A Dynamical Systems Model for Improving Gestational Weight Gain Behavioral Interventions

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Abstract

Excessive gestational weight gain (GWG) represents a major public health concern. In this paper, we present a dynamical systems model that describes how a behavioral intervention can influence weight gain during pregnancy. The model relies on the integration of a mechanistic energy balance with a dynamical behavioral model. The behavioral model incorporates some well-accepted concepts from psychology: the Theory of Planned Behavior (TPB) and the principle of self-regulation which describes how internal processes within the individual can serve to reinforce the positive outcomes of an intervention. A hypothetical case study is presented to illustrate the basic workings of the model and demonstrate how the proper design of the intervention can counteract natural trends towards declines in healthy eating and reduced physical activity during the course of pregnancy. The model can be used by behavioral scientists to evaluate decision rules for adaptive time-varying behavioral interventions, or as the open-loop model for hybrid model predictive control algorithms acting as decision frameworks for such interventions.

I. INTRODUCTION

High pre-pregnancy body mass index (BMI) and excessive gestational weight gain (GWG) have become increasingly important public health issues. Over 60% of women of

childbearing age in the United States are currently classified as overweight or obese (BMI 25 kg/m^2 and BMI 30 kg/m^2 respectively) [1]. High pre-pregnancy BMI and gaining weight in excess of the 2009 Institute of Medicine (IOM) GWG guidelines contributes to maternal complications (e.g., gestational diabetes, preeclampsia), postpartum weight retention, and subsequent obesity, type 2 diabetes, and cardiovascular disease later in life [2], [3]. Even more importantly, they are independent predictors of infant macrosomia, accelerated weight gain in the first year of life, and childhood obesity [2], [4]. Thus, preventing high GWG during pregnancy can impact the etiology of obesity development for offspring at a critical time in the life cycle.

Interventions aiming to promote GWG within the IOM guidelines [2] appear to reduce the risk of adverse pregnancy outcomes among normal weight women [5], [6], however, these interventions have been less effective among overweight and obese women. Despite focused prevention efforts, nearly 60% of overweight women and 50% of obese women exceed the GWG guidelines [2]. Thus, there is a critical need to develop scalable, effective, and affordable interventions to prevent high GWG, particularly among overweight and obese pregnant women, which also provide continuous objective feedback to participants as indicated in the 2009 IOM report [2]. To meet this need, there has been an increasing interest in the design and implementation of adaptive behavioral interventions using dynamical systems and control engineering methods to increase intervention effectiveness and improve participant response [7], [8]. In this paper we consider the initial problem of modeling the dynamics of such an intervention, with the long-term goal of designing, and ultimately implementing, an optimized behavioral intervention based on modern control engineering concepts, such as hybrid model predictive control [9].

The overall simulation model for GWG developed in this paper can be divided into four main segments (Fig. 1): a two-compartment energy balance (EB) model that predicts changes in body mass as a result of energy intake (EI) and physical activity (PA), two Theory of Planned Behavior (TPB) models that describe how EI and PA, respectively, are affected by behavioral variables, an intervention delivery module that relates the magnitude and duration of intervention components to the inflows of the TPB models, and two self-regulation modules that model how success expectancies during the intervention influence a participant's motivation to achieve a goal. The overall model can play a useful role in the evaluation of decision policies in an adaptive intervention or in the development of advanced control strategies, which constitutes future work for this research.

This paper is organized as follows. Section II presents a modeling overview which includes a brief description of the energy balance (EB) model, the TPB model (and its fluid analogy), the behavioral intervention inputs, and self-regulation effects in the model. Section III discusses the simulation results for a hypothetical case study. Section IV gives a summary of our conclusions and future work.

II. MODELING OVERVIEW

A. Energy Balance Model

In this section, we present the basic dynamics governing energy balance for GWG based on the two-compartment model developed by Thomas *et al.* [10]. The total body mass (BM) corresponds to the sum of two compartments: fat mass (FM) and fat-free mass (FFM).

$$BM(t) = FM(t) + FFM(t) \quad (1)$$

The energy balance model can be expressed in general form based on the first law of thermodynamics as follows,

$$ES(t) = EI(t) - EE(t) \quad (2)$$

$ES(t)$ is the energy stored, $EI(t)$ is the energy intake and $EE(t)$ is the energy expenditure at time t, measured daily.

