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Person-Specific Dose-Finding for a Digital Messaging Intervention to Promote Physical Activity

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Abstract

OBJECTIVE: Digital messaging is an established method for promoting physical activity. Systematic approaches for dose-finding have not been widely used in behavioral intervention development. We apply system identification tools from control systems engineering to estimate dynamical models and inform decision rules for digital messaging intervention to promote physical activity.

METHODS: Insufficiently-active emerging and young adults (n = 45) wore an activity monitor that recorded minute-level step counts and heart rate, and received 0–6 digital messages daily on their smartphone for six months. Messages were drawn from three content libraries (move more, sit less, inspirational quotes). Location recordings via location services in the user's smartphone were used to lookup weather indices at the time and place of message delivery. Following system identification, responses to each message type were simulated under different conditions. Response features were extracted to summarize dynamic processes.

RESULTS: A generic model based on composite data was conservative and did not capture the heterogeneous responses evident in person-specific models. No messages were uniformly ineffective but responses to specific message content in different contexts varied between people. Exterior temperature at the time of message receipt moderated the size of some message effects.

CONCLUSIONS: A generic model of message effects on physical activity can provide the initial evidence for context-sensitive decision rules in a just-in-time adaptive intervention, but it is likely to be error-prone and inefficient. As individual data accumulates, person-specific models can be estimated to optimize treatment and evolve as people are exposed to new environments and accumulate new experiences.

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Keywords

mobile health; precision medicine; prevention; social ecology; patient-specific computational modeling

Physical activity is a widely recommended behavior across the lifespan because it reduces risk for chronic diseases and improves well-being but only 1 in 3 adults achieves the recommended level of physical activity (Bennie et al., 2019). Over 95% of emerging and young adults have smartphones that afford new possibilities for promoting physical activity during the transition into adulthood (Pew Research Center, 2019). Digital messages via text messages or notifications have become a popular mode for motivating physical activity (Smith et al., 2020). The timing and frequency of messages varies considerably between interventions but dosing parameters have typically been constant for all participants receiving the intervention. We recently proposed that the optimal dosing of digital messages for physical activity promotion may be person-specific (Conroy et al., 2020). In this paper, we apply methods from control systems engineering to address the challenge of person-specific dose-finding for a digital messaging intervention.

Physical Activity Promotion

Physical activity has been called the "best buy" in public health because of its multi-system benefits for health (Powell et al., 2011). The World Health Organization and the United States Department of Health and Human Services have issued guidelines for health-enhancing physical activity (Bull et al., 2020; U.S. Department of Health and Human Services, 2018). Both guidelines recommend accumulating at least 150 minutes/week of moderate-intensity or 75 minutes/week of vigorous-intensity physical activity (or an equivalent combination). Yet most American adults, including emerging and young adults, fail to achieve this recommended level of aerobic physical activity (Bennie et al., 2019).

Inactivity during the transition into adulthood is a particular concern because physical inactivity tracks across the lifespan. Although the biggest decreases occur in adolescence and midlife, emerging and young adulthood represent a time of increased independence and identity exploration that can have lasting effects on physical activity in adulthood (Nelson et al., 2008). Promoting physical activity during this period, when contextual cues are frequently disrupted, can promote long-term health outcomes. For example, the CARDIA study found that young adults who engage in regular physical activity are more likely to have a low risk profile (i.e., no cardiovascular events) 20 years later (Liu et al., 2012).

Unfortunately, this segment of the population often eludes the reach of traditional health care interventions because they feel healthy, have not developed chronic conditions that would require care, and do not see physicians regularly for preventive care (Dietz, 2017; Monaghan, 2014). One way to reach them may be through the digital environment. Over 95% of emerging and young adults in the United States have smartphones (Pew Research Center, 2019). Wearable activity trackers, smartphone applications, and text messages produce small-to-moderate effects on physical activity (Armanasco et al., 2017; Laranjo et al., 2020; Smith et al., 2020).

Consumer-grade activity trackers have popularized the step count as a physical activity index over the intensity-specific activity durations noted in guidelines. Bassett argued that steps are "intuitive and readily interpretable to the layperson…measured easily and accurately…[and] objective" (Bassett et al., 2017, p. 1306). Although a consensus evidence-based goal for daily step counts has not been established for adults (Tudor-Locke et al., 2011), there is clear evidence that daily step counts are linearly and inversely associated with risk for mortality and cardiovascular disease (Hall et al., 2020; Kraus et al., 2019; Saint-Maurice et al., 2020). Yet little is known about the optimal dosing of digital messaging interventions for increasing step counts. For example, it is unclear if messages to "move more" or "sit less" are more effective, or if the same dose should be delivered on weekends and weekdays.

