themselves but can be used to simulate expected responses to different digital messages under varying conditions.

Responses to momentary intervention content can be simulated using coefficients corresponding to each message type at different lags and plotted to reveal the timing and magnitude of instantaneous and cumulative behavioral responses to momentary interventions in impulse response curves and cumulative step response curves, respectively. These curves illustrate expected instantaneous behavior changes during specific epochs (e.g., 15 min following message delivery, 60 min following message delivery) and cumulative behavior changes over time. They can be compared visually or quantitatively by extracting features of the responses for statistical analysis [11]. For example, features such as initial delay, peak magnitude, and peak delay can be extracted from impulse response curves to describe how quickly and with what magnitude a momentary intervention has its largest instantaneous effects on behavior [12]. Likewise, features such as the steady state, rise time, settling time, and effective time can be extracted from cumulative step response curves to describe the ultimate effect of a single momentary intervention, how quickly that effect initiates, and how much time is required both to achieve the maximal effect and to have an effect above the noise level [12].

Previous studies applying this approach have led to important insights. First, both daily and momentary physical activity dynamics are regulated differently on weekends and weekdays [13]. As a consequence, it is best to model physical activity dynamics as a switched system; that is, as a pair of models that describe weekend and weekday dynamics separately. Second, although a generic model of physical activity dynamics can be estimated, it is overly conservative for estimating the effects of digital messages on physical activity [12]. Person-specific models are better suited to describing the idiosyncratic effects of different messages on physical activity. Third, features of the momentary environment can alter responses to digital messages as evidenced by temperature-graded responses to digital messages [12]. Understanding the context around a person can lead to more accurate predictions about their expected responses to different types of messages at that moment.

This last finding about momentary weather indices moderating the size of expected effects of digital messages on future behavior is important in the context of the COVID-19 pandemic. System dynamics—the processes that reflect how people regulate their behavior—can be altered by contextual changes. At one level, the need for switched models to capture differences in physical activity dynamics on weekends and weekdays and linear-parameter varying models to capture temperature-graded behavioral responses illustrate how context impacts behavior [12, 13]. The COVID-19 pandemic provides another example of an abrupt change in context that can affect both physical activity and the systems that organize physical activity responses to interventions.

Effects of the COVID-19 Pandemic on Physical Activity

Beginning in March of 2020 in the US, the COVID-19 pandemic became a significant life event with a variety of psychological, social, environmental, and policy implications. Workplaces, schools, childcare centers, universities, and non-essential businesses were shut down or moved to virtual environments and people were ordered to stay-at home. Many daily behaviors and routines were affected such as physical activity, sleep, alcohol use, and substance use [14–16]. Research evaluating post-pandemic declaration physical activity changes have shown an approximately 20% decrease in step counts in the US [5]. Furthermore, survey research with participants enrolled in behavioral interventions indicated that 68.4% felt that COVID-19 impacted their ability to adhere to behavioral recommendations [17].

Developmental systems theory proposes that severe changes in a person's habitual environment can result in functional system disorganization and prompt reorganization processes to reconcile the change [18]. The reorganized system will reflect altered behavioral dynamics in the new context. Responses to system disorganization are proposed to be person-specific given the variety of factors (at multiple levels) that influence physical activity. To date, evaluations of physical activity changes following the COVID-19 pandemic have primarily focused on behavior aggregated over time across groups of people [5, 19]. Less is known about how the dynamics of behavior changed over time despite evidence that physical activity involves substantial variance within the person over time [9, 20]. Person-specific dynamical models can reveal if the pandemic impacted physical activity dynamics or behavioral changes in response to intervention messages.

The Present Study

Leading up to and following the pandemic declaration, we were actively collecting data from a cohort enrolled in a physical activity promotion study for insufficiently-active young adults. Participants randomly received 0–6 messages throughout the day. Messages were drawn at random from three content libraries: Move More, Sit Less, or Inspirational Quotes, and minute-level step counts were continuously monitored via a wearable activity tracker. We previously published models based on the subset of data collected entirely before the pandemic [12]. This manuscript used data from a unique subset of participants who were enrolled prior to and following the pandemic declaration. The analyses reported here capitalize on the temporally-dense data collected from wearable devices and the unique contextual change caused by the pandemic declaration to evaluate impacts of that declaration on physical activity and person-specific dynamics.

The first research question addressed whether physical activity volume (i.e., daily step counts) changed following the pandemic declaration. Our hypothesis was that daily step counts would decrease on both weekdays and weekends following the pandemic declaration. The second and third research questions examined absolute and relative changes in system dynamics by message type. The second research question addressed whether person-specific response dynamics changed in absolute terms following the pandemic declaration (i.e., mean level differences from before to after the pandemic declaration). We hypothesized that the pandemic declaration would slow overall system dynamics and weaken the effects of each message type on subsequent physical activity responses. The third question examined whether the relative changes (rank ordering) of response features from the person-specific dynamic models were consistent from before to after the pandemic declaration. We hypothesized that corresponding dynamic characteristics of behavioral responses to each message type would be positively associated (i.e., participants with larger relative response characteristics before the pandemic would tend to have larger relative responses after the pandemic declaration). Specific characteristics of interest included the initial delay, peak magnitude, peak delay, steady state, rise time, settling time, and effective time of message-specific responses, and the response speed. To test these hypotheses, piecewise dynamical models of weekday and weekend step counts were estimated for each person before and after the pandemic declaration. Features of those models were extracted from the impulse response and cumulative step responses and compared to determine whether specific message effects or response speed were systematically impacted by the pandemic declaration.