We expand the ES term into the instantaneous change of the sum of the two compartments (FFM and FM), multiplying by their respective energy densities as follows:

$$ES(t) = 771 \frac{dFFM(t)}{dt} + 9500 \frac{dFM(t)}{dt} \quad (3)$$

$EE(t)$ is a function of $FFM(t)$ based on the BMI of the participant. Table II shows the $EE(t)$ formulas derived from data [11] that are used within the energy balance equation. The change ΔPA on the dimensionless physical activity level (PAL) from baseline is used to express changes in physical activity; its effect on the energy balance model is obtained by multiplying $EE(t)$ by $(1+\Delta PA)$. ΔEI is used to represent daily changes in energy intake during gestation. Our final energy balance model is as follows, with g as nutrient partitioning constant and EI_0 the initial energy intake.

$$771 \frac{dFFM}{dt} + 9500 \frac{dFM}{dt} = (1-g)(EI_0 + \Delta EI(t)) - (1 + \Delta PA(t)) EE(t) \quad (4)$$

B. Dynamic Theory of Planned Behavior (TPB) Model

The TPB [12] is a general social-cognitive theory that can be used to describe the behavioral component of human weight change interventions. Fig. 2 shows the path diagram for TPB which is based on Structural Equation Modeling [13] and depicts the steady-state relationships between variables. η_i represents endogenous variables, ξ_i exogenous variables, β_{ij} and γ_{ij} are regression weights and ζ_i are disturbance variables. In TPB, behavior η_5 is determined by intention η_4 and perceived behavioral control (PBC) η_3. Intention, meanwhile, is influenced by attitude towards the behavior η_1, subjective norms η_2 and PBC η_3. The exogenous inflow variables are expressed as follows,

$$\xi_1 = b_1 \times e_1 \quad \xi_2 = n_1 \times m_1 \quad \xi_3 = c_1 \times p_1$$

b_1 represents the strength of beliefs about the outcome, e_1 the evaluation of the outcome, n_1 the strength of normative beliefs, m_1 the strength of the motivation to comply to the different normative beliefs, c_1 the strength of the control belief and p_1 the perceived power of the control factor. The application of the TPB in control engineering contexts includes the work of Vanderwater and Davison [14].

A dynamic TPB model can be postulated as a fluid analogy [15] consisting of five inventories where each component of the TPB is represent by an inventory as depicted in Fig. 3, with inflows corresponding to the exogenous variables ξ_1, ξ_2, and ξ_3. To generate the dynamical system description, the principle of conservation of mass is applied to each inventory, from which a system of differential equations can be obtained:

$$\tau_1 \frac{d\eta_1}{dt} = \gamma_{11}\xi_1(t-\theta_1) - \eta_1(t) + \zeta_1(t) \quad (5)$$

$$\tau_2 \frac{d\eta_2}{dt} = \gamma_{22}\xi_2(t-\theta_2) - \eta_2(t) + \zeta_2(t) \quad (6)$$

$$\tau_3 \frac{d\eta_3}{dt} = \gamma_{33}\xi_3(t-\theta_3) - \eta_3(t) + \zeta_3(t) \quad (7)$$

$$\tau_4 \frac{d\eta_4}{dt} = \beta_{41}\eta_1(t-\theta_4) + \beta_{42}\eta_2(t-\theta_5) + \beta_{43}\eta_3(t-\theta_6) - \eta_4(t) + \zeta_4(t) \quad (8)$$

$$\tau_5 \frac{d\eta_5}{dt} = \beta_{54}\eta_4(t-\theta_7) + \beta_{53}\eta_3(t-\theta_8) - \eta_5(t) + \zeta_5(t) \quad (9)$$

τ_i are time constants, θ_i time delays, and ζ_i disturbances. In this dynamical representation, the regression weights β_{ij} and γ_{ij} from the structural equation model correspond to gains of the system. Higher-order derivatives with corresponding parameters can be used to enhance the model in (5) – (9) to capture underdamped responses, inverse response, and the like. For reasons of simplicity these will not be considered in this paper, but are discussed in work describing weight change interventions with non-pregnant individuals [15].

C. Intervention Components and Delivery Modeling

A number of diverse behavioral interventions for GWG have been developed, emphasizing healthy eating habits (HE) and/or physical activity (PA) [5], [6], [16]. It has been reported that the most effective interventions combine both elements [16]. In this paper, we consider a hypothetical intervention whose goal is to help pregnant women meet the recommended targets for GWG established in a 2009 IOM report (Table I).

The list of intervention components for this hypothetical intervention is summarized in Table III. Intervention components can be classified according to two types. The first consists of manipulated variables whose magnitude or "dosage" can be changed over time; examples include HE and PA education (I_1 and I_5), HE and PA weekly plans (I_2 and I_6), HE active learning (I_3), goal setting (I_4) and PA sessions (I_7). The second type of intervention component consists of signals that are used by either the closed-loop decision rules or influence the participant's self-regulation (described in more detail in the ensuing subsection). These intervention components include daily weighing ($I_8(y_1)$), dietary records ($I_9(y_2)$), and PA monitoring ($I_{10}(y_3)$). The role these components play as either inputs to the TPB and energy balance models, or as outputs from the TPB and energy balance models but inputs to the self-regulation modules are depicted in Figure 1.