Dose-Finding Methods in Early Stage Intervention Development

Behavioral interventions are complex and development can proceed more efficiently using a phased approach. The Obesity-Related Behavioral Intervention Trials framework was modeled on the drug development pipeline (Czajkowski et al., 2015). Dose-finding is a key task during early-phase intervention development. With a digital messaging intervention, delivering too few messages can compromise behavior change but delivering too many messages may be disruptive and threaten user engagement. Although dose-finding methods are well-established and widely used in drug development, dose-finding has not been approached as systematically in developing behavioral interventions, and particularly digital health interventions (McVay et al., 2019; Towner et al., 2020; Voils et al., 2014).

Given the low risk for harm from digital messages that promote physical activity, our focus was on identifying the minimally-effective dose. Dosing is often described in terms of the duration, frequency, and amount of treatment (Voils et al., 2012). For digital messaging, doses can represent the number of messages sent, the content of those messages, and the timing of the messages. An optimized digital messaging dose will deliver the right content at the right time in the fewest number of messages needed to achieve a behavioral goal. Determining how to tailor message content and timing to achieve this goal is challenging because behavior is multiply determined and the contexts in which behavior unfolds are dynamic. Computational modeling of dynamic systems via system identification can be useful for determining how to tailor message content and timing (Conroy et al., 2020).

We have previously shown that it is possible to apply system identification tools from control systems engineering to develop person-specific dynamic models of behavioral responses to digital messages (Ashour et al., 2016; Conroy et al., 2019). In this context, the focus is on both how the dynamics of behavior unfold in the presence or absence of micro-interventions, and how that knowledge can inform the selection and timing of interventions to attain behavioral goals (Albertos & Mareels, 2010). Continuous streams of physical activity data can be modeled as a function of recent behavior and message content, and model coefficients can be used to simulate expected changes in future behavior if different types of messages were delivered following recent behavior. When dynamics differ during clearly-defined periods – such as on weekends versus weekdays – piecewise dynamic models can be estimated to characterize complementary behavioral systems.

In this paper, we extend this approach in two important ways. First, we simulate responses to different message types under different conditions and, for the first time, extract features of those responses to compare person-specific models with a generic model based on composite data from the sample as a whole. Second, we enrich the dynamic model of physical activity by using momentary weather conditions as inputs to improve predictions of behavioral responses. Adults frequently describe poor weather as a barrier to exercise (Salmon et al., 2003). Our recent scoping review indicated that device-measured physical activity has an inverted-U shaped association with temperature and a negative association with precipitation (Turrisi et al., 2021). We hypothesized that the effects of digital messages would vary as a function of momentary temperature and precipitation indices, with the greatest effects observed during dry conditions with moderate temperatures.

The Present Study

The Physical Activity Guidelines for Americans assert that, "adults should move more and sit less throughout the day [and] some physical activity is better than none" (Piercy et al., 2018, p. 2025). Translating that recommendation into action is an ongoing challenge. Technology provides a means of promoting physical activity during the transition into adulthood but little is known about the optimal dosing of a messaging-based intervention. In this study, we applied system identification tools to determine the optimal dosing for a context-specific, just-in-time digital messaging intervention to promote physical activity. For six months, insufficiently-active emerging and young adults wore a consumer-grade smartwatch and received randomly-assigned intervention messages (Random AIM) in this trial. The number, timing and content of messages varied randomly. Location data at the time of message receipt and acknowledgement was used to lookup current weather conditions to enrich model predictions. The primary purpose of this study was to identify and characterize the heterogeneity of dynamical models of physical activity responses to digital messages. A second purpose was to determine whether person-specific dosing of digital messages may be warranted by comparing the performance to a generic dynamical model based on composite data from the entire sample to person-specific dynamical models. A third purpose was to extend and enrich the model by accounting for varying environmental conditions at the time of message receipt.

Methods

Participants

Emerging and young adults were recruited using fliers and online advertisements from April 2019 to July 2020. 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 also needed to own a smartphone using the iOS (v10 or later) or Android (v7 or later) operating system. Participants were excluded if self-reported physical activity levels were greater than 90 minutes of moderate or higher physical activity per week, if unable to be physically active or with medical contraindications for physical activity, if pregnant or had a prior diagnosis of cancer, cardiovascular disease, diabetes, or metabolic disorder. Participants completed a telephone screening with a researcher followed by a 1-week ambulatory monitoring period wearing an Actigraph wGT3X-BT activity monitor. Participants were excluded if the device recorded the equivalent of more than 150 total minutes of moderate-intensity or greater physical activity based on five or more days with 10+ hours of monitor wear time during the 1-week monitoring period.

The World Health Organization declared the COVID-19 pandemic on March 11, 2020. Stay-at-home orders associated with the pandemic reduced physical activity levels (Pépin et al., 2020; Tison et al., 2020). To prevent confounding of message and pandemic effects, analyses were restricted to participants who completed 6 months of data collection prior to the pandemic declaration (n = 45).