Methods

Participants

Insufficiently-active young adults were recruited using fliers posted on campus and community bulletin boards, university listservs, and Studyfinder, a web-based recruitment tool for Penn State researchers. Eligible participants were 18–29 years of age, ambulatory, free of functional activity limitations, free of visual impairment that would interfere with smartphone use, had verbal, and written fluency in English and were capable of giving informed consent. Participants had to be smartphone users (iPhone iOS v10.0 or later or Android operating system v7 or later) willing to place the Random AIM (custom software) and Fitbit apps onto their phone. Participants were excluded from the screening stage if they reported engaging in 90 min or more of moderate- or greater intensity physical activity per week, were part of organized programs with mandated physical activity, needed assistive devices for mobility, had a prior diagnosis of cancer, cardiovascular disease, type I, or type II diabetes, or metabolic syndrome, were pregnant, or had a plan to become pregnant in the following 6 months, or had any contradictions to engaging in physical activity according to the Physical Activity Readiness Questionnaire.

The United States of America declared the COVID-19 pandemic on March 13, 2020. All participants included in this analysis were enrolled between November 2, 2019 and January 24, 2020 to ensure that each had at least 6 weeks of data for each of the pre- and post-pandemic models. A total of 54 completed screening during that period and 32 were excluded due to excessive physical activity (n = 28), failing to meet wear time requirements (n = 2), or insufficient data either before or after the pandemic declaration (defined as ≤ 3 messages from a library with accompanying physical activity data; n = 2). The study lasted 6 months for all the participants but the precise number of days for pre-pandemic and post-pandemic stages was different for each individual due to variability in enrollment dates.

Measurements

Demographic and Anthropometric Characteristics

Participants self-reported age, sex, race, ethnicity, educational attainment, and employment status. Researcher measured weight (to the nearest 0.1 lb.) and height (to the nearest

0.5 inch) in duplicate using a digital scale and wall-mounted stadiometer, respectively.

Physical Activity Screening

Participants were instructed to wear a wGT3X-BT activity monitor (Actigraph, Pensacola, FL) for a week during their waking hours for a minimum of 10 hr each day. The participants kept a paper record of the times that the device was placed on in the morning and removed at night, as well as other removals for bathing, swimming, or other reasons. The wGT3X-BT monitor was worn at the waist on the participant's dominant side at the midline of their thigh. The monitor used a 3-axis accelerometer to measure high-resolution activity with a defined 30 Hz sampling rate. Activity data was collected in minute intervals. Wear time was validated using the proprietary Troiano 2007 algorithm in the ActiLife v.6.13.4 software [21]. Non-wear times, defined as greater than 90 min with zero activity counts, were excluded from the analysis. Valid days were defined as those with at least 600 min of wear time. At least 5 valid days of wear were required for analysis in order to be considered for qualification into the intervention study. The Freedson algorithm was used to classify minutes as light (≤ 1952 counts/min), moderate (1952–5724 counts/min), and vigorous (> 5724 counts/min) physical activity [22].

Ambulatory Physical Activity Monitoring

Participants wore a Fitbit Versa/Versa Lite smartwatch on their wrist for 6 months to track minute-level step counts and heart rate. These devices have demonstrated similar accuracy for step counting to research-grade Actigraph monitors and are suitable for use in adults with no limitations on mobility [23, 24]. Minute-level step count and heart rate data were used to classify minutes as valid wear time or device non-wear. Specifically, a minute was classified as valid if step counts were greater than zero or a valid heart rate was recorded [12].

Procedures

Participants were enrolled in two stages with separate informed consent processes: screening and intervention. All procedures were approved by the Institutional Review Board at The Pennsylvania State University (Study#00009455).

Screening Stage

A researcher conducted individual telephone interviews with participants and scheduled provisionally-eligible participants for a lab visit. In the lab visit, participants provided informed consent and completed questionnaires. The participant's height and weight were measured and the participant was provided with an Actigraph wGT3X-BT activity monitor to wear at the waist during waking hours for one week (along with a paper wear time log to document device removals).

After 7 complete days in the field, participants returned the activity monitors to the lab and were compensated ($25). Participants who had at least 5 days of valid device wear (600 min/day) and accumulated less than an average of 21.4 min/day of moderate-to-vigorous physical activity (the equivalent of 150 min/week) were invited to participate in the second stage of the study.

Intervention Stage

Eligible participants provided informed consent for the next stage of research and received a Fitbit Versa/Versa Lite smartwatch to wear for the next 6 months. The researcher assisted the participants with installing the Random AIM (custom research software) and Fitbit mobile applications on their personal smartphone. Participants were asked to enable location services for the Random AIM app to record periodic GPS data. Participants identified an availability window of 10+ hr of time on weekdays and weekends when they were available to receive digital messages. They could adjust this availability window at any time during the study by contacting the researcher. Participants were provided with information about the US Physical Activity Guidelines for Adults to assign a goal, potential benefits from increasing physical activity, and the principle of progressive adaptation to reduce musculoskeletal injury risk. Participants were asked to contact study personnel if they were injured or ill as it may impact their activity levels.