The modeling of the intervention delivery dynamics is considered as follows: we treat each input ($I_1 \ldots I_7$) as contributing to the inflows $\xi_1 \ldots \xi_3$ for each of the two TPB models. We would expect that the effect of the intervention on the beliefs, evaluations, and other variables that comprise the inflows $\xi_1 \ldots \xi_3$ accumulate and hence integration is required. At the intervention delivery level we include the possibility of delayed effects and disturbances that could potentially undermine the intervention delivery. We use Laplace transforms and vector-matrix notation to obtain

$$\xi(\mathbf{s}) = \frac{1}{s}\mathbf{K^I(s)I(s)} + \xi_{\mathbf{b}} + \zeta^{\mathbf{I}}(\mathbf{s}) \quad (10)$$

where $\xi(s)$, $\xi_b(s)$, and $\zeta^I(s)$ are all 6×1 vectors, representing the new inflows, the baseline inflows and disturbances respectively; $\mathbf{I(s)}$ is a 7×1 vector, representing the manipulated intervention inputs, $\mathbf{K^I(s)}$ is a 6×7 matrix for intervention gains and whether its entry is zero is based on how intervention component works on EI or PA TPB models listed in Table III. All are defined below,

$$\xi(\mathbf{s}) = \left[\xi_1^E(s)\, \xi_2^E(s)\, \xi_3^E(s)\, \xi_1^P(s)\, \xi_2^P(s)\, \xi_3^P(s) \right]^T \quad (11)$$

$$k_{ij}^I = k_{ij}e^{-\theta_{ij}^x s}, x = E \text{ (for EI) or } x = P \text{ (for PA)} \quad (12)$$

$$\mathbf{K^I(s)} = \begin{bmatrix} k_{11}^I & k_{12}^I & k_{13}^I & k_{14}^I & 0 & 0 & 0 \\ k_{21}^I & k_{22}^I & k_{23}^I & k_{24}^I & 0 & 0 & 0 \\ k_{31}^I & k_{32}^I & k_{33}^I & k_{34}^I & 0 & 0 & 0 \\ 0 & 0 & 0 & k_{44}^I & k_{45}^I & k_{46}^I & k_{47}^I \\ 0 & 0 & 0 & k_{54}^I & k_{55}^I & k_{56}^I & k_{57}^I \\ 0 & 0 & 0 & k_{64}^I & k_{65}^I & k_{66}^I & k_{67}^I \end{bmatrix} \quad (13)$$

$$\mathbf{I(s)} = \left[\begin{array}{ccccc} I_1(s) & I_2(s) & \cdots & I_6(s) & I_7(s) \end{array} \right]^T \quad (14)$$

$$\xi_{\mathbf{b}} = \left[\begin{array}{cccccc} \xi_{1b}^E & \xi_{2b}^E & \xi_{3b}^E & \xi_{1b}^P & \xi_{2b}^P & \xi_{3b}^P \end{array} \right]^T \quad (15)$$

$$\zeta^{\mathbf{I}}(s) = \left[\zeta_1^E(s)\, \zeta_2^E(s)\, \zeta_3^E(s)\, \zeta_1^P(s)\, \zeta_2^P(s)\, \zeta_3^P(s) \right]^T \quad (16)$$

k_{ij} in (13) correspond to intervention gains that will be a function of personal characteristics or baseline conditions such as age, social economic status, and social support; Since these interventions are used to improve the attitude towards the behavior in TPB, all the gains are positive-valued.

The PA sessions (PAS) I_7 represent a special intervention component in that these will directly impact PA in the energy balance model. Accounting for this requires including an extra gain (K_{I7}) associated with I_7 in the ΔPA expression of the energy balance model (4).

D. Self-Regulation

Self-regulation theory in psychology has been largely influenced by the work of Carver and Scheier [17] who proposed that human behavior is goal-directed and regulated by feedback control processes (Fig. 4). Self-regulation reflects the capacity of individuals to alter the behavior, enabling people to adjust actions to a broad range of social and situational demands. Individuals tend to engage in activities they believe they can succeed in; this confidence in performance success influences the inflow of PBC, which reflects the individual's perception of her ability to perform a given behavior.