Measures

During the first laboratory visit, participants self-reported demographic characteristics including age, ethnicity, race, sex, educational attainment, employment status and occupation. Research staff measured height and weight in duplicate using a wall-mounted stadiometer and a digital scale upon removal of the participant's shoes.

Actigraph wGT3XP-BT activity monitors were worn at the waist over the midline of the dominant thigh to assess the duration of moderate-to-vigorous intensity physical activity during the secondary screening process (without providing behavioral feedback that could elicit reactivity). This device and placement are widely-used as a gold-standard for ambulatory physical activity assessment. Established cutpoints were used to classify minutes as moderate (1952–5724 counts/min) and vigorous (>5724 counts/min) physical activity (Freedson et al., 1998).

The Fitbit Versa/Versa Lite smartwatch, a widely-available consumer-grade monitor that could be used to scale an intervention later in development, was worn on the non-dominant wrist to track step counts during the 6-month intervention period. This device recorded minute-level step counts and heart rate (in 5-minute moving averages). Fitbit devices have demonstrated accuracy for step counting that is comparable to research-grade Actigraph monitors and suitable for use in adults without mobility limitations (Feehan et al., 2018; Imboden et al., 2018).

Protocol

The protocol and compensation schedule are summarized in Figure S1 (available online). All procedures were approved by the Institutional Review Board at The Pennsylvania State University (Study#00009455).

Screening & Lab Visit #1.—Prospective participants provided verbal consent (day 0) and completed a telephone screening interview to determine eligibility. Provisionally-eligible participants were scheduled for a laboratory visit to complete screening. During that first lab visit (day 1), the researcher described the study and participants provided written informed consent. The researcher provided the participant with an Actigraph wGT3X-BT activity monitor and instructions to wear it at their waist on an elastic waistband over the midline of their dominant leg for the next week during waking hours for a minimum of 10 hours/day, and to remove it when bathing or swimming. The researcher provided a paper wear log and asked participants to record times when they placed the device each morning, removed the device in the evening, and removed or re-placed the device during the day.

Lab visit #2.—During the second lab visit (day 9), the researcher collected the activity monitor and wear log, downloaded data, reviewed non-wear classifications from the "Troiano 2007" algorithm in the ActiLife v.6.13.4 software and determined eligibility. The researcher described the second phase of the study and participants provided written informed consent to enroll. The researcher then assisted the participant with installing the Random AIM (custom-designed for this study) and Fitbit mobile applications on her or his smartphone, registered the participant on the backend system, confirmed Random AIM functionality with a test message, provided the participant with a Fitbit Versa/Versa Lite smartwatch, and assisted participants in authorizing Fitbit to share their data via Fitabase. The researcher asked the participant to identify separate Do Not Disturb periods for weekdays and weekends (<14 hours to provide at least a 10-hour messaging window), and informed participant that these times could be changed at any point by contacting the researcher.

Intervention period.—For the next 6 months, the Random AIM app delivered 0–6 messages/day as notifications via the operating system. The number, timing, and content of messages were determined at random each night with the constraints that no message could be delivered within 15 min of the previous message or within the Do Not Disturb window for that day. Messages were drawn from three content libraries: move more (108 messages), sit less (108 messages), and inspirational quotes (54 messages). Half of the messages were accompanied by a stock photography image corresponding to message content (i.e., physical activity for move more messages, standing for sit less images, scenic landscapes for inspirational quotes). Notifications with each message were available for viewing and acknowledgement for 30 minutes after which time they disappeared and were recorded as received but not acknowledged.

For each message, the backend system recorded the time that the message was sent from the server to the mobile app, delivered and displayed on the participant's device, and acknowledged by the participant (three separate timestamps). The mobile app used location services within the operating system to record latitude and longitude coordinates each time a message was received and acknowledged. The timestamped location data at display and acknowledgement were used to lookup location-specific momentary weather indices via the AccuWeather Current Conditions application programming interface (AccuWeather, n.d.). Weather indices are recorded approximately hourly but are rarely available immediately so, 3 hours after message receipt, the server looked up location-specific weather indices using the Historical Current Conditions (past 6 hours) application programming interface. Recorded weather indices included temperature (Fahrenheit), dew point (Fahrenheit), relative humidity (%), Real Feel temperature (Fahrenheit), apparent temperature (Fahrenheit), wind chill temperature (Fahrenheit), wet bulb temperature (Fahrenheit), wind direction (degrees), wind direction (English), wind speed (miles/hour), wind gust speed (miles/hour), UV index, cloud cover, past-hour precipitation (liquid equivalent, inches), and past 3-hour precipitation (liquid equivalent, inches). The researcher monitored the backend dashboards for both the Random AIM and Fitbit apps daily to detect compliance problems. A researcher contacted participants via telephone or email anytime 3 consecutive days without Fitbit heart rate data (suggesting device non-wear) or 3 days without acknowledging Random AIM messages were observed.