For the next 6 months, participants received between 0 and 6 messages/day via the Random AIM app. The frequency (0–6 messages for the day), timing within the availability window, and content of daily messages were determined randomly every night by the backend server. The only restriction was that consecutive messages could not be delivered within 15 min of each other. Messages were drawn from three content libraries: (i) "Move More" motivational messages (108 messages), (ii) "Sit Less" motivational messages (108 messages), and (iii) "Inspirational Quotes" (with no relation to physical activity or sitting time; 54 messages). Move More and Sit Less messages were based on social-cognitive theory, typically highlighting an affective or instrumental outcome of physical activity and prompting use of a self-regulation strategy (e.g., setting a goal, planning an activity). Half of the messages were accompanied with a relevant image (e.g., physical activity for Move More messages, standing activity for Sit Less messages, and natural landscapes for Inspirational Quotes). Participants were asked to acknowledge receipt by clicking on the message when they read it (triggering a round-trip message to the backend server). Participants received a micro-incentive for each message acknowledgement ($0.25) and message notifications were removed if a message was not acknowledged within 30 min of delivery. The mobile app recorded timestamped participant locations at the times that each message was scheduled to be sent to the participant's mobile device, displayed on the device, and acknowledged by the participant. Participants were compensated at 2 months intervals throughout the study to support engagement and protocol compliance.

After 6 months, a Zoom meeting was scheduled to guide the participants through the processes for removing the Random AIM app from their smartphone and switching their Fitbit app to a personal email account. Participants answered end of study questionnaires and engaged in a brief interview on their experience with the app and the intervention.

Data Analysis

Pre-processing

Fitbit and message data were downloaded for the study period. Days prior to the start date or following the end date were removed. Next, any days corresponding to dates when participants reported injury or illness, notifications being off, etc., were trimmed. Data were then separated for the pre-pandemic and post-pandemic stages. Dates were labeled as weekdays and weekends. For all days, Fitbit data were trimmed to exclude data recorded more than 2 hr before the availability window opened or more than two hours after the availability window closed. This choice provides enough data for identifying the models of the physical activity behavior changes after receiving a message either at the beginning or end of the availability window. Appropriate pre-processing steps were taken for participants with changes in their provided availability time through the study. Minute-level heart rate and step counts data were used to classify minutes as valid or missing. If heart rate was recorded, the corresponding step count for that minute was valid. If heart rate was not recorded but steps were greater than 0, the step count for that minute was valid. If heart rate was not recorded and zero steps were recorded, the step count for that minute was classified as missing. If the missing minutes were smaller or equal to three, step counts for those minutes were interpolated using linear interpolation method. Finally, minute-level step data were aggregated up to 15-min summaries (total step counts for the 15 min epoch).

Modeling and Statistical Analysis

The system identification methods used to generate person-specific models are described in Supplemental File S1. Based on those person-specific models, simulated impulse and cumulative step responses were computed for each message type using the six coefficients for each message type (corresponding to model order, that is five plus the present epoch) and coefficients related to past five epochs of step counts. Impulse responses represent the expected step count changes during each 15-min epoch following receipt of each message type (compared to what would be expected if the message was not received). Cumulative step responses represent the total expected effect of each type of individual message (compared to what would be expected if the message was not received). Error bounds were computed for each response curve to differentiate patterned behavior change from mere noise in the data and modeling error. The magnitude of the dominant pole in each model was also extracted as a summary measure of intervention response speed.

Descriptive statistics were used to characterize the participant sample and identify mean and standard deviations for step counts and model features. Normality of the distributions for pre- and post-pandemic declaration values for step count, intervention response speed, and message-specific response features was assessed. Based on the findings of the normality check, we ran paired *t*-tests or Wilcoxon signed-rank exact tests to test the statistical significance of the change in means after the pandemic declaration. Cohen's *d* (standardized mean difference) and *r* were calculated to provide an estimate of effect size for parametric tests and non-parametric tests, respectively. Pearson or Spearman rank correlations between model features segmented by message type and day type were calculated to understand the consistency of rank orderings between pre- and post-pandemic averages for person-specific dynamic model features.

Results

As shown in Table 1, the analytic sample (n = 22) comprised women (55%) and students (82%) with a mean age of 22.2 years (SD = 1.7, range = 20–27). The sample consisted of White (n = 9 [41%]), African-American (n = 8 [36%]), and Asian (n = 5 [23%]) participants; the majority were not Hispanic or Latino (n = 21 [95%]). Participants had an average BMI of 27.1 (SD = 7.1, range = 20.3–46.6) with 27% having obesity (BMI ≥ 30), 27% having overweight (BMI = 25–29.9), and 45% having a normal weight (BMI =18.5–24.9).

