Using Sensor Data and Model Inference to Tailor Home Health Interventions for the Elderly

Across the world, many societies are experiencing a health-care crisis as their aging demographic grows and overall health-care expenditures escalate. The societal challenge to providing quality care for the elderly needs to be addressed with changes in practice on several fronts, including reimbursement policies, clinical workflow, and a move toward more proactive and out-of-hospital continuous care. Technology and model-based approaches for home monitoring and home-based health interventions can play a large role in this transformation.

There are several important approaches to using computational modeling to augment the effectiveness of technology-based health interventions in the home (see [S1] and [S2]). First, we need computational models to make inferences about behaviors and health states based on streaming sensor data from the home and environment. This is a new area of research where behavioral markers of health states based on unobtrusive sensor data provide clinically useful metrics for the early detection of conditions and for monitoring that is useful for providing input and evaluation of the effectiveness of ongoing health interventions.

Second, it is important to use sensor data to monitor adherence to action plan activities associated with health interventions. These data inform model estimates of an individual's readiness to change, motivations, and barriers. Finally, computational models are necessary in taking the estimates of health states, motivations, barriers, readiness to change, and preferences to inform a dynamic user model of an individual. The computational inferences from this user model can then be used to tailor just-in-time messages for encouragement and feedback to better enable a person's ability to change.

An example of a system that uses unobtrusive sensor data along with computational models to infer health states and features of behavior change to tailor messaging in health interventions is shown in Figure S1. This diagram represents the information flow in the Health Coaching Platform used for interventions with seniors in the Oregon Center for Aging and Technology's (ORCATECH) Living Lab. The participants using this system are typically around 85 years of age with multiple chronic conditions. They live independently in their homes and have consented to try a variety of new technologies. Each home has motion sensors for inferring activities of daily living, walking speed, and sleep quality; contact switches (e.g., for the exterior door used to infer time out of the home or apartment); and all participants have computers that they use to play our adaptive cognitive computer games, specifically designed to monitor metrics of working memory, executive function, divided attention, and verbal fluency.

The monitoring of computer interactions also includes typing speed and linguistic complexity measures from written materials. In addition, some participants have Bluetooth-enabled medication dispensers for intelligent medication reminding, phone monitors, and a Kinect camera for our interactive video exercise intervention. Various