In this paper, self-regulation is implemented as a controller that adjusts the inflows to perceived behavioral control (PBC) in the TPB models based on how body mass compares

with IOM guidelines. The self-regulatory controller is parametrized as derivative-only. The reason for this choice is that when a participant improves on her GWG, the presence of improvement will nonetheless strengthen her confidence in aiming to maintain her GWG within target goals, which in turn, promotes PBC and hence behavior in both the EI and PA TPB models. However, if the participant tries her best to only find that she cannot control her GWG as she desires, her control belief will go down, with PBC and behavior correspondingly reduced. The expressions for the self-regulation control system used in this work are:

$$e(t) = BM(t) - IOM(t) \quad (17)$$

$$\Delta e(t) = \frac{e(t) - e(t-T)}{T} \quad (18)$$

$$\Delta \xi_3(t) = K_e \Delta e(t) \quad (19)$$

$$\xi_3(t) = \xi_{3b}(t) - \Delta \xi_3(t) \quad (20)$$

where $e(t)$ represents the discrepancy between IOM guidelines and the measured body mass; T is the sampling time at which the participant regularly checks her weight; $\Delta e(t)$ expresses the rate of improvement; K_e is the controller gain which varies at different periods in time and will depend on personal characteristics and baseline parameters; $\xi_{3b}(t)$ is the PBC inflow independent of self-regulatory control action.

E. Decision Rules

In an adaptive, time-varying intervention, the frequency or intensity of intervention dosages will change over time, based on the result of important outcomes of the intervention (also known as tailoring variables [7]). Decision rules operationalize these changes, which can correspond to eliminating or adding some intervention components based on participant response during the intervention, or altering the dosage of existing components (for example, increasing the number of physical activity sessions). Adaptive, time-varying interventions constitute feedback control systems [8] and are amenable to hybrid model predictive control approaches [9]. Developing optimal decision rules based on hybrid MPC constitutes a future activity in this work.

III. SIMULATION RESULTS AND DISCUSSION

In this section, we consider two hypothetical simulation scenarios that rely on our proposed dynamical systems model. The simulations consider a 32-year old pregnant woman with pre-gravid parameters of height (=1.6m) and weight (=70 kg), which places the participant (BMI=27.34) in the overweight BMI category. For the sake of simplicity we will only focus on the effects that intervention components and self-regulation play on the PBC inflow in the TPB models. The intervention gains of the PBC inflow in EI-TPB are set to 0.0012 for all relevant intervention components ($K_{31}^I, \ldots, K_{34}^I = 0.0012$), while the ones in PA-TPB model are similarly fixed to 0.0024 ($K_{64}^I, \ldots, K_{67}^I = 0.0024$). No time delay or disturbances are assumed in the intervention delivery dynamics. Dosages for all intervention components are fixed according to the frequency stated in Table III. The gain for PAS (K_{I7}) is set as 0.005×initial Physical Activity Level.

The decision on whether or not to start the intervention is made based on the discrepancy between a threshold value and the participant's weight. The threshold value in this paper is set as 20% above the upper bound of the GWG target set by the IOM. The intervention starts if the participant's weight exceeds a threshold, and stops once the participant's weight enters within the threshold.

External deterministic disturbances considered in this simulation apply to the behavior disturbance variable ζ_5. This signal is selected to mimic a natural trend within the participant for increasing EI and reducing PA during the latter stages of pregnancy. These disturbances will have little influence at the beginning, but will play a significant role later. The disturbances are represented in the simulation as sine wave functions starting at day 14 and parametrized in (21) below, with A as the amplitude of the sine wave, ω the frequency. As output disturbances, these directly lower the participant's behavior (Fig. 5):

$$\zeta_5(t) = A\sin\left[\omega(t-14)+\frac{\pi}{2}\right]-A \quad (21)$$

Table IV summarizes the model parameters in the simulation studies, including the behavioral parameters, time constants τ_i, time delays θ_i, gains assumed for the participant, and the deterministic disturbance parameters respectively. All these values are hypothetical but have been selected such that the simulated responses mimic those of an actual participant.

We assume that there is no self-regulation effect before the participant is aware of her pregnancy (prior to day 14). When her weight exceeds the threshold, K_e should have a small magnitude. On the contrary, when the participant's gestational weight is below the threshold, K_e should correspondingly increase as a result of the improvement that she has accomplished. The sign of K_e depends on the sign and magnitude of $\Delta e(t)$. A positive $\Delta e(t)$ indicates that the participant is not making as great progress as she did the day before, while a negative $\Delta e(t)$ indicates improvement. Therefore, K_e should be positive for (20) to be computed properly. Table V lists the values for K_e in the simulations.

Fig. 6 shows the participant's response for the EI-TPB and PA-TPB models, as well as the changes in maternal body mass and the energy balance variables.