Message Delivery

In total, 10,805 messages were received and displayed on mobile devices (M = 491.1 messages/person, SD = 81.7) of which 5860 (54%) messages (M = 266.4 messages/person, SD = 101) were received in the pre-pandemic stage and 4945 (46%) messages (M = 224.8 messages/person, SD = 70.8) were received after pandemic declaration. Received messages were distributed between the "Move More" (pre-pandemic: n = 2327 [40%]; post-pandemic declaration: n = 1994 [40%]), "Sit Less" (pre-pandemic: n = 2313 [39%]; post-pandemic declaration: n = 1945 [39%]), and "Inspirational Quotes" (pre-pandemic: n = 1220 [21%]; post-pandemic declaration: n = 1006 [20%]) content libraries. Messages were randomly distributed across each participant's availability window. A total of 8994 (75%) messages met criteria for system

Table 1 Sample characteristics

Characteristic	n (%)
Age (years; mean [SD])	22.2 (1.7)
Sex	
Female	12 (55)
Male	10 (45)
Educational attainment	
Completed high school or a received GED	3 (14%)
Some college/Associate's degree	7 (32%)
Completed college	9 (41%)
Graduate or professional degree	3 (14%)
Employment status	
Employed full-time	1 (5%)
Employed part-time	2 (9%)
Student	18 (82%)
Unemployed and not looking for work	1 (5%)
Race	
Asian	5 (23)
Black/African-American	8 (36)
White	9 (41)
Ethnicity	
Hispanic or Latino	1 (5)
Not Hispanic or Latino	21 (95)
BMI (kg/m^2; mean [SD])	27.1 (7.1)
BMI classification	
Normal weight (18.5–24.9)	10 (45)
Overweight (25–29.9)	6 (27)
Obesity (≥ 30)	6 (27)

Note. SD standard deviation; *GED* General Educational Development credential.

identification through evidence of step count and heart rate data collection at the time of the message receipt.

Changes in Physical Activity

In total, 2,422,306 min of physical activity were used to identify the models, of which 1,373,960 min preceded the pandemic declaration and 1,048,346 min followed the pandemic declaration. On weekdays, participants took an average (M ± SD) of 6170.36 ± 2008.4 steps/day before the pandemic declaration and 3278.1 ± 1733.4 steps/day after the pandemic declaration. This difference represented a large and statistically-significant decrease, $t(21) = 6.55$, $p < .001$, Cohen's $d = -1.40$. On weekends, participants took an average of 4199.7 ± 1650.5 steps/day before the pandemic declaration and 3645.7 ± 2185.1 steps/day after the pandemic declaration. This difference was not statistically-significant, $t(21) = 1.23$, $p = .23$, Cohen's $d = -0.26$. Supplementary Table 1 summarizes participant-level data on average daily steps before and after the pandemic declaration.

Response Dynamics

Seven features were extracted from the simulated impulse response and cumulative step response curves. Each feature was extracted separately for weekends and weekdays before and after the pandemic declaration. These features include initial delay, peak magnitude, peak delay, steady state, rise time, settling time, and effective time, and are illustrated in Fig. 1. This figure represents all these features on the impulse and cumulative step responses of one participant to "Move More" messages. As shown, *initial delay*, *peak magnitude*, and *peak delay* extracted from the simulated impulse response curve (left panel) represent features of the latency to initiate a momentary message effect, i.e., the time that it takes for the message to start having a momentary effect, magnitude of peak momentary message effects, i.e., the maximum momentary effect that the message has, and latency to peak momentary message effects, i.e., how long it takes for the message to have its maximum momentary effect, respectively. In the cumulative step response plot (right panel), the curved line is the upper error bound, and the thin straight black lines depict lines y = 10%, 90%, 95%, and 105% of the steady state. *Steady state* value is the ultimate amount of the cumulative step response, i.e., the summation of all step counts taken after receiving the message. *Rise time* is the time that it takes for the cumulative step response to advance from 10 to 90% of the steady state, i.e., the time that takes for the message to rise from low to high effect, as a ratio of the ultimate step counts. *Settling time* describes the time that the step response enters a boundary around the steady state with the upper- and lower-bounds being 95% and 105% of the steady state which means the time that the response settles down around and close to the ultimate value. *Effective time* is the duration that the system response is above the noise level (outside the error bounds), i.e., the time that the effect of the message is measurable/differentiable from noise. Initial delay was uniformly zero for this dataset, thus we focus on reporting results based on the other six features.

Tables 2 and 3 summarize descriptive statistics for overall response speed of the system and features of the simulated impulse response and cumulative step response based on the person-specific models before and after the pandemic declaration for weekdays and weekends, respectively. Of note, the range of participant values for each response feature is very wide. Supplementary Tables 2–4 provide participant-level data for each of these variables on weekdays and weekends.

