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A control system model of capability-opportunity-motivation and behaviour (COM-B) framework for sedentary and physical activity behaviours

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Abstract

Objective: Theoretical frameworks are essential for understanding behaviour change, yet their current use is inadequate to capture the complexity of human behaviour such as physical activity. Real-time and big data analytics can assist in the development of more testable and dynamic models of current theories. To transform current behavioural theories into more dynamic models, it is recommended that researchers adopt principles such as control systems engineering. In this article, we aim to describe a control system model of capability-opportunity-motivation and behaviour (COM-B) framework for reducing sedentary behaviour (SB) and increasing physical activity (PA) in adults.

Methods: The COM-B model is explained in terms of control systems. Examples of effective behaviour change techniques (BCTs) (e.g. goal setting, problem-solving and social support) for reducing SB and increasing PA were mapped to the COM-B model for illustration.

Result: A fluid analogy of the COM-B system is presented.

Conclusions: The proposed integrated model will enable empirical testing of individual behaviour change components (i.e. BCTs) and contribute to the optimisation of digital behaviour change interventions.

Keywords

Digital behaviour change, theory, control systems, sedentary behaviour, physical activity

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Introduction

Theories of behaviour change are essential to understand and explain health behaviours such as sedentary behaviour and physical activity and provide an organising framework for developing effective interventions.[1] Theory has been defined as 'a set of concepts and/or statements which specify how phenomena relate to each other. Theory provides an organising description of a system that accounts for what is known and explains and predicts phenomena' (p. 327).[2] Theoretical frameworks help define the study variables, provide structure for the relationship between variables, overview assumptions for how the variables should operate, allow for study replication and generalisation, and facilitate the process for testing and falsifying hypotheses.[1] Thus, theoretical frameworks are regarded as essential in physical activity science.[3]

Previous interventions targeting physical activity (PA) and sedentary behaviour (SB) have shown they are complex behaviours that are difficult to change and maintain improvement.[4] In addition, traditional theories of behaviour change have been shown to be insufficient to explain the effect sizes in PA interventions.[5] One of the predominant theories applied to PA and SB has been social cognitive theory, which posits that people form, and subsequently act upon, expectancies of behavioural events and outcomes.[6] More valued outcomes and expectancies are considered critical to subsequent action (e.g. being active).[6] Models such as social cognitive theory typically define the inter-relationship between variables and predictability of the intervention on an outcome (direction and magnitude of effect on an endpoint).[7] Modelling of social cognitive theory has tended toward traditional longitudinal path modelling with relatively simplistic unidirectionality. This basic representation of the theory is inadequate for advanced testing of behavioural, cultural, social and structural intermediate points along the causal pathways[8]; thus, they fail to capture the complexity of human behaviours (e.g. SB and PA).

Technological developments, including the pervasive use of sensors, the Internet and mobile technologies (termed the Internet of Things), have resulted in a data-rich environment. Analyses that utilise big data and real-time data may assist in developing more testable and dynamic models (i.e. computational models), resulting in the development of more responsive and adaptive interventions for an individual at any time and over a period of time.[4] Specifically, leveraging mobile technologies and the Internet of Things, there has been increased interest in using dynamic models to develop Just-In-Time Adaptive Interventions or JITAIs.[4,9,10] JITAIs adapt the intervention components to the individual's changing context (where) and status (when) using the information gathered during the course of the intervention.[4,9]

Computational models of behaviour are mathematically defined testable versions of behavioural theories. They consider the relationship between variables and outcome and also take into account relationship dynamics, including the timescale of an effect, response patterns (linear or non-linear), latency, and decay, as well as boundary or threshold conditions describing the context (e.g. when, where, for whom, and in what state of the person) an intervention will result in the desired effect.[7] Computational modelling can provide more precise representations of dynamic feedback systems (e.g. human behaviour) than statistical and conceptual modelling.[10] Riley et al.[10] suggested adopting control systems engineering principles[11,12] to reshape conventional health behaviour theories into dynamic theories for the development of real-time and adaptive digitally delivered interventions. Control systems engineering explores how to influence a dynamic system (e.g. time-varying adaptive PA intervention) and regulate it.[13,14] To achieve the desired goal (i.e. changing PA behaviour), the input (the intervention content) is adapted dynamically in terms of the output (feedback) making a feedback control process.[13,14] While, in the context of SB and PA research, there is scarcity of dynamic model-based studies using smartphones,[15] one of a few studies is conducted by Korinek et al. (2019) which has successfully applied control systems principles (i.e. system identification open loop) to a PA intervention[16,17] confirming feasibility and effectiveness on improving PA.