Lab visit #3.—The researcher scheduled a final lab visit (day 190) after participants completed the 6-month intervention period to assist the participant with removing the study apps.

Data Analysis

Pre-processing.—Four data tables were combined to model physical activity dynamics following messages: person-level availability for messages, minute-level physical activity, minute-level heart rate, and messages with weather indices at the time of delivery and receipt. Timestamps were harmonized in four source data files and the files were merged. Physical activity and heart rate data were truncated to the period from one hour before the messaging availability window started to one hour after it ended to ensure sufficient activity data when messages were sent early or late in the day. Activity data was separated for weekdays and weekends, and classified as missing if zero steps were recorded and heart rate data was not available for a minute epoch. Minutes with missing heart rate and zero step counts were not included in the model (weekends: 15% missing, weekdays: 13% missing). Messages scheduled and sent from the server that were not received and displayed on a participant's device were excluded from the model because future intervention decisions will be made without regard to whether a message will be read or not. The available and valid minute-level physical activity data was aggregated into sums for each 15-minute epochs. Message and weather data were merged with those 15-minute epochs. Days were treated as independent and message effects on physical activity were not modeled across days.

System identification.—The Python programming language was used to implement the system identification algorithms used to identify the models (Van Rossum & Drake, 2009). Building on prior work, physical activity was modeled as a switched system with separate models to reflect the different amount and patterns of physical activity on weekdays and weekends (Conroy et al., 2019; Phatak et al., 2018). The first stage of analyses was based on a linear regression model with multiple variables and noise of the form

$$y(kd) = a_0 + \sum_{i=1}^{5} a_i y(kd - id) + \sum_{j=1}^{3} \sum_{i=0}^{5} b_{ij} u_j(kd - id) + \varepsilon(kd) \tag{1}$$

where $y(kd)$ is the system output at time kd which is the step counts for the 15-minute epoch at time kd, $u_j(kd - id)$ are the inputs for the three message types (move more, sit less, inspirational quotes) at time $kd - id$ (0 [message not sent], 1 [message sent]), d is the sampling time, $\varepsilon(kd)$ is noise at time kd, and a_0, a_i, b_{ij} are the unknown coefficients of the model. To manage the trade-off between model complexity and size of the model error, model order was constrained to 5 which means that the last five epochs were used in predicting the next epoch.

In the second stage of analyses, a linear parameter-varying (LPV) system was modeled. This LPV model described how the dynamics of behavioral responses to messages varied as a function of time-varying parameters. In this study, the time-varying parameter was temperature. The LPV model with noise is of the form

$$y(kd) = a_0(p(kd)) + \sum_{i=1}^{5} a_i(p(kd))y(kd - id) + \sum_{j=1}^{3} \sum_{i=0}^{5} b_{ij}(p(kd))u_j(kd - id) + \varepsilon(kd) \quad (2)$$

where $a_0(p(kd)), a_i(p(kd)), b_{ij}(p(kd))$ are the unknown functions in the model that vary with parameter p at time kd. In this work, the parameter p is considered to be temperature and the coefficients $a_0(p(kd)), a_i(p(kd)), b_{ij}(p(kd))$ are considered to be quadratic function of parameter p at time kd. A quadratic function was selected based on evidence that physical activity has an inverted-U relation with temperature (Turrisi et al., 2021).

Models from both stages of analyses were used to simulate responses to each message type. Impulse responses represent expected step count changes during each 15-minute epoch following receipt of each message type (compared to expected step counts had a message not been received). Cumulative step responses represent the total expected effect of each type of individual message. Error bounds were estimated for each response curve to indicate whether effects exceeded the threshold of noise in the model. Full details on estimation and optimization methods are provided in a Supplemental File.

Seven features were extracted to describe person-specific impulse response and cumulative response curves (Conroy et al., 2019). *Initial delay* describes the delay between message delivery and the first effects (non-zero impulse response) of the message. *Peak magnitude* describes the absolute value of the maximum change in step count during any individual epoch following message receipt. *Peak delay* describes the latency between message receipt and achieving peak response magnitude. These first peak features indicate how quickly messages have their largest instantaneous effect on behavior. *Steady state* describes the expected overall effect (step count change) of a single message and was defined as the value when the cumulative response curve becomes stable. *Rise time* describes the time required for physical activity responses to progress from 10% to 90% of the expected total response (steady state). *Settling time* describes the duration between message receipt and cumulative responses achieving ±5% of their steady state. Steady state, rise time, and settling time indicate the overall effect of a single message, how quickly that effect emerges, and how much time is required to achieve most of the effect. *Effective time* describes the duration that the expected overall effect of a single message is expected to exceed the cumulative threshold for noise (i.e., outside the error margin). This feature indicates the time that a message is expected to be actively influencing behavior in the face of progressively accumulating noise which adds uncertainty to long-term prediction of behavior change.