Absolute Changes in the Intervention Response Speed

The magnitude of the dominant poles represents the speed of the response. Poles were estimated separately for weekdays and weekends using data from before and after the pandemic declaration. On weekdays, the average dominant pole magnitude was 0.70 (SD = 0.10) before the pandemic declaration and 0.68 (SD = 0.08) after the pandemic declaration. On weekends, the average dominant pole magnitude was 0.73 (SD = 0.10) before the pandemic declaration and 0.70 (SD = 0.06) after the pandemic declaration. As seen in Tables 2 and 3, dominant poles did not change significantly from before to after the pandemic declaration on either weekdays or weekends (p > .05). We concluded that, on average, the overall

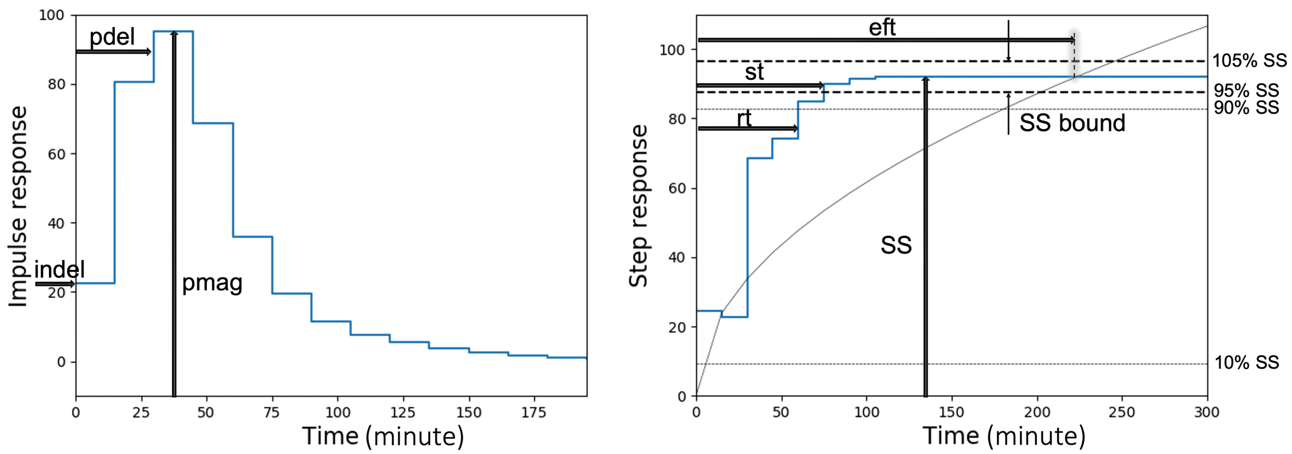

Fig. 1. Features of the simulated impulse response (left panel) and cumulative step response (right panel) represented on the response of a participant to "Move More" messages shown in blue. *indel* Initial delay; *pmag* peak magnitude; *pdel* peak delay; *SS* steady state; *rt* rise time; *st* settling time; *eft* effective time.

Table 2 Average values of impulse and step response features and response speed for all person-specific models for pre-pandemic and post-pandemic stages over the weekdays; all times are measured in minute scale

Response features and message type	Pre-pandemic		Post-pandemic		Test statistic	p	Effect size
	Mean (SD)	Range	Mean (SD)	Range			
Response speed	0.70 (0.10)	0.47, 0.86	0.68 (0.08)	0.54, 0.85	$t(21) = -0.84$	.408	$d = -0.18$
Peak magnitude							
Move more	69.18 (51.14)	16.03, 195.05	43.97 (35.55)	7.97, 180.93	$z = -2.09$	.036	$r = -.45$
Sit less	58.78 (32.93)	15.11, 130.27	39.60 (26.75)	15.53, 118.59	$z = -2.16$	.031	$r = -.46$
Inspirational quotes	81.00 (81.64)	15.27, 413.79	49.80 (43.80)	9.29, 198.59	$z = -1.32$	.189	$r = -.28$
Peak delay							
Move more	25.23 (22.39)	0, 60	26.59 (23.11)	0, 60	$t(21) = 0.18$	.856	$d = 0.04$
Sit less	33.41 (23.11)	0, 60	25.23 (22.86)	0, 60	$t(21) = -1.05$	.307	$d = -0.22$
Inspirational Quotes	28.64 (21.17)	0, 60	31.36 (23.56)	0, 60	$t(21) = 0.39$	.699	$d = 0.08$
Steady state							
Move more	96.75 (263.86)	-472.77, 784.59	61.56 (262.98)	-240.24, 1106.29	$z = -0.70$	.485	$r = -.15$
Sit less	-40.37 (203.49)	-583.64, 264.1	-19.02 (176.96)	-550.75, 279.76	$t(21) = 0.48$	.635	$d = 0.10$
Inspirational quotes	-2.38 (326.65)	-470.83, 1072.26	0.95 (148.38)	-326.14, 354.66	$z = 0.05$	.961	$r = .01$
Rise time							
Move more	82.50 (64.60)	0, 270	103.64 (54.56)	0, 225	$z = 0.96$	.337	$r = .20$
Sit less	87.95 (56.75)	0, 225	85.91 (61.09)	0, 255	$z = -0.49$	.623	$r = -.10$
Inspirational quotes	94.09 (52.41)	15, 225	64.09 (55.78)	0, 195	$t(21) = -2.61$	.016	$d = 0.56$
Settling time							
Move more	159.55 (66.21)	60, 360	160.91 (54.81)	75, 330	$z = 0.28$	.778	$r = .06$
Sit less	163.64 (63.46)	75, 360	150.00 (60.53)	75, 315	$z = -1.47$	.142	$r = -.31$
Inspirational quotes	162.27 (61.70)	60, 315	169.77 (71.92)	60, 315	$t(21) = 0.48$	.637	$d = 0.10$
Effective time							
Move more	197.73 (249.31)	15, 600	239.32 (280.49)	15, 600	$t(21) = 0.48$	.634	$d = 0.10$
Sit less	137.73 (218.73)	15, 600	262.50 (269.12)	15, 600	$z = 1.40$	.161	$r = .30$
Inspirational quotes	235.91 (264.31)	15, 600	111.14 (200.16)	15, 600	$z = -1.45$	.147	$r = -.31$