The scenario without intervention shows that behavioral change is accomplished by the self-regulation effect of PBC in the TPB models. The simulation results indicate that the PBC inflow in the TPB models will stay constant until day 14. Following the initial ramp increase in EI, the PBC inflow first ramps up (due to no weight increase at the very beginning) and soon diminishes, indicating that the participant is not confident of controlling her GWG. However, PBC inflow improves with the passage of time as the participant checks her weight daily, compares her weight with the target data, and realizes that the situation is not as bad as she expects. Because of self-regulation, the PBC and intention inventories η_3 and η_4 increase gradually. However, the behavior in the PA-TPB model does not improve overall as a consequence of the disturbance ζ_5. In this scenario, we can see that the PBC inflow eventually turns back to initial levels, with gestational weight always remaining outside of IOM guidelines, up until the time of delivery. This shows that self-regulation has a limited effect on GWG control.

The simulation for the intervention scenario in Fig. 6 shows that the intervention starts at day 105 and ends at day 216. The whole process can be divided into four stages. The first stage occurs during the first 14 days with constant PBC inflows and no significant weight changes. The second stage starts from day 15 to the day before the intervention. The

participant increases her EI due to the pregnancy, which results in decreases in PBC, intention and behavior. When the participant's weight exceeds the threshold value, the intervention starts; this is the third stage. In this stage, the PBC inflow increases almost linearly as a result of the integrator in the intervention delivery dynamics. When compared with the PBC curve for the intervention-only case in the TPB models, we can see that at early intervention, the self-regulation effect tries to counteract the effect of the intervention by lowering the expected increase in the PBC inflow, which means the participant does not have much faith believing that she can succeed in controlling her weight gain. However, as the intervention proceeds, the participant's confidence is greatly enhanced as a result of the improvement contributed by the intervention. Consequently, in the latter part of the third stage, self-regulation works together with the intervention to enable better gestational weight control despite the existence of external disturbances. The fourth stage occurs once the intervention stops. In this stage, the participant may feel initially aimless with the termination of intervention, therefore, PBC inflow reduces a little, but turning back to increasing very soon. In this scenario, we can see that with the help of the intervention and self-regulation, it is possible for a woman to control her GWG, even in the presence of disturbances.

IV. CONCLUSIONS AND FUTURE WORK

A comprehensive dynamical model for a behavioral intervention to control GWG has been proposed. In two case study results, we showed how self-regulation helps adjust perceived behavioral control (PBC), which consequently changes the participant's intention and ultimately behavior with respect to HE and PA during pregnancy. When the intervention components are introduced in the model, their effect is at first offset by self-regulation; however, as intervention outcomes improve, these two effects work with each other to greatly increase the PBC inflow in the TPB models. Consequently, the resulting behavioral improvements counter the effect of natural disturbances that work to worsen behavior during the latter stages of pregnancy.

We are currently using the model to evaluate decision rules that will enable time-varying, adaptive behavioral interventions [7], [8] to manage GWG, particularly for the case of overweight and obese women; these will ultimately lead to hybrid model predictive control algorithms as decision policies [9]. Well-designed clinical trials will be required in order to accomplish the system identification tasks that will validate the model and enable the real-life implementation of decision rules and hybrid MPC for this problem.