Results

Participant flow in the Random AIM trial is summarized in Figure S2. Approximately 45% of interested participants qualified and enrolled. The analytic sample (n = 45) was mostly women (n=30 [67%]) who identified as White (n=29 [64%]) and not Hispanic or Latino (n=43 [96%]). The sample included participants who identified as Asian (n=10 [22%]), African-American (n=4 [9%]) and two or more races (n=2 [4%]). The mean age was 24.4 years (SD = 3.1, range = 18 – 29) and participants' highest level of education included no college education (15.9%), some college (22.7%), bachelor's degree (34.1%), and graduate or professional degrees (27.3%).

Message Delivery

For the 45 participants in the analytic sample, a total of 24,123 messages were scheduled on the server (M = 3.05 messages/person/day, SD = 0.16). Of the scheduled messages, 96.0% were received and displayed on the mobile device with the total of 23,149 messages (M = 2.92 messages/person/day, SD = 0.33), and 78.2% were acknowledged within 30 minutes of receipt (M = 2.38 messages/person/day, SD = 0.33). The mean latency of acknowledgements was 00:05:26 (*SD* = 00:20:46). Received messages were distributed between "move more" (n=9093 [39%]), "sit less" (n=9363 [40%]), and "inspirational quotes" (n=4693 [20%]) message libraries. A total of 20,735 of the messages were available with corresponding data from the physical activity monitoring device, with a similar distribution of messages between "move more" (n=8161 [39%]), "sit less" (n=8351 [40%]), and "inspirational quotes" (n=4223 [20%]) in the received messages.

Most messages were delivered on weekdays (72%). The average Do Not Disturb window for participants spanned from 19:50 (95% CI = 16:30–23:10) to 09:20 (95% CI = 06:40–12:00) for weekdays and 20:30 (95% CI = 18:00–23:00) to 10:10 (95% CI = 08:00–12:20) for weekends. Acknowledged messages were distributed across the day so messages provided suitable coverage during waking hours outside the Do Not Disturb window (Figure S3, top row). Messages were distributed across all four seasons (Figure S3, bottom row). Due to the 6-month protocol duration, no participant was sampled in more than three seasons. Weather conditions at the time of message acknowledgement varied considerably. When weather indices at message acknowledgement were aggregated within person, the average temperature was 62°F (SD = 15, 95% CI = 31–92°F), and an average of 8.3% of the messages were received after measurable past-hour precipitation (SD = 2.2, 95% CI = 3.9–12.7). Based on the limited proportion of messages sent during moments with measurable precipitation, precipitation models were excluded from this study.

System Identification

Do person-specific models match a generic model?—Two dynamical models of physical activity were estimated for each person based on their recent physical activity and the types of messages received on weekdays and weekends. The simulated impulse response and cumulative step response curves for two participants can be seen in Figures S4–S5.

For the participant in Figure S4, the steady state of physical activity responses differed from weekdays to weekends and as a function of the type of message sent. On weekdays, a single "sit less" message would be expected to lead to 87 more steps than if he or she did not receive the message, but "move more" and "quotes" messages were expected to reduce step counts. In contrast, on weekends, "sit less," "move more" and "quotes" messages were expected to lead to 133, 183, and 65 more steps, respectively, than if he or she did not receive the message.

For the participant in Figure S5, the steady state of physical activity responses also differed from weekdays to weekends and as a function of message type, but the pattern was different from the previous participant. On weekdays, “move more” and “sit less” messages were expected to lead to 136 and 132 more steps, respectively, than if he or she did not receive the message, but “quotes” messages were not expected to lead to non-trivial changes in step counts. On weekends, “quotes” messages were expected to lead to 166 more steps than if he or she did not receive the message, but neither “move more” nor “sit less” messages were expected to lead to non-trivial changes in step counts.

As a contrast to these person-specific models, a generic model was estimated using composite data from all eligible participants. Figure S6 presents the impulse (left panel) and cumulative response (right panel) curves for weekdays and weekends. On weekdays, “sit less” messages would be expected to lead to 25 more steps than if the message was not sent but neither “move more” nor “quotes” messages would be expected to change behavior. On weekends, “move more,” and “sit less” messages would be expected to lead to 46 and 53 more steps, respectively, than if the message was not sent; however, “quotes” messages were not expected to lead to non-trivial changes in step counts.