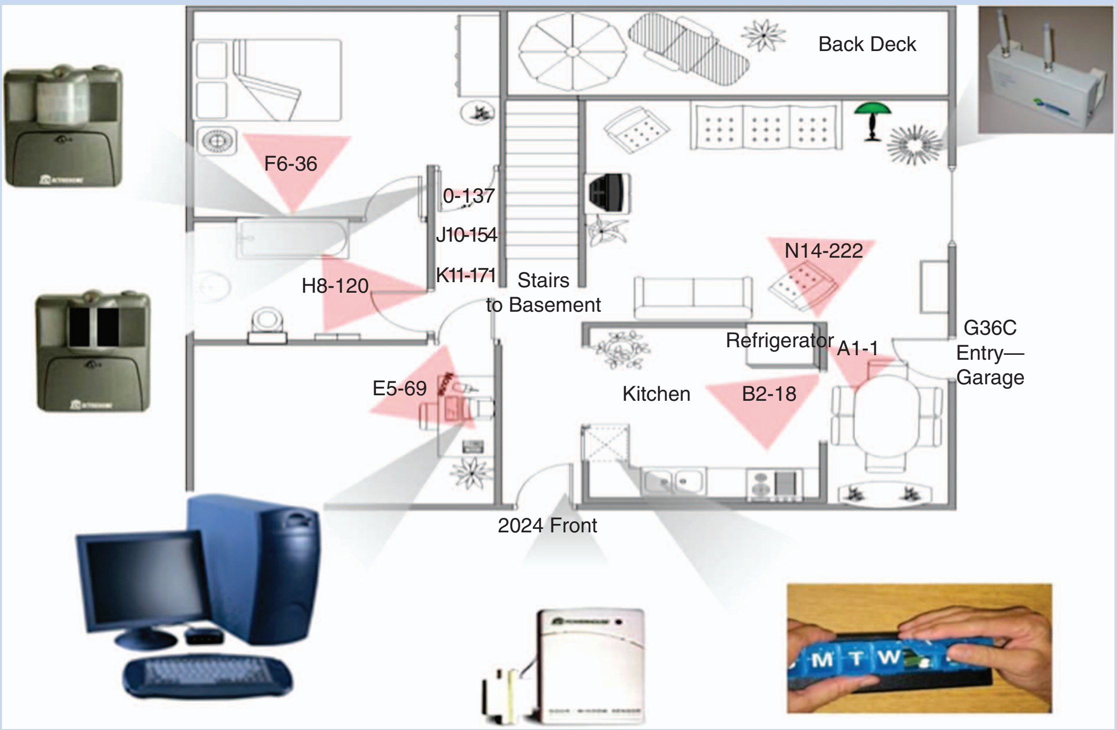

FIGURE S1 A variety of sensors used in the ORCATECH participants' homes. These include passive IR motion sensors for activity monitoring, reduced field-of-view motion sensors for measuring walking speed, computers with software for measuring cognitive function and motor speed, door switches, phone sensors, and Bluetooth-enabled medication monitoring [S2].

computational modeling techniques are used in first describing robust behavior inference metrics such as walking speed, socialization behaviors, or a description of sleep. These estimates require a careful understanding of optimal sampling methods, a model and representation of noise versus the inherent variability in behaviors, and a careful model that takes indirect data from a variety of inputs to infer an individual's behavior in real time.

The classified and quantified behavior measures can then inform models of health states. For example, repeated measures of walking speeds can serve as an early indicator of cognitive decline. Similarly, typing speed, the linguistic complexity of typed text, and cognitive measures derived from computer game interactions also inform estimates of cognitive health. Our measures of balance, flexibility, and strength derived from the skeletal representation from the Kinect camera during use of the interactive physical exercise module are an example of using computational modeling to infer an individual's physical health state.

Figure S2 describes how the home-based unobtrusive sensor technology is used as input to computational modeling components of the system to derive measures of behaviors and health states, shown in the "Inference" box. These estimates, along with assessments of preferences, motivations, barriers, and readiness to change, are then used as part of a dynamic user model. The diagram shows information flow from a message database and the dynamic user model to automatically create tailored messages for the user. Our semiautomated messages contain the following:

- *greeting*: a randomly selected greeting phrase using the participant's preferred name
- *review of the past week's activities*: based on comparing action plan activities with sensor data monitoring, e.g., "You came close to completing your goal of three chair exercise sessions this week and did a great job in achieving your memory game goals"
- *plan for next week*: e.g., progress to the next phase of the physical exercise program, with the content automatically tailored based on previous performance and estimated readiness to change
- *complementary closure*: randomly selected closure using the health coach's name.

The knowledge representation and computational technique for the tailored message generation is based on active methods, where active components in the dynamic user model database trigger the