In this short article, we aim to introduce a control system model of capability-opportunity-motivation and behaviour (COM-B) for reducing SB and increasing PA in adults. The COM-B model recognises that **B**ehaviour is part of an interacting system involving **C**apability, **O**pportunity and **M**otivation.[18] According to the COM-B, at any given moment, a person will engage in a particular behaviour only when they are capable of performing, have the opportunity to engage, and are more motivated to perform the behaviour.[18] COM-B can help identify behavioural targets for developing interventions to reduce SB and promote PA. COM-B is a meta-model with more robust transferability than social cognitive theory and a larger range of operational constructs. It comprises not only constructs from the social cognitive tradition but also dual process theories. Nearly all behavioural theories can 'fit' within the conceptions of COM-B. Thus, COM-B offers a useful approach to develop a control system model with wide application. Additionally, we have used the theoretical domains framework (TDF), a framework that fits well with the COM-B model,[19] provides a more granular understanding of behavioural theories and examines the environmental, social, affective and cognitive factors that influence behaviour.[20] COM-B is categorised into the TDF for understanding the determinants of behaviour (i.e. mechanism of action). Using validated linkage,[21,22] the TDF can then be mapped onto behaviour change techniques (BCTs), which are active ingredients of interventions.[23] Examples were presented in the model.

Explaining the COM-B model in terms of control systems

Fluid analogy is used to obtain a mathematical model from the relationship between inputs and outputs that form a structured framework.[24,25] A fluid analogy of the COM-B system is presented in Figure 1, in which behavioural constructs (components) of COM-B and other variables are considered as physical objects. Components of COM-B are output variables and TDF variables are considered input variables. A few theoretical domain variables are presented in the fluid analogy and used to test a few related BCTs. Selected BCTs have been found to be effective for reducing SB and increasing PA[26–28] including self-monitoring, goal setting (behaviour), problem-solving, prompts and social support, are used to present the model. It is important to acknowledge that not all of these techniques demonstrate the most robust association. The primary rationale for selecting these techniques is that we are currently evaluating them in a smartphone-based real-time and adaptive intervention study.

Mathematical equations for each tank (e.g. COM-B variables or inventories) are provided.

COM-B model constructs (inputs) represent inventories and other input variables represent inflows or outflows (see Table 1). In the fluid analogy schematic, behaviour ($\eta 4$) inventory will change as the behaviour changes. Different aspects of the behaviour may change (e.g. duration of PA, intensity of PA, etc.) over time and based on other factors.

Capability (η_1), opportunity (η_2) and motivation (η_3) are other output variables that fluctuate between and within an individual over time. These variables function as both dependent variables influenced by other input variables (ξs, e.g. goals: $\xi 3$) at any given time and independent variables increasing the likelihood of performing the behaviour (η_4). Moreover, unexplained and unmeasured variations caused by external factors is represented by ζ. coefficients (γ and β), represent resistances that inflow or outflow from inventories.

To explain the dynamic of change in the system, a mathematical model will be derived from a fluid analogy. For this purpose, inventories and their associated inflows,