Table 1 compares the features of the simulated responses to messages on weekdays and weekends based on the person-specific models and the generic model. The initial delay of responses was zero in all models so this feature excluded from the table. Three observations can be made based on the remaining features. First, response features in the person-specific models vary considerably. Peak response magnitudes in a single 15-minute epoch ranged from quite small (<10 step increase) to quite large (~200 step change). Some people are expected to have immediate peak responses to messages but others are expected to have quite delayed peak responses to messages (60 min). Cumulative responses to messages varied considerably with greater responses evident on weekends than weekdays. The “average” participant would be expected to increase their activity slightly following most messages but individual responses varied. Some participants would be expected to increase and others would be expected to decrease activity following messages. The latency of total effects was highly variable as indicated by the range of settling time, rise time, and effective time in the person-specific models. Second, no single message type appeared to be uniformly ineffective. As illustrated by Figures S4–S5, participants exhibited differential responsivity to messages both as a function of message content and whether that content was sent on a weekday or weekend. Third, the generic model features were within the range of features from the person-specific models for 81% (29/36) of the features. Peak magnitude estimates from the generic model were especially conservative, account for 5 of the 7 out-of-range values. In general, features from the generic model failed to address the heterogeneity of responses observed in the person-specific models.

Do person-specific responses to messages vary as a function of temperature?—Building on the heterogeneity of responses in our initial models, we sought to determine whether participants’ responses also varied under time-varying environmental conditions (specifically, temperature at the time of message receipt). Figures S7–S8 present cumulative response curves from person-specific models of two participants' weekday (top row) and weekend (bottom row) responses to three message types: "move more" (left panel), "sit less" (center panel) and "quotes" (right panel). These figures represent data for the same participants shown in Figures S4–S5, respectively. The range of temperatures plotted approximates the 95% confidence interval for observed temperatures during the 6-month study (36°F to 90°F for the participant enrolled from June to December; 23°F to 72°F for the participant enrolled from August to February).

For the participant depicted in Figure S7 (cf. Figure S4), the effects of "move more" messages on weekdays were trivial regardless of temperature but, on weekends, "move more" message effects on physical activity increased monotonically with the temperature. On a hot weekend day (90°F), a single "move more" message would be expected to lead to more than 500 additional steps compared to what would be expected if the message was not sent. On a cold day (≤63°F), "move more" messages had little to no effect on this participant's physical activity. "Sit less" messages exhibited a different pattern. On weekdays, "sit less" message effects increased monotonically with temperature. A single "sit less" message on a hot day (90°F) would be expected to lead to nearly 300 more steps compared to what would be expected if the message was not sent, but effects were progressively smaller as temperatures dropped. On weekends, "sit less" messages would be expected to have their greatest effect (>300 step increases) for this participant during more extreme – hot or cold – conditions.

For the participant depicted in Figure S8 (cf. Figure S5), message effects consistently varied as a function of message type, timing, and temperature. Of note, temperature-related differences in effects were not consistently monotonic. The largest effects of "move more" messages would be expected on weekdays with extreme temperatures (hot or cold). On weekdays, the largest effects of "sit less" and "quotes" messages would be expected at times with warmer temperatures. On weekends, "sit less" and "quotes" messages would be expected to have their greatest impact on physical activity at moderate temperatures. Surprisingly, "sit less" messages were expected to decrease physical activity by over 300 steps at extremely cold moments on weekends.

Figure S9 (cf. Figure S6) presents the corresponding cumulative response curves from a generic model based on composite data from all participants. The generic model simulation implies smaller expected effects than the person-specific models, particularly on weekdays. Overall, the generic model implied that most message types sent under most conditions would have little to no effect on participants' behavior. The effects of "sit less" message increased monotonically as a function of temperature on both weekdays and weekends, though the gradient of effects between message types was minimal. "Move more" messages had limited effects (~70 step increase) under most conditions with the exception being on hot (90°F) weekends. Surprisingly, the generic model implied that "quotes" messages on hot (90°F) days would lead to the largest expected effects of all message types on weekdays.

Discussion

This research applied an engineering-inspired approach to determine the optimal dose for a digital messaging intervention. The approach extends the toolkit for dose-finding in behavioral intervention development (McVay et al., 2019; Towner et al., 2020; Voils et al., 2014). It extended our prior work on dynamical modeling of physical activity and the effects of digital messages by obtaining a larger sample with a longer time series enriched by data on current weather conditions at the participant's location when they receive a message (Ashour et al., 2016; Conroy et al., 2019). A heterogeneous suite of person-specific models of individual participant's responses to messages under different conditions were estimated along with a generic model based on composite data. The heterogeneity of responses was notable considering that the sample was delimited to a narrow age range of adults who were verified as insufficiently active. Rather than comparing model coefficients directly, expected behavioral responses were simulated for different types of messages under different conditions and key features of those responses were compared.

These dynamical models provide an evidence-based foundation for future work developing algorithms that are optimized to achieve behavior change goals with the smallest number of messages possible. Such algorithms represent the decisions rules that determine dosing in a just-in-time adaptive intervention as an optimization problem to be solved (Nahum-Shani et al., 2018). By applying the computational model at prespecified decision points to simulate the expected responses to a variety of intervention options at that decision point, these algorithms can determine which message type would yield the greatest benefit under current conditions and, if the expected effect of a particular message type exceeds the threshold for a minimally-effective dose, trigger delivery of that message. These results provide new insights for dose-finding with digital messaging interventions to promote physical activity.

