Dynamical Systems Modeling using EMA Data: An Illustration from Smoking Cessation


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Outline

• What is dynamical systems modeling?

• UW-CTRI Ed Sr. data description.

• Approaches:
  - Modeling craving dynamics as a result of quitting.
  - Dynamical mediation (with craving as a mediator, and cigarettes smoked as outcome).
  - Smoking as a feedback system involving craving self-regulation.

• Summary and conclusions.
Our end goal is to apply principles from *control systems engineering* towards optimizing smoking cessation interventions; our focus for today is on the important subproblem of *dynamical systems modeling* from intensive longitudinal data obtained via EMA (or related means).
Dynamical Systems Modeling

- Dynamical systems thinking considers how to characterize the transient response resulting from changes in manipulated inputs (e.g., intervention component dosages) and disturbance inputs (e.g., external influences) on outputs (e.g., proximal or distal outcomes, mediators).

- The above is a block diagram “signals and systems” representation (not to be confused with path diagrams).

Why dynamical systems for behavioral interventions?

- Serves to better understand the concepts of change and effect in interventions; this includes:
  - what to measure, and how often
  - within and between participant variability

- Allows more efficient use of intensive longitudinal data

- Enables the application of control engineering principles for achieving time-varying adaptation of intervention components based on participant response.
Gain ($K$), time constant ($\tau$), delay ($\theta$), and settling time ($T_{95\%}$) are all part of the “lingo” of dynamical systems...

- Rise time, settling time, overshoot, oscillation, and inverse response are important characteristics of this model response.
• Data from study described in McCarthy et al., *Addiction*, Vol. 103, pgs. 1521-1533, 2008. Active drug is bupropion SR.

• 11 week study; randomization ($n = 463$)
  - Drug: Drug, Placebo
  - Counseling: Yes, No

• Treatment Conditions:
  - Active Drug with Counseling ($AC; n=101$)
  - Active Drug, No Counseling ($ANc; n = 101$)
  - Placebo with Counseling ($PC; n =100$)
  - Placebo, No Counseling ($PNc ; n =101$)

• $T = 42$ daily observations for each participant

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**AC and PNC Treatment Groups; Averaged Responses**

![Graph showing comparison of craving scores versus quit for two treatment groups](image)

- Comparison of craving scores versus quit for two treatment groups (active drug with counseling ($AC$, blue) vs. placebo-no counseling ($PNc$, red)).
Parameter Estimation

- Parameter estimation performed using the **Process Models** feature in Matlab’s System Identification Toolbox (one-step ahead prediction-error minimization for continuous differential equation structures).

- *Functional data analysis* (FDA) is well-suited as a parameter estimation scheme for this model (Trail et al., 2012); estimating time-varying coefficients is a natural extension of this work.

- *Model parsimony* is an appealing aspect of differential equation modeling, given the diversity of responses that can be obtained from a relatively small number of parameters.

- The proper choice of *sampling interval* is a very important consideration in this type of analysis.

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Dynamical Model Fits for Treatment Group Averages

- The *PNc* group has more pronounced “inverse response” ($\tau_a$).
- The *AC* group has higher magnitude gains ($K_p$).
- The *AC* group has faster speed of response ($\tau$).

- Second-order models fit 63.8 and 86.1% of the variance for the *PNc* (red) and *AC* (blue) treatment groups, respectively.
Dynamical Mediation Model
(Timms et al., 2012a)

All variables observed; $M$ and $Y$ continuous; $X$ can be categorical.
• A signals and systems block diagram, not a path diagram.
• $P_a$, $P_b$, and $P_c'$ represent transfer functions; these are compact representations of differential equation models.
• Arrangement allows for a generalization of dynamic mediation analysis beyond fluid analogies.

Comparison of average cigarettes smoked and craving scores for two treatment groups (active drug with counseling ($AC$, blue) vs. placebo-no counseling ($PNC$, red)).
**AC group displays more substantial initial “quit”** (direct path $K_p$) Outcome: Cigsmked

**AC group has slower and lower magnitude resumption** (mediated path $K_p, \tau$)

The mediated pathway contributes more to the net outcome in the **PNc** group as compared to the **AC** group.

**Idiographic results for a representative participant from the **PNc** and **AC** groups.**
Dynamical systems analysis (Timms et al., 2012b, in press) suggests that a feedback model involving the self-regulation of craving through smoking describes the smoking process more comprehensively than traditional mediation analysis. This concept is consistent with nicotine regulation theories and extensions as discussed by Walls and Rivera (2009 Society for Prevention Research).

The feedback/craving self-regulation model (Timms et al. 2012b) displays similar fits to the mediation model structures; however, only one model structure is needed to comprehensively capture the dynamical relationship between variables.
Summary and Conclusions

• Dynamical systems modeling of ILD/EMA data from the Ed Sr. smoking cessation intervention has been examined.

• The differential equations associated with dynamical systems modeling can be readily estimated using algorithms from system identification (engineering) or functional data analysis (statistics).

• Dynamical models offer a parsimonious, effective means for describing change over time that makes them useful in optimized smoking cessation interventions relying on control engineering approaches.

• Dynamic mediation model structures related to smoking cessation were examined; these can be generalized through a feedback model structure based on craving self-regulation that is inspired by nicotine regulation theories.

Some Questions and Issues to Consider

• How can behavioral theories be reconciled (and better integrated) with the physical (fluid) analogies and generalized dynamical system structures that have been presented?

• Experimental design in support of dynamic modeling represents an interesting topic for future research.

• Research towards generalized approaches for dynamical systems modeling of smoking cessation interventions that incorporates mediation, moderation, confounding, latent variables, and gene-environment interactions.

• Use of these models in optimized adaptive behavioral interventions using model predictive control (Nandola and Rivera, 2012).


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