Note. All times are measured in minute scale.

speed of the response describing physical activity dynamics did not change.

Absolute Changes in System Dynamics by Message Type

On weekdays, steady state, settling time, effective time, and peak delay did not significantly change after the pandemic declaration for any message type ($p > .05$). As seen in Table 2, Wilcoxon signed-rank tests indicated that the median peak magnitude decreased significantly for both (a) "Move More" messages from before ($Mdn = 54.7$) to after the pandemic declaration ($Mdn = 35.8$), and (b) "Sit Less" messages from before ($Mdn = 51.5$) to after the pandemic declaration ($Mdn = 30.1$). The mean rise time for "Inspirational Quotes" also decreased significantly after the pandemic declaration.

On weekends, peak magnitude, peak delay, and effective time did not significantly change after the pandemic declaration for any message type. As seen in Table 3, the mean steady state and rise time for "Move More" messages decreased following the pandemic declaration, such that both the overall step response decreased and the time it took to move from 10 to 90% of that overall step response decreased after the pandemic declaration. Settling time increased significantly for "Move More" messages, indicating that more time was required for responses to reach their ultimate level following the pandemic declaration. Steady state, rise time, and setting time did not change significantly for "Sit Less" or "Inspirational Quotes" messages.

Relative (Rank-Order) Changes in System Dynamics by Message Type

Table 4 presents correlations between corresponding features of each message type before and after the pandemic declaration. Overall response speed pre-pandemic was not significantly correlated with post-pandemic declaration response speed on weekdays or weekends. Specific model features before and after the pandemic declaration were, with a few exceptions, weakly correlated, and not statistically-significant. On weekdays, rise time for pre- and post-pandemic declaration responses to "Sit Less" and "Inspirational Quote" messages exhibited statistically-significant positive correlations, as did settling time for pre- and post-pandemic declaration responses to "Sit Less" messages. None of the other weekday response features were significantly correlated nor were any weekend response features significantly correlated.

Discussion

We investigated the impact of the pandemic declaration on physical activity and person-specific response dynamics to a digital messaging intervention. Step counts significantly decreased on the weekdays after pandemic declaration but

Table 3 Average values of impulse and step response features and response speed for all person-specific models for pre-pandemic and post-pandemic stages on weekends

Response features AND message type	Pre-pandemic		Post-Pandemic		Test statistic	*p*	Effect size
	Mean (SD)	Range	Mean (SD)	Range			
Response speed	0.70 (0.10)	0.73 (0.10)	0.54, 0.88	0.70 (0.06)	$z = 0.86$	.389	$r = .18$
Peak magnitude							
Move more	60.53 (35.80)	19.78, 145.28	61.00 (45.68)	6.32, 209.86	$z = 0.18$	.858	$r = .04$
Sit less	62.51 (47.17)	22.14, 217.46	70.00 (52.79)	13.47, 238.50	$z = -0.11$	.910	$r = -.02$
Inspirational quotes	97.85 (115.44)	26.66, 532.27	74.54 (55.55)	13.70, 216.33	$z = 0.60$	.548	$r = .13$
Peak delay							
Move more	23.86 (21.54)	0, 60	15.00 (16.69)	0, 60	$z = 1.52$	.128	$r = .32$
Sit less	27.27 (20.51)	0, 60	23.86 (22.04)	0, 60	$t(21) = -0.57$	.576	$d = -0.12$
Inspirational quotes	23.86 (24.78)	0, 60	29.32 (21.45)	0, 60	$t(21) = 0.86$	.401	$d = 0.18$
Steady state							
Move more	54.23 (195.05)	-359.64, 428.56	-87.16 (225.44)	-902.87, 235.93	$t(21) = -2.32$	.031	$d = -0.49$
Sit less	39.24 (246.55)	-325.55, 773.19	29.27 (253.44)	-614.32, 522.56	$z = -0.08$	.935	$r = -.02$
Inspirational quotes	131.58 (400.83)	-200.49,1458.44	-3.47 (218.04)	-455.16, 399.50	$z = 0.80$	.426	$r = .17$
Rise time							
Move more	115.91 (73.51)	0, 285	75.00 (48.55)	0, 150	$t(21) = -2.37$	.028	$d = -0.50$
Sit less	102.95 (68.39)	0, 210	85.91 (66.63)	0, 270	$z = 1.09$	.276	$r = .23$
Inspirational quotes	90.68 (60.26)	0, 210	90.00 (51.75)	0, 225	$t(21) = -0.04$	.966	$d = -0.01$
Settling time							
Move more	205.23 (73.10)	105, 420	158.86 (65.08)	90, 405	$z = 2.31$	.021	$r = .49$
Sit less	190.23 (76.54)	60, 330	158.86 (67.82)	90, 375	$z = 1.32$	.186	$r = .28$
Inspirational quotes	176.59 (63.46)	90, 300	184.09 (59.31)	105, 300	$t(21) = 0.35$	.729	$d = 0.08$
Effective time							
Move more	240.00 (268.17)	15, 600	246.82 (271.97)	15, 600	$t(21) = 0.10$	.921	$d = 0.02$
Sit less	297.95 (284.31)	15, 600	301.36 (279.66)	15, 600	$t(21) = 0.05$	.961	$d = 0.01$
Inspirational quotes	256.36 (265.80)	15, 600	296.59 (280.39)	15, 600	$t(21) = 0.48$	.635	$d = 0.10$