Acknowledgments

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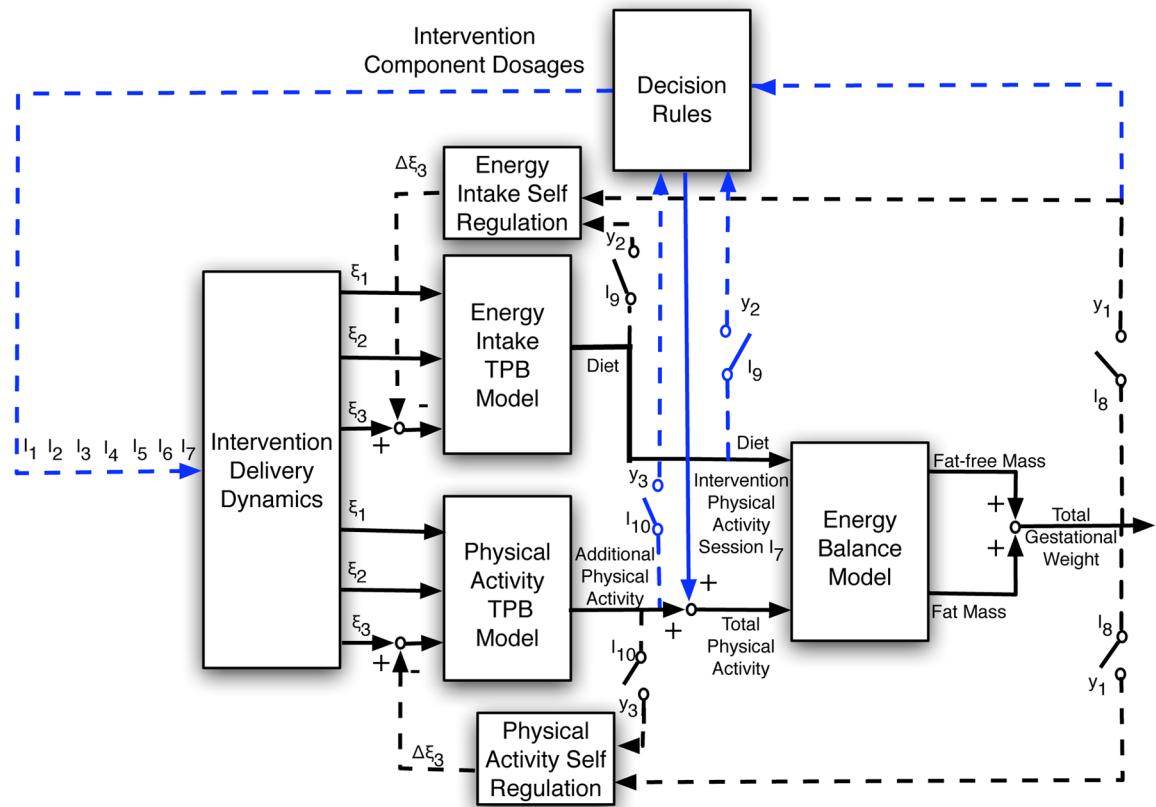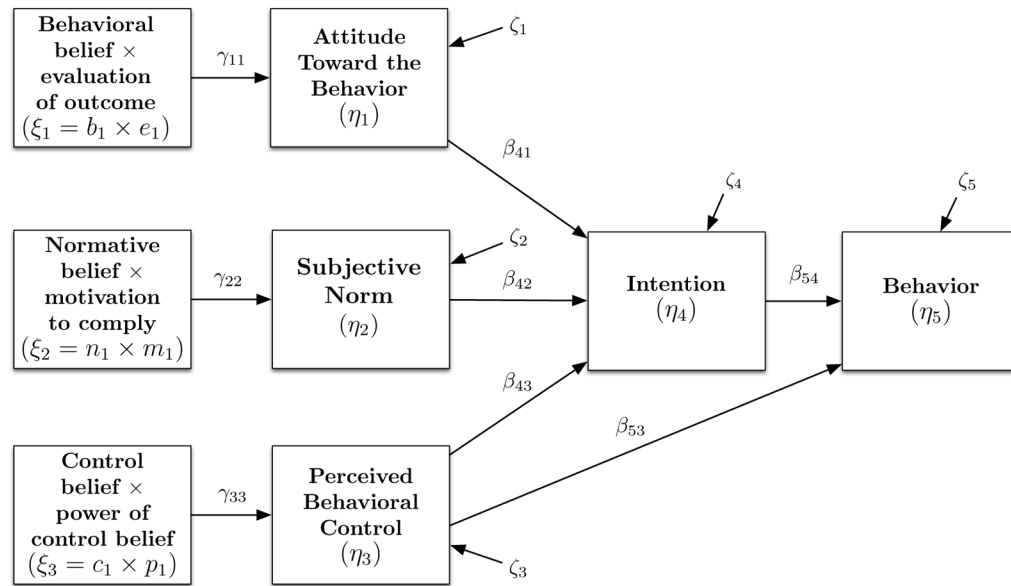17. Carver, CS.; Scheier, MF. On the Self-Regulation of Behavior. Cambridge University Press; 1998.

Fig. 1.
Overall schematic representation for an adaptive gestational weight gain (GWG) intervention.