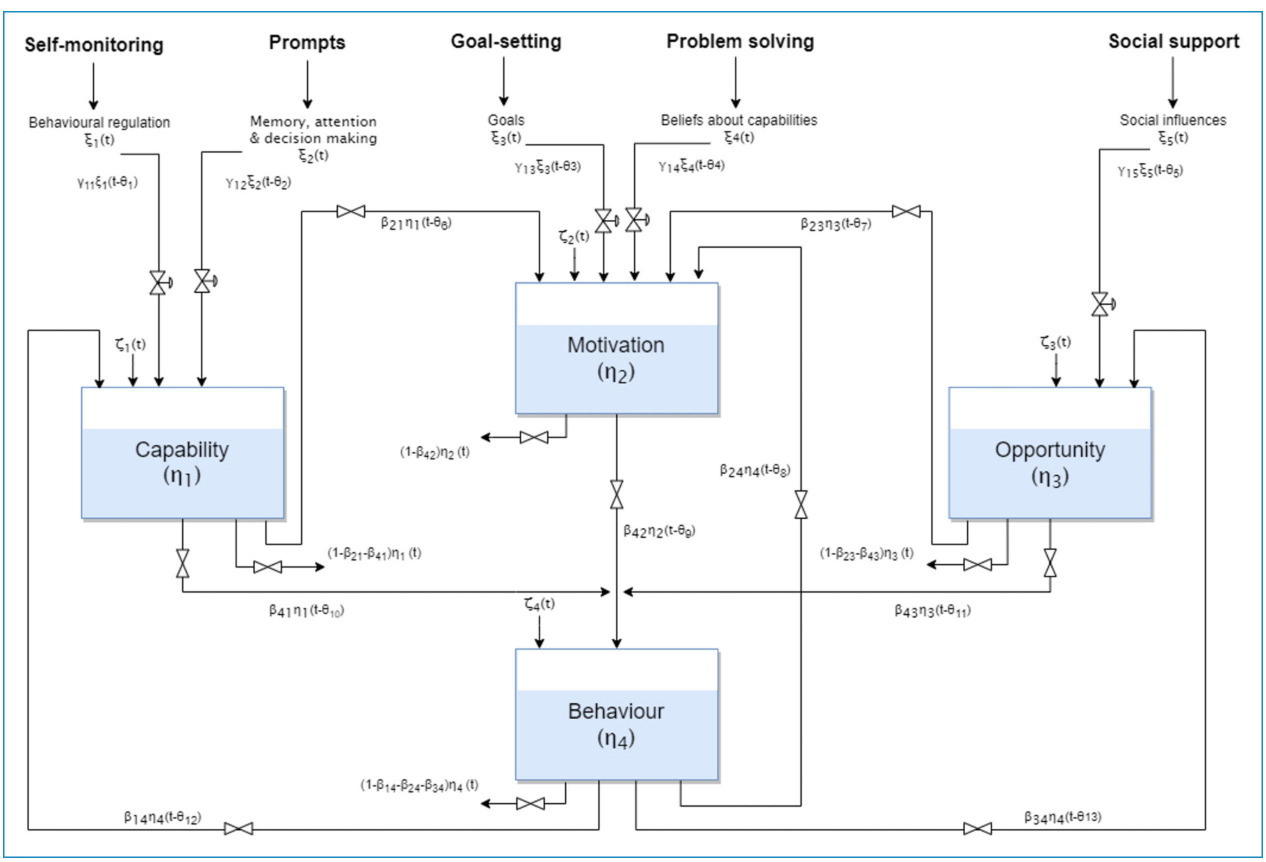

Figure 1. A fluid analogy for the COM-B model. Presenting selected BCTs for reducing SB and increasing PA and their associated TDF domain.
COM-B: capability-opportunity-motivation and behaviour; BCT: behaviour change technique; SB: sedentary behaviour; PA: physical activity.

Table 1. COM-B and TDF signals in the fluid analogy.

Inventory levels (output from the system)	
Name	**Symbol**
Capability	η_1
Opportunity	η_2
Motivation	η_3
Behaviour	η_4
Inflows/outflows (inputs to the system)	
Name	**Symbol**
Behavioural regulation	ξ_1
Memory, attention and decision-making	ξ_2
Goals	ξ_3
Beliefs about capabilities	ξ_4
Social influences	ξ_5

COM-B, capability opportunity motivation and behaviour; TDF, theoretical domain framework.