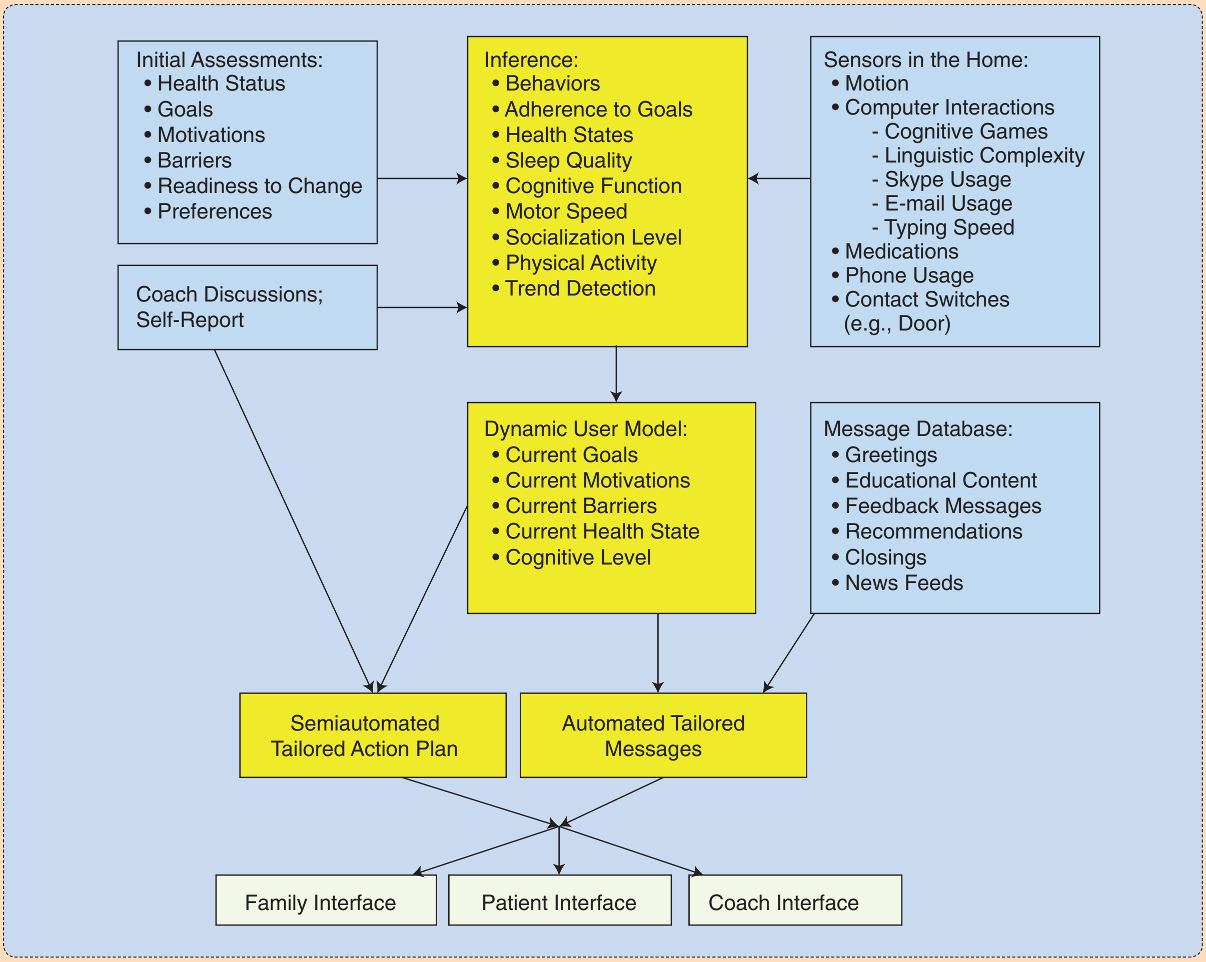

FIGURE S2 Information flow diagram for the ORCATECH Health Coaching Platform, highlighting the components using computational modeling algorithms to tailor a health intervention.

concatenation of a sequence of message phrases from the message database. This modeling approach serves as a framework for tailoring health interventions.

Thus far, 33 elderly participants (average age 80.3 ± 9.4 years) have participated in the health coaching study and have tested the feasibility of modules on cognitive training, sleep management, socialization, and physical exercise. For each of these modules, we first use an in-home visit or Skype conferencing to assess current activity levels, health behavior goal selection, readiness to change, motivations, and barriers (when appropriate). For example, with our sleep intervention, we assess sleep hygiene behaviors anxiety, and circadian rhythm patterns before recommending changes to the environment or relaxation exercises. A tailored action plan is created and updated each week.

Although we make use of a human health coach for face-to-face training and assessments, the computational modeling and analysis described earlier offers a mechanism for facilitating this health coach in keeping the intervention personal and tailored to each individual's needs and preferences while enabling the coach to manage a large group of clients simultaneously. This approach of using computational analysis for inferring behaviors and health states and incorporating models of health behavior change provides a method for improving the effectiveness of health interventions through tailoring and for improving the scalability through automated message generation.

References

[S1] H. B. Jimison and M. Pavel, "Integrating computer-based health coaching into elder home care," in *Proc. 2007 Int. Conf. Technology and Aging (FICCDAT)*, 2008.

[S2] M. Pavel, H. B. Jimison, H. D. Wactlar, T. L. Hayes, W. Barkis, J. Skapik, and J. Kaye, "The role of technology and engineering models in transforming healthcare," *IEEE Rev. Biomed. Eng.* vol. 6, pp. 156–177, 2013.

[S3] J. A. Kaye, S. A. Maxwell, N. Mattek, T. L. Hayes, H. Dodge, M. Pavel, H. Jimison, K. Wild, L. Boise, and T. Zitzelberger, "Intelligent systems for assessing aging changes: Home-based, unobtrusive and continuous assessment of aging," *J. Gerontol.: Psychol. Sci.*, vol. 66B (suppl 1), pp. i180–i190, 2011.