Fig. 2.
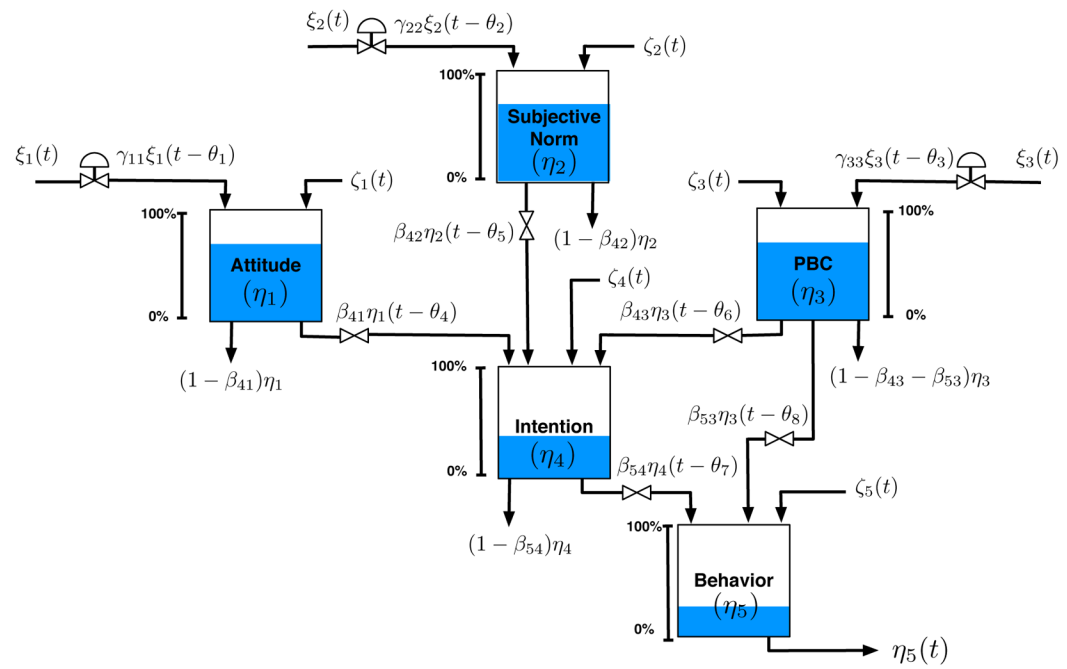Path diagram for the TPB, obtained from Structural Equation Modeling [13].
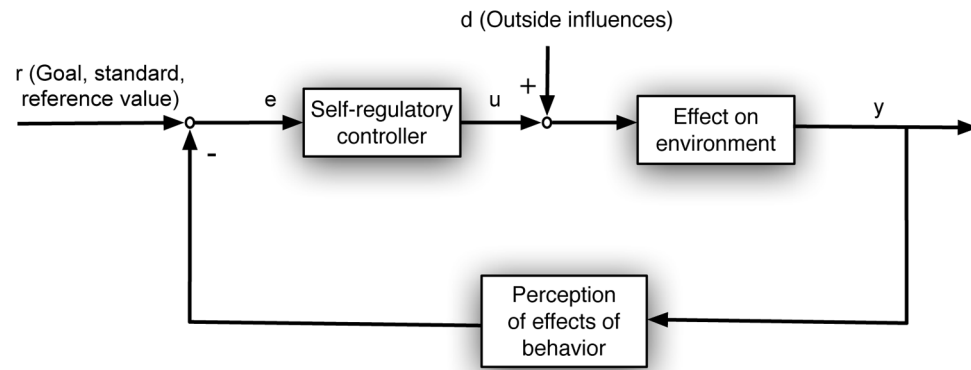
Fig. 3.
Fluid Analogy for the TPB.

Fig. 4.
Behavior and perception as elements of a feedback loop guiding human action per the self-regulation theory of Carver and Scheier [17].
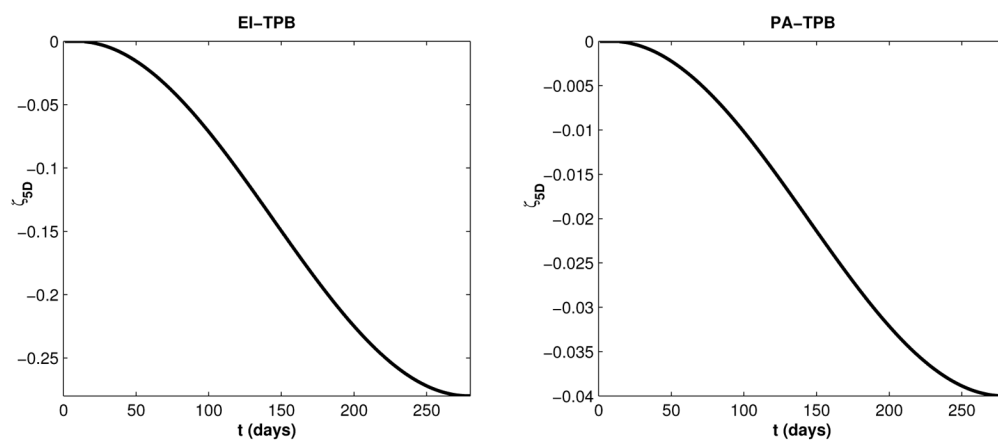
Fig. 5.
Deterministic disturbance signals for behavior inflow ζ_5 in the EI-TPB (left) and PA-TPB (right) models.
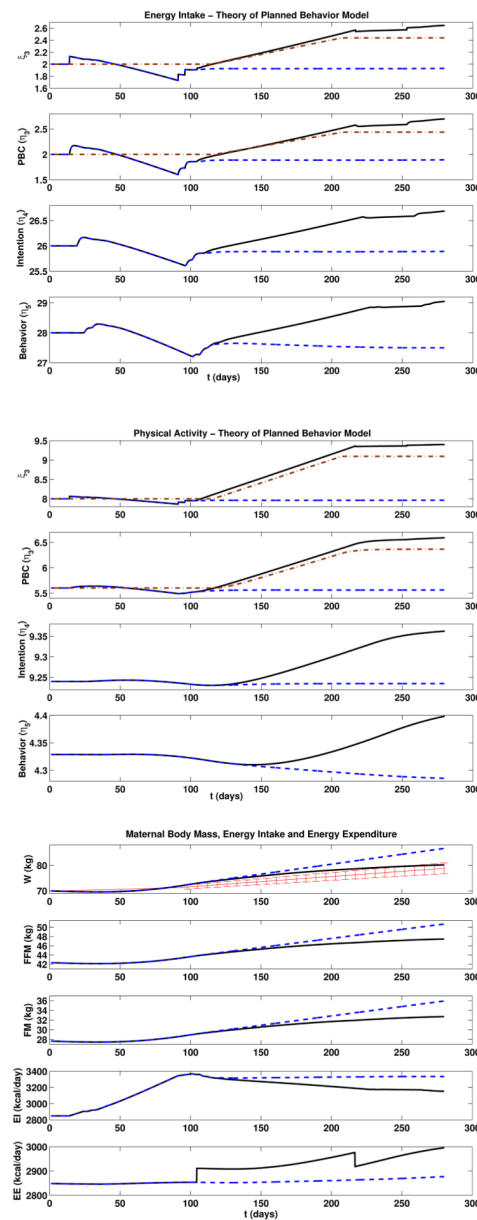
Fig. 6.
Simulation responses for the energy intake behavior (EI-TPB) and physical activity behavior (PA-TPB) models (top two) and maternal energy balance (bottom). Red lines represent the 2009 IOM guidelines applied on a daily basis; the blue dashed line represent the case with no intervention (self-regulation only) while the black solid line represents the case with the intervention. The brown dashdot line in the TPB model variables (top two) shows the simulation responses in these variables for no self-regulation.