Note. All times are measured in minute scale.

not on weekends. We hypothesized that overall intervention response speed would slow after the pandemic declaration and that message-specific response features would change; however, on average, overall response speed did not significantly change and, with few exceptions, most model response features did not change either. Finally, we hypothesized that the rank ordering of model features would remain consistent after pandemic declaration and they would be significantly positively correlated; however, for the most part, correlations were weak showing that model features were not consistent within participants after the pandemic declaration. Together, these results support the notion that significant changes in context can impact physical activity behavior and participant response dynamics within a digital messaging intervention.

A key contribution of these findings is that the pandemic declaration impacted physical activity more on weekdays than on weekends. Prior work evaluating the impacts of the COVID-19 pandemic on physical activity in the United States have reported significant decreases in physical activity following the pandemic declaration [5, 25, 26]. Compared to analyses that specifically evaluated step counts, the change we observed was greater (1000 step/day decrease across 239,543 people [5]; 2232 steps/day decrease in 268 adults [26]). This could be due to age differences; our sample focused specifically on insufficiently-active young adults whereas those studies sampled any US Argus app users ([5]) and US adults 18–74 years old ([26]). A longitudinal study in England that looked at the effects of age showed that younger people 14–34 years old experienced the most change in activity after lockdown and remained the least active throughout compared to persons 35–44, 45–54, 55–64, and 65 years or older [27]. However, our work contrasts with an analysis of US college students physical activity based on pre-pandemic activity level [28]. Active students were the only group that experienced decreases, while inactive, and moderately-active students experienced increases or no change based on activity intensity. Our entire sample was composed of insufficiently-active individuals. Another key difference is that we used device-based measures that could capture behavior before and after the pandemic declaration, whereas Barkley et al. [28] used self-report measures that asked students to recall their activity before and after the pandemic declaration, which may have been susceptible to recall bias.

To our knowledge, this is the first evaluation that shows different physical activity changes on weekdays and weekends after the pandemic declaration. Physical activity is a dynamic behavior that can vary by time of day or from day to day across groups, and demonstrate significant variability within individuals [10, 20]. Given prior work showing different physical activity patterns on weekends and weekdays, it stands to reason that the impacts of the pandemic on physical activity would differ by day type. Lockdown/stay-at-home orders directly impacted engagement with work and school, which occupy a significant amount of time, typically only on the weekdays. The weekends inherently involve

Table 4 Correlations between pre- and post-pandemic response speed and response features to different message types for weekday and weekends

Response feature	Message type	Weekdays		Weekends	
		r	*p*	*r*	*p*
Response speed		.26	.24	-.15	.50
Peak magnitude					
	Move more	.08	.73	-.07	.76
	Sit less	-.05	.81	.00	.99
	Inspirational quotes	-.08	.74	.10	.67
Peak delay					
	Move more	-.18	.43	-.12	.60
	Sit less	-.27	.22	.13	.57
	Inspirational quotes	-.06	.79	.17	.44
Steady state					
	Move more	.13	.57	.08	.73
	Sit less	.41	.06	-.16	.48
	Inspirational quotes	-.05	.75	-.13	.58
Rise time					
	Move more	.04	.86	.17	.46
	Sit less	.54	.01	-.12	.60
	Inspirational quotes	.50	.02	.13	.57
Settling time					
	Move more	.28	.21	.17	.45
	Sit less	.68	< .001	-.14	.53
	Inspirational quotes	.40	.06	-.33	.13
Effective time					
	Move more	-.16	.47	.30	.18
	Sit less	.26	.24	.34	.12
	Inspirational quotes	.05	.83	-.03	.91

less exogenous control; thus, people may have experienced a less significant change in their routine on the weekends or they were able to adapt better to experienced changes due to having more discretionary time.