[S4] H. B. Jimison, M. Pavel, J. McKanna, and J. Pavel, "Unobtrusive monitoring of computer interactions to detect cognitive status in elders," *IEEE Trans. Inform. Technol. Biomed.*, vol. 8, no. 3, pp. 248–252, Sept. 2004.

[S5] H. B. Jimison, M. Pavel, P. Bissell, and J. McKanna, "A framework for cognitive monitoring using computer game interactions," in *Medinfo 2007: Proceedings of the 12th World Congress on Health (Medical) Informatics; Building Sustainable Health Systems*, K. A. Kuhn, J. R. Warren, and T. Y. Leong, Eds. Amsterdam, The Netherlands: IOS Press, 2007.

[S6] H. B. Jimison, J. McKanna, K. Ambert, S. Hagler, W. J. Hatt, and M. Pavel, "Models of cognitive performance based on home monitoring data," in *Proc. IEEE Engineering in Medicine and Biology Conf.*, Buenos Aires, Argentina, Sept. 2010.

Dynamical Systems Modeling of a Gestational Weight Gain Intervention

Dynamical systems modeling has the potential to improve behavioral theories and, by extension, improve health interventions. However, there is still much debate among behavioral scientists regarding the best theoretical models of behaviors, and the best methods for studying and developing behavioral theories. One illustration of how dynamical systems, concepts, and behavioral theories can inform the modeling of behavior change is a model of an intervention to prevent excessive weight gain during pregnancy. This is part of the activities of a recently funded National Institutes of Health grant between Penn State and Arizona State (Grant R01HL119245: "Control systems engineering for optimizing a prenatal weight intervention," Downs, PI; Rivera, consortium PI).

High prepregnancy body mass index (BMI) and excessive gestational weight gain (GWG) are serious health concerns. Research shows that excessive weight gain during pregnancy is often associated with many adverse maternal and neonatal outcomes, including gestational diabetes, pregnancy-related hypertension, complications through labor and delivery, infant macrosomia, and childhood obesity. Pregnancy thus represents an opportune moment in a woman's life to promote healthy lifestyle behaviors and learn effective techniques for proper weight management.

A dynamical model for a gestational weight intervention is developed through the integration of a mechanistic energy balance model for gestational weight gain and a fluid analogy of the theory of planned behavior (TPB), augmented with self-regulation. TPB is a broad-based psychological theory that can be understood conceptually through the path diagram shown in Figure S3(a) [S7].

While there are many different and competing theoretical models about behavior and behavioral change, a path diagram such as the one describing the TPB provides a solid starting framework for expressing behavioral change as a dynamical system represented via a fluid analogy. In TPB, behavior (η_5) is determined by intention (η_4) and perceived behavioral control (PBC; η_3). Intention, meanwhile, is influenced by attitude toward the behavior (η_1), subjective norm (η_2), and PBC (η_3). Navarro et al. [S8] show that the path diagram associated with TPB represents a steady-state association between these variables. Each block in the TPB path diagram can be viewed as an inventory, as depicted in Figure S3(b), with inflows corresponding to exogenous variables reflecting the strength of beliefs (e.g., ξ_1, ξ_2, and ξ_3) or (for intention and behavior) the outflows from other inventories in the network. The levels of the various inventories accumulate or deplete over time based on the magnitude and changes occurring in the exogenous variables as well as the corresponding changes in the outflows of the other interconnected tanks.

To generate the dynamical system equations, the concept of conservation of mass is applied to each inventory, from which a system of differential equations is obtained. An illustration for the equation describing intention (η_4) is

$$\tau_4 \frac{d\eta_4}{dt} = \beta_{41}\eta_1(t-\theta_4) + \beta_{42}\eta_2(t-\theta_5) + \beta_{43}\eta_3(t-\theta_6) - \eta_4(t) + \zeta_4(t). \qquad \text{(S1)}$$