First, based on the heterogeneity of person-specific models, person-specific decision rules would appear to be superior to a generic decision rule for optimizing dosing. Features of impulse responses (peak magnitude, peak delay) in the generic model were consistently dampened in comparison to the mean of person-specific model features. Some features of the generic cumulative response curves (steady state, settling time) approximated the mean of person-specific cumulative response curves, but those estimates were fixed and failed to account for the tremendous variation in individual responses. This insensitivity of the generic model to individual differences could result in counter-productive treatment decisions if decision rules were based on that model. For example, the generic model implied a small but uniform positive effect of the "move more" and "sit less" messages. In contrast, the person-specific models revealed that approximately one in three participants would be expected to reduce their physical activity following one of these messages (see Supplementary Tables 1–2). Decision rules should be designed to accommodate this heterogeneity because group-level models are unlikely to generalize to individual-level processes (Molenaar, 2004). If not, treatment decisions will be error-prone (selecting the wrong message content for delivery or sending messages at the wrong moments) and inefficient (sending too many messages to achieve a goal). These characteristics could jeopardize engagement and efficacy. Thus, findings point to the promise of using a small data paradigm for dose-finding (Hekler et al., 2019).

Second, although clearly sub-optimal, the generic model may still serve an important role in developing person-specific decision rules. Person-specific decision rules are developed based on person-specific models, and person-specific models can only be estimated when sufficient time-series data are available. Such time series are not immediately available when onboarding new users. One solution is to use the generic model of group-level physical activity dynamics to generate an initial decision rule (i.e., warm-start optimization). This initial generic decision rule could be replaced by progressively more refined person-specific decision rules as information accumulates for an individual. In this way, the intervention could be doubly adaptive – first adapting individual intervention decisions (i.e., whether to send a message and which message to send at each decision point) and second adapting individual decision rules as individual data accumulates and person-specific models are refined (Conroy et al., 2020; Wongvibulsin et al., 2020).

Third, this study revealed that real-time temperatures provide a potentially-valuable tailoring variable for decision rules in a digital messaging tool for promoting physical activity. Temperature exhibits one of the clearest relations between the natural environment and device-measured physical activity but research has been observational and largely based on aggregated temperature data over time (Turrisi et al., 2021). In behavioral intervention research, perceived weather has been identified as a barrier to physical activity (Salmon et al., 2003). Temperatures also appear to function as an operating condition for physical activity interventions. Prior work supported this proposition at the daily time scale but used average daily temperature readings from a single (fixed) weather station in Chicago (Welch et al., 2018). To accommodate human mobility patterns and weather dynamics from hour to hour, the present study extended that support using momentary GPS coordinates to lookup temperature indices recorded (or forecast) for the users' actual location.

The dose-finding approach described here complements methods like the microrandomized trial which has been used to develop evidence-based decision rules for just-in-time adaptive interventions (Klasnja et al., 2015). For example, the microrandomized trial design was used to develop a decision rule for the HeartSteps intervention (Klasnja et al., 2018) and that approach is currently being extended using reinforcement learning techniques to adapt the decision rule as data accumulates (Liao et al., 2020). System identification techniques used here can also be extended to design effective controllers (decision rules) that maximize the probability of achieving a desired goal while avoiding unsafe or ineffective operating regions.

One of the differentiating features of the system identification approach applied in this study involved its flexibility in accommodating smaller streams of data. Although reinforcement learning algorithms can be applied to adapt individual's intervention in real time, they still face many challenges such as a need for accommodating noisy data, learning quickly, and accommodating model mis-specification (Liao et al., 2020). On the other hand, system identification techniques can operate well in the presence of uncertainty and noisy datasets.

The expected effects reported here may seem modest in relation to normative daily step counts but keep in mind that these estimates are specific to individual digital messages and messaging interventions can send multiple messages each day. Additionally, behavioral interventions for physical activity rarely involve single components and there may be additional effects from and interactions with other components (e.g., behavioral feedback, goal setting, social support; Conroy et al., 2014; Michie et al., 2009). Decisions about whether to include digital messaging components with person-specific decision rules can be informed by factorial experiments to optimize treatment packages for different target populations, goals, and resource constraints (Collins, 2018).

Limitations

One limitation of this approach is that the person-specific models are opaque input-output models that do not reveal the mechanism(s) of behavior change. System identification has been applied to test social-cognitive models on slower (e.g., daily) time scales (Freigoun et al., 2017; Hekler et al., 2013; Phatak et al., 2018; Riley et al., 2016). Few health behavior theories articulate dynamic processes clearly (Riley et al., 2011) but obtaining intensive self-reports of motivational targets following message delivery may be disruptive. It may be possible to code messages within each content library based on their social-cognitive targets to identify which targeted messages affect behavior. Elaborating the number of message categories will reduce the data available to model the effects of each message and the risk of overfitting models will increase when model coefficients are based on smaller datasets. For that reason, caution is warranted in interpreting findings from contexts with fewer observations (e.g., extreme temperatures on weekend days); predicted effects under those conditions will be more uncertain.