After evaluating absolute and relative changes in response dynamics by message type, we concluded that change occurred in intervention response post-pandemic declaration and the type and magnitude of the change differed within and between people. Relative changes in model features show that some aspects of intervention responses were more stable on weekdays than weekends. This finding could be due to instability in the model due to having less weekend data or it could reflect larger reorganizations of behavior given the greater discretionary time that people have on the weekends compared to the weekday. Developmental systems theory proposes that when humans experience transformational change, they can reject or suppress the change and maintain existing organization, they can change aspects of themselves to accommodate the change, or they can change their relationship with their environment to accommodate the change [18]. This array of options for how change can be accommodated may provide a framework for responses across varying contexts. It could be that pandemic-induced contextual changes affected cognitive, affective, or motivational processes resulting in a change in behavioral response to message content. However, we are unable to test this mechanistic speculation because this study design focused on measuring what excites the system and elicits a response rather than what changes inside the person.

This work extends a prior publication from our group on dose-finding by showing that person-specific models vary as the context of behavior evolves [12]. We have previously found that generic models are conservative in representing the physical activity of individuals and there is a need for person-specific models [12, 13]. The person-specific models in this analysis showed considerable variability in extracted model features before and after the pandemic declaration, adding support that person-specific approaches are needed for dynamic behaviors. Additionally, differences in individuals' responses over the weekends and weekday reinforce the need for switch systems based on the day of week [13]. These findings are consistent with prior findings that a structure describing group-level variations cannot describe the variations in the individual level and thus person-specific approaches may yield efficient treatment decisions for individuals [29]. Failure to deploy person-specific decision rules could lead to less effective interventions and potential treatment fatigue by users [30]. Furthermore, this analysis adds support for the development of continuous tuning interventions since it provides evidence that abrupt changes in context impact health behavior and intervention response within and between people. Continuous tuning interventions "use data about the individual to progressively refine and 'tune' the intervention content, delivery feature(s) or timing to the idiosyncrasies of the individual" [31]. We hope that we will not experience another pandemic, but other normal life events could dramatically impact behavioral systems (e.g., pregnancy, parenting a child, adopting a pet, moving, starting school, or a new career). Physical activity interventions may need to be person-specific and continuously-tuned in order to have the greatest effect across people. Future work is needed to empirically test the efficacy and effectiveness of person-specific adaptive interventions for physical activity promotion.

Limitations and Challenges

The small sample size reduced our ability to detect statistical significance, thus explaining the differences observed in significant *p*-values and meaningful effects. Findings were based on insufficiently-active young adults and may not generalize to more active young adults or to midlife and older adult populations. Physical activity behavior was measured with a wrist-worn Fitbit device, which may not be as accurate as a research-grade activity monitor worn at the waist or thigh. We investigated the effect of the pandemic as an external factor on physical activity behavior and intervention response; however, given that this was a natural experiment, other unmeasured factors may have influenced these changes, such as physical or mental health. Young adults may have experienced temporary changes in living arrangements during campus closures or after loss of employment. From a statistical standpoint, assumptions were checked before running each test, however, there were some potential concerns with linearity for the correlation analyses. All of our dynamical models assumed similar memory (all order 5) and model parameters were constants and not allowed to vary as a function of other conditions at the time of message receipt, such as location or weather.

Notwithstanding these assumptions, dynamical system modeling provided a solid framework for developing person-specific models and interpreting the dynamic physical activity behavior of the participants. Other techniques like reinforcement learning algorithms cannot be applied to the amount of data used in this study. Additionally these methods are not capable of handling the noisy data [32]. System identification methods applied in this paper make a balance between using sensor collected data to explore the dynamic physical activity behavior of the participants and the efficiency in the amount of data required for analysis. Additionally, these tools are well-suited to handle noisy datasets.

Conclusions

This study revealed that the abrupt change(s) in daily life following the COVID-19 pandemic declaration significantly impacted both physical activity levels and the dynamics of physical activity, including how people responded to digital messaging interventions. Researchers evaluating behavioral interventions may want to consider the implications of the COVID-19 pandemic when assessing the efficacy or effectiveness of their intervention as this event may have impacted participant responses to other interventions as well. The implications of this work demonstrate the importance of developing person-specific, continuously-tuned interventions that take into consideration external factors that can cause reorganization of behavioral systems.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflicts of interest.

Ethical Approval All procedures were approved by the Institutional Review Board at The Pennsylvania State University.

Informed Consent Informed consent was obtained from all individual participants included in the study.

Study Registration The study was pre-registered at http://clinicaltrials.gov (NCT03907683).

Analytic Plan Pre-registration The analysis plan was not formally pre-registered.

Data Availability De-identified data from this study are not available in a public archive but may be requested by emailing the corresponding author.

Analytic Code Availability Analytic code used to conduct the analyses presented in this study is not available in a public archive but may be requested by emailing the corresponding author.

Materials Availability Materials used to conduct the study may be available by emailing the corresponding author.

Author Contributions Sah.H.—conceptualization, data curation, formal analysis, software, writing—original draft, review and editing; A.M.L.—conceptualization, formal analysis, writing—original draft, review and editing; Sar.H.—data curation, software, writing—review and editing; C.M.L.—conceptualization, formal analysis, supervision, funding acquisition, writing—review and editing; D.B.-R.—investigation, writing—review and editing; D.E.C.—conceptualization, funding acquisition, supervision, writing—original draft, review and editing.

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study. This article does not contain any studies with animals performed by any of the authors.

Supplementary Material

Supplementary material is available at *Annals of Behavioral Medicine* online.

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