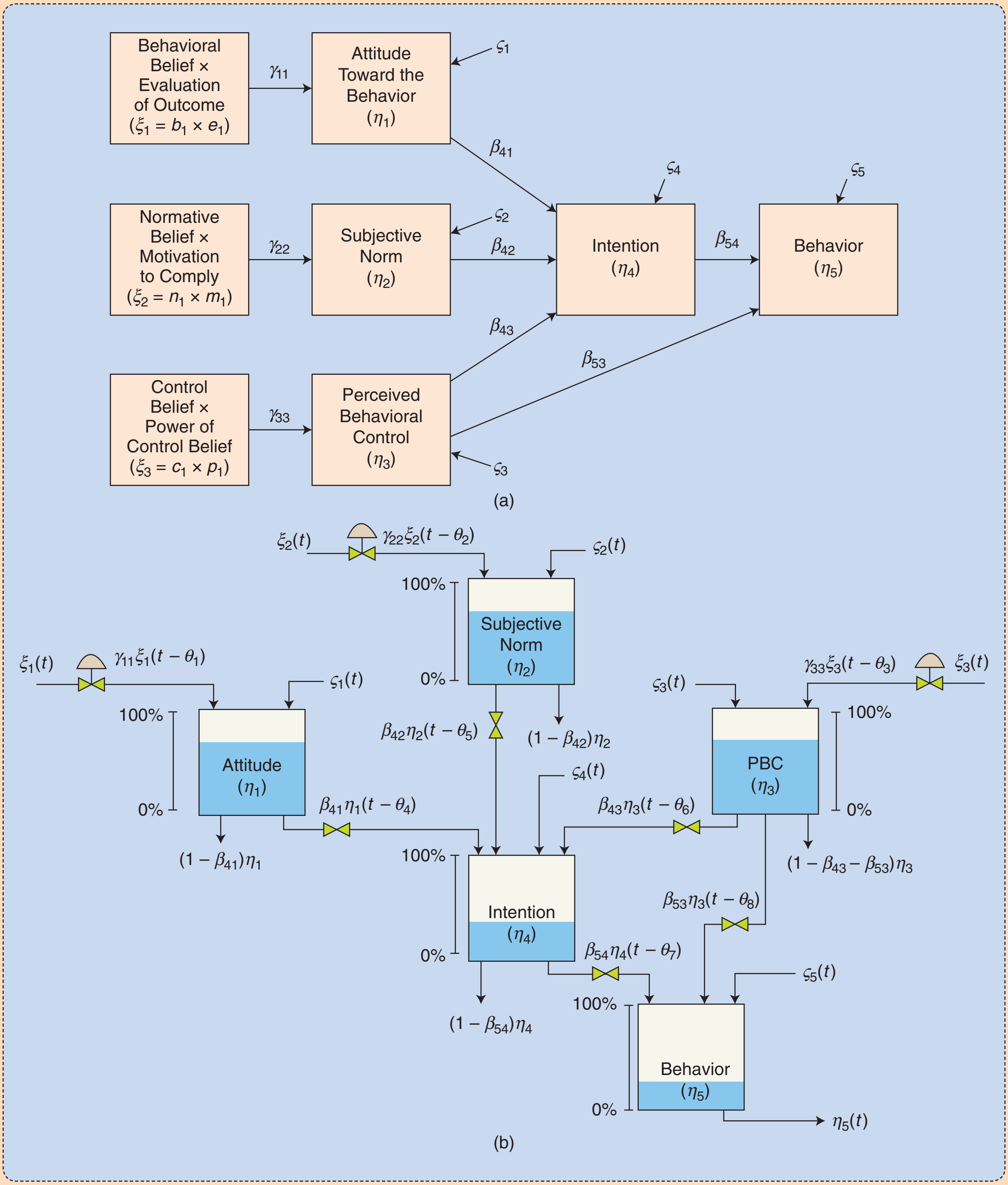

FIGURE S3 (a) A path diagram representing the TPB and (b) a corresponding fluid analogy.

In (S1), the parameters β_{ij} and γ_{ij} represent gains of the system, while variables τ_i and θ_i are time constants and delays, respectively, which dictate the speed of response of the system. ζ_i corresponds to disturbances.

Self-regulation, as depicted in Figure S4, is an important aspect of behavior change that forms part of this model. The self-regulation theory in psychology has been largely influenced by the work of Carver and Scheier [S9] who proposed that human behavior is goal directed and regulated by feedback control processes. Self-regulation reflects the capacity of individuals to alter their behavior, enabling individuals to adjust their actions to a broad range of social and situational demands. Repeated measurement of behavioral outcomes provides a major stimulus to self-regulation.