outflows and relationships will be specified. The application of such fluid analogies in behaviour change is based on previous research.[24,25,29] Figure 1 shows four inventories or output variables by $\eta_1,\ldots,\eta_4$. Five external input variables (TDF items) are shown by $\xi_1,\ldots,\xi_5$. Coefficients $\gamma_{11},\ldots,\gamma_{15}$ and $\beta_{21},\ldots,\beta_{43}$ indicate inflow and outflow resistances from each inventory, respectively. These resistances are used to estimate the fraction of each input or output (inventory) that leaves the previous instance and feeds the next inventory. Furthermore, βs explain the feedback loops when there is a relationship. For instance, β_{14} illustrates a learning feedback loop that influences capability (η_1) either by filling or depleting it. Some other parameters reflect the physical aspect of each flow and inventory. These exert significant effects on the dynamic of the system. $\tau_1, \ldots, \tau_4$ are time constants that show the capacity and consider the exponential decay or growth of each inventory. Time delays for each signal are expressed by ($\theta_1, \ldots, \theta_{13}$). Unexplained variations caused by disturbances are shown by $\zeta_1, \ldots, \zeta_4$.

The law of conservation of mass can be used for calculations, as outlined in previous research by Martin et al. (2014) and Riley et al. (2016). In chemistry, the law of conservation of mass states that ‘mass is neither created nor destroyed in chemical reactions’.[30] In a chemical reaction, the total mass of all reactants and products will be the same in any closed system at any point in time.[30] Using this definition, in the proposed model, the sum of the inflows to an inventory (e.g. motivation) minus the outflows from the same inventory yields an accumulation term denoted by the time constant τ times (x) the rate of change in the level of the same inventory.

To describe how the equations are derived from this model, consider respective inflows and outflows of “capability” as an inventory (η_1). The law of conservation of mass is applied:

Capability (1)

$$\tau_1 \frac{d\eta_1}{d_t} = \gamma_{11}\xi_1(t-\theta_1) + \gamma_{12}\xi_2(t-\theta_2) + \zeta_1(t) + \beta_{14}\eta_4(t-\theta_{12}) - \beta_{21}\eta_1(t-\theta_6) - \beta_{41}\eta_1(t-\theta_{10}) - (1-\beta_{21}-\beta_{41})\eta_1(t)$$

This equation is a representation of first-order dynamics. Equations for other inventories are as follows:

Motivation (2)

$$\tau_2 \frac{d\eta_2}{d_t} = \gamma_{13}\xi_3(t-\theta_3) + \gamma_{14}\xi_4(t-\theta_4) + \zeta_2\,(t) + \beta_{21}\eta_1(t-\theta_6) + \beta_{23}\eta_3(t-\theta_7) + \beta_{24}\eta_4(t-\theta_8) - \beta_{42}\eta_2(t-\theta_9) - (1-\beta_{42})\eta_2(t)$$

Opportunity (3)

$$\tau_2 \frac{d\eta_3}{d_t} = \gamma_{15}\xi_5(t-\theta_5) + \zeta_3(t) + \beta_{34}\eta_4(t-\theta_{13}) - \beta_{43}\eta_3(t-\theta_{11}) - \beta_{23}\eta_3(t-\theta_7) - (1-\beta_{23}-\beta_{43})\eta_3(t)$$

Behaviour (4)

$$\tau_4 \frac{d\eta_4}{d_t} = \beta_{41}\eta_1(t-\theta_{10}) + \beta_{42}\eta_2(t-\theta_9) + \beta_{43}\eta_3(t-\theta_{11}) + \zeta_4(t) - \beta_{14}\eta_4(t-\theta_{12}) - \beta_{24}\eta_4(t-\theta_8) - \beta_{34}\eta_4(t-\theta_{13}) - (1-\beta_{14}-\beta_{24}-\beta_{34})\eta_4(t).$$

is the initial model that describes first-order linear equations. As outlined by Navarro-Barrientos et al., higher-order equations might be needed that extend the fluid analogy to consider self-regulation responses in each inventory.[29]

Tools such as smartphones and sensors can be used to collect data to inform such computational models. As stated previously, we are currently conducting a real-time and adaptive pilot study using a smartphone and a third-party activity sensor. Individuals’ current activity states (e.g. sitting or moving), location (home or workplace), and time of day (morning, afternoon, etc.) are being collected via sensors and phone GPS and sent to the server for processing. The collected data is utilised to identify opportunities for delivering push intervention messages. When prolonged sitting (i.e. more than 1 hr) is detected, the system triggers a message suggesting a break from sitting or encouraging the individual to visit a nearby park to increase their activity time. Moreover, the study is exploring individual responsiveness to specific intervention messages containing BCTs such as social support. It is anticipated that individuals may respond better to certain messages while they are at their workplace and during prolonged sitting periods.