Second, these models are based on a limited number of people’s historical responses to messages in a finite range of environmental conditions and locations. More representative samples with respect to people, environmental conditions, and geographic locations may reveal even more heterogeneous responses. If future contexts differ from those tested or assumptions of stationarity are violated, decisions based on these models may not be optimal. Nesselroade and Molennar (2010) “conceive[d] of each person as a system of interacting dynamic processes, the unfolding of which produces an individual life trajectory in a high-dimensional psychological space” (p. 36). Assuming that people (i.e., systems) are constantly developing and adapting to environmental exposures and accumulated experiences (a core assumption of developmental system theory; Ford & Lerner, 1992), periodic model adaptations based on accumulating data may prove valuable in future work because people who learn can benefit from decision rules that learn and adapt with them.

These results provide an empirical strategy for iteratively-refining person-specific models. Such models can inform the design of person-specific decision rules but it is not yet clear whether person-specific decision rules are superior to simpler rules based on random selections or ad hoc decision parameters (with or without contextual information). Comparative effectiveness and cost-benefit studies are needed to answer those questions.

Conclusions

Digital messaging is an established tool for promoting physical activity (Smith et al., 2020). Historically, dosing parameters have been determined by experts’ domain knowledge or user preferences. Efforts to amplify effects using a range of personalization strategies have not been successful (Armanasco et al., 2017). This study provided an approach for person-specific dose-finding with a digital messaging intervention. This approach incorporates contextual data (recent behavior, day-of-week, weather conditions) and historical responses to different treatments (i.e., message types) to inform future decisions about treatment (i.e., whether or not to send a message and which message to send). Dose-finding is an important task for early-phase behavioral intervention development (Czajkowski et al., 2015). The challenge of dose-finding for complex behaviors that are multiply-determined and possibly regulated idiographically is substantial. Similar to the generic model estimated in this study, this study provides a starting point. The next steps in developing this method involve translating the generic model into a warm-start controller and developing methods for periodically updating that decision rule based on incoming data. That work is underway.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1.

Features of step and impulse responses in the distribution of person-specific models and a generic model.

		Person-Specific Models				Generic Model	
		Weekday		Weekend			
Response Feature	Type of messages	M (SD)	Range	M (SD)	Range	Weekday	Weekend
Peak Magnitude							
	Move more	35.40 (17.91)	(8.07, 92.98)	50.94 (22.50)	(14.17, 105.45)	6.1	8.8
	Sit less	33.95 (19.11)	(7.91, 108.3)	48.52 (20.74)	(8.94, 106.42)	7.8	9.05
	Inspirational quotes	49.22 (22.45)	(17.66, 110.59)	65.60 (36.50)	(19.67, 197.33)	9.84	8.67
Peak Delay							
	Move more	28.33 (23.11)	(0, 60)	27.66 (22.82)	(0, 60)	0	15
	Sit less	25 (24.77)	(0, 60)	29.33 (21.91)	(0, 60)	0	60
	Inspirational quotes	26.33 (22.42)	(0, 60)	25.33 (23.89)	(0, 60)	0	30
Steady State							
	Move more	17.26 (93.42)	(−263.45, 239.68)	47.88 (164.97)	(−338.48, 445.79)	7.61	45.83
	Sit less	30.62 (91.29)	(−221.58, 319.36)	54.41 (163.73)	(−287.12, 504.76)	25.18	53.37
	Inspirational quotes	20.85 (115.49)	(−186.37, 267.67)	−11.54 (224.35)	(−467.42, 550.72)	11.11	−18.09
Settling Time							
	Move more	138.33 (44.75)	(75, 300)	167.33 (53.22)	(75, 330)	60	150
	Sit less	140.66 (63.01)	(45, 360)	163.66 (53.01)	(75, 315)	135	165
	Inspirational quotes	126.66 (44.60)	(75, 285)	157.33 (63.93)	(60, 360)	60	195
Rise Time							
	Move more	62 (42.85)	(0, 150)	80.66 (59.16)	(0, 210)	15	120
	Sit less	64 (48.75)	(0, 225)	95 (57.56)	(0, 255)	90	135
	Inspirational quotes	63 (38.85)	(0, 165)	79.33 (52.51)	(0, 195)	15	105
Effective Time							
	Move more	175.66 (238.53)	(15, 600)	154 (228.70)	(15, 600)	30	240
	Sit less	129.66 (202.69)	(15, 600)	225.33 (256.52)	(15, 600)	240	315
	Inspirational quotes	224.66 (263.51)	(15, 600)	231 (266.25)	(15, 600)	45	15