The collective integration of self-regulation, the TPB, and energy balance in the form of a fluid analogy is depicted in Figure S5 for the energy intake portion of the gestational weight gain intervention. The energy balance model can predict changes in fat mass and fat-free mass as functions of energy intake and characteristics of the mother. Daily weight measurement and dietary records of energy intake generate the signals that drive two self-regulation loops that influence perceived behavioral control along with other components of the behavioral intervention. Intervention components I_1 through I_n represent structured intervention programs such as healthy eating education, active learning, and goal setting, which, through the TPB model, ultimately influence healthy eating behavior and, consequently, meeting gestational weight gain targets.

The usefulness of a dynamic model for a behavioral intervention comes in many forms, from simulation, evaluation of decision policies, and, most importantly, the opportunity to optimize an intervention through an adaptive, just-in-time approach. Adaptive just-in-time interventions represent feedback or combined feedback–feedforward control systems that make decisions on the magnitude and sequencing of intervention components by relying on assessments of tailoring variables that

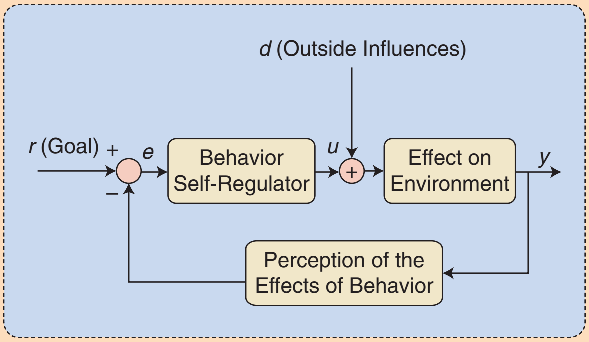

FIGURE S4 Behavior and perception as elements of a feedback loop guiding human action per the self-regulation theory of Carver and Scheier [S9].

reflect outcomes, adherence to treatment, or other important measures of participant response during the course of an intervention. Decision policies for this class of interventions can range from simple "IF-THEN" decision rules [S10] to model-based