Subsequently, real-time behavioural and contextual data can be used to test the proposed computational model and validate it. Techniques such as system identification constitute a data-driven suite of methods that can be employed to formulate individual dynamical models.[12] These models are constructed by analysing input–output measurements along with prior physical and conceptual knowledge. The primary goal is to explore and model variations and responses within longitudinal data on an individual basis. System identification in this context involves investigating the relationships between manipulated variables (e.g. interventions) and time-varying disturbance variables (e.g. weather) in predicting specific outcomes of interest (such as daily steps taken).[12,31]

Also, the development of an individualised model will guide the intervention strategy in the long run, meaning that individuals will gradually receive more interventions tailored to their responsiveness, while less responsive messages and contexts will be minimised. In addition to conducting pilot trials to collect data informing the initial values of the computational model, researchers can also refer to existing literature for effective data to guide the initial values.

The model proposed in this article exemplifies the description of COM-B by employing principles of control systems and incorporating BCTs and TDF domains as inputs. It is advised that researchers adjust the inputs according to their own rationale. For instance, Cane et al. (2015) classify *prompts* within the TDF's environmental context and resources domain while we have classified prompts within the memory, attention and decision-making domain which is based on Carey et al.'s study.[32] Researchers who wish to follow a such modified approach must provide a clear explanation within their paper and present the adapted figure and calculations.

It is essential to take into account the limitations associated with employing computational modelling of human behaviour. Computational models have the potential to oversimplify intricate psychological and behavioural processes, failing to fully capture the complexities inherent in real-world human behaviour.[33] Moreover, computational models rely on assumptions which can introduce biases into the results.[33] If these assumptions are not fully examined or challenged, it could potentially restrict the validity of the predictions.

Implications and future directions

Control systems modelling offers computational robustness and rigour, providing a strong foundation for testing health behaviour theories and developing interventions. This short article describes the application of control systems to the COM-B model, presented as a fluid analogy schematic to understand the interaction between COM-B variables for behaviour change. Introducing control systems to existing behavioural frameworks (i.e. COM-B) will enable future researchers to empirically test the active ingredients of behaviour change (i.e. BCTs) and measure their real-time and overall effectiveness in various contexts, influenced by other unknown factors over a certain period.

Moreover, dynamic modelling of COM-B can reveal the interrelationship between COM-B constructs that go beyond covariation and specify the magnitude and directionality of the influences between variables. These altogether contribute to the optimisation of digital behaviour change interventions and enhance theoretical precision. Dynamic modelling allows for the illustrating potential impacts when manipulating inputs (e.g. BCTs) to target behavioural constructs, providing insights into the attenuated impacts expected from these manipulations. The proposed model is applicable for health care providers in public health and primary care settings to develop individualised interventions for people at risk or living with chronic conditions (e.g. diabetes). These interventions target sedentary behaviour and physical activity based on real-time data. Additionally, organisations can operationalise this model in workplace wellness programmes, adapting interventions to employees' changing contexts (e.g. during work hours). Finally, this conceptual model serves as an initial roadmap for further testing and refinement based on empirical data and technological advancements.

Contributorship

RD, DD, SMSI and RM devised the idea of model integration; RD, DD, SMSI, RR, MA, EH and RM conceptualised the model and components; RD, SH and RM defined behavioural variables and explained them in terms of control systems; RD and SH modified the model and equations; RD, DD, SMSI, RR, MA, BM and RM prepared the first draft. RD, DD, SMSI, RR, SH, MA, EH, BM and RM critically reviewed the manuscript, provided feedback and modified it.

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