TABLE I

Target gestational weight gain (GWG) recommended by the 2009 Institute of Medicine guidelines [2].

Classification	Pre-gravid BMI (kg/m²)	Target GWG (kg) Trimester	
		1	**2 – 3**
Underweight	<20	0.5 – 2.0	11.4 – 15.8
Normal	20 – 25	0.5 – 2.0	9.1 – 13.0
Overweight	25 – 30	0.5 – 2.0	6.0 – 8.6
Obese	>30	0.5 – 2.0	4.4 – 7.0

TABLE II

Expressions for total energy expenditure as a function of fat-free mass (FFM) per BMI category, from [10].

BMI Category	Energy Expenditure (EE(t)(kcal/d))
Low BMI	12.3FFM+1822
Normal BMI	33.0FFM+1008.7
High BMI	10.5FFM+2403.8

TABLE III

Intervention components for hypothetical GWG intervention. EI corresponds to "Energy Intake" while PA corresponds to "Physical Activity". TPB is the Theory of Planned Behavior.

	Description	Influence	Frequency
I_1	Healthy Eating Education	EI-TPB	weekly
I_2	Healthy Eating Weekly Plan	EI-TPB	weekly
I_3	Healthy Eating Active Learnings	EI-TPB	weekly
I_4	Goal Setting	EI-TPB & PA-TPB	weekly
I_5	Physical Activity Education	PA-TPB	weekly
I_6	Physical Activity Weekly Plan	PA-TPB	weekly
I_7	Physical Activity Sessions	PA-TPB & Energy Balance	bi-weekly
$I_8(y_1)$	Daily Weight Scale	PA & EI self-regulation	daily
$I_9(y_2)$	Dietary Record	EI self-regulation	daily
$I_{10}(y_3)$	PA monitor output	PA self-regulation	daily

TABLE IV

Model parameters for the simulation studies. Time constants (τ_i) are in units of days.

Parameter	EI-TPB	PA-TPB	Parameter	EI-TPB	PA-TPB
b_1	3	1	e_1	6	4
n_1	2	7	m_1	3	8
p_1	1	4	c_1	2	2
τ_1	1	30	γ_{11}	1	0.7
τ_2	1	30	γ_{22}	1	0.5
τ_3	1	10	γ_{33}	1	0.7
τ_4	1	20	β_{41}	1	0.34
τ_5	1	30	β_{42}	1	0.27
$\theta_1 \cdots \theta_3$	0	0	β_{43}	1	0.13
$\theta_4 \cdots \theta_6$	5	10	β_{53}	1	0.08
θ_7, θ_8	10	20	β_{54}	1	0.42
A	0.14	0.02	ω	$\frac{\pi}{270}$	$\frac{\pi}{270}$

TABLE V

Tabulation for self-regulatory controller gains K_e applied in the simulations.

If-Else Condition	EI-TPB	PA-TPB
Day 14	0	0
Day >14 and BM >threshold value	2	1
Day >14 and BM threshold value	4	2