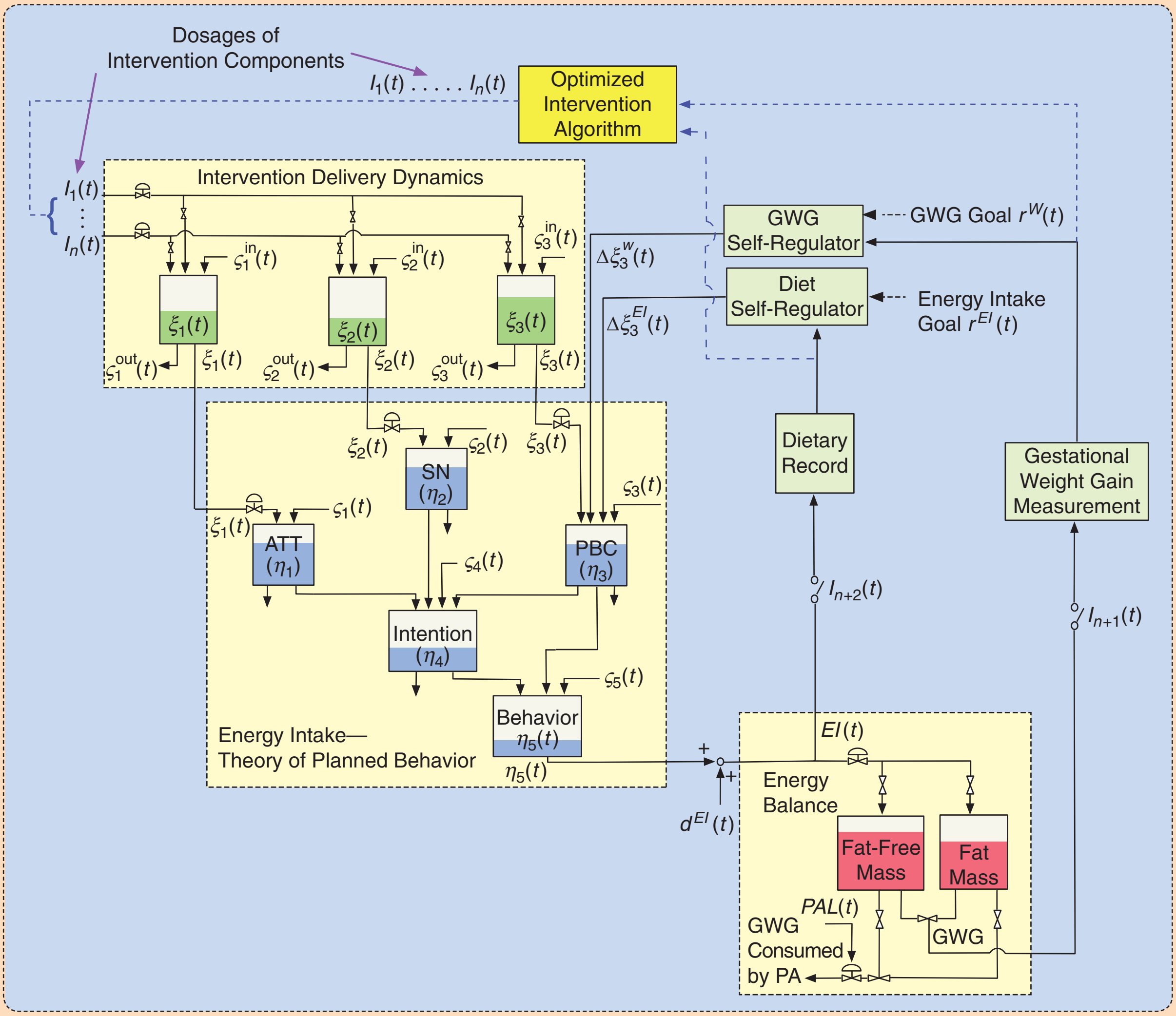

FIGURE S5 A fluid analogy for the energy intake portion of a comprehensive dynamical systems model for an optimized gestational weight gain intervention.

control-theoretic formulations that fully incorporate the dynamical behavior model, such as model predictive control (MPC) [S11]. Since adaptive interventions mirror clinical decision-making, these individualized, tailored forms of treatment delivery can serve as helpful aids to clinicians by improving effectiveness over a larger participant population, lowering costs, and overall resulting in much greater intervention potency.

Our work to date [S12], [S13] has shown proof of concept for the use of dynamical modeling in a gestational weight gain intervention and the benefits that enhancing behavioral theory with a systems perspective can have in providing useful predictive models of behavior. Behavioral theories and energy balance provide an initial structure for the dynamical model; however, data-driven tasks involving experimental design, parameter estimation, and model validation need to be accomplished to reach at a final model. These are problems that fall within the realm of semiphysical system identification [S14]. The increasing availability of intensive longitudinal data from repeated measurement and assessment of behavioral variables enhances the feasibility of obtaining these kinds of dynamical system behavioral change models.

References

[S7] I. Ajzen, *Attitude, Personality, and Behavior.* Milton Keynes, U.K.: Open University Press, 1998.

[S8] J. E. Navarro-Barrientos, D. E. Rivera, and L. M. Collins, "A dynamical model for describing behavioral interventions for weight loss and body composition change," *Math. Comput. Model. Dynam. Syst.*, vol. 17, no. 2, pp. 183–203, 2011.

[S9] C. S. Carver and M. F. Scheier, *On the Self-Regulation of Behavior.* Cambridge, U.K.: Cambridge Univ. Press, 1998.

[S10] D. E. Rivera, M. D. Pew, and L. M. Collins, "Using engineering control principles to inform the design of adaptive interventions: A conceptual introduction," *Drug Alcohol Depend.*, vol. 88, no. 2, pp. S31–S40, 2007.

[S11] N. N. Nandola and D. E. Rivera, "An improved formulation of hybrid model predictive control with application to production-inventory systems," *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 1, pp. 121–135, 2013.

[S12] Y. Dong, D. E. Rivera, D. M. Thomas, J. E Navarro-Barrientos, D. S. Downs, J. S. Savage, and L. M. Collins, "A dynamical systems model for improving gestational weight gain behavioral interventions," in *Proc. 2012 American Control Conf.*, Montreal, Canada, 2012, pp. 4059–4064.

[S13] Y. Dong, D. E. Rivera, D. S. Downs, J. S. Savage, D. M. Thomas, and L. M. Collins, "Hybrid model predictive control for optimizing gestational weight gain behavioral interventions," in *Proc. 2013 American Control Conf.*, Washington DC, 2013, pp. 1973–1978.

[S14] D. E. Rivera, "Optimized behavioral interventions: What does system identification and control engineering have to offer?," in *Proc. 16th IFAC Symp. System Identification (SYSID 2012)*, Brussels, Belgium, July 11–13, 2012, pp. 882–893.