2.21 On the Development of a Deterministic Three-Dimensional Radiation Transport Code

MODSIM WORLD Conference & Expo

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Health Care Policy Analysis and Decision Support using Agent Based Simulation Techniques

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Project Objectives

- Provide a technical capability to analyze complex interactions in complex systems
  - Model human decisions and multi-level interactions
  - Address client needs that we can not currently support
  - Extend some of our existing, successful work in ontology modeling
  - Develop a ***reusable solution*** that is easily transported to multiple client needs and extensible within current solution development
- Apply this new capability to chronic disease research problem
  - Demonstrate the this solution meets National Institute of Health needs
  - Department of Health & Human Services, National Institute of Health, Office of Behavioral and Social Sciences Research
  - Show ability to analyze impacts of policy on human lifestyle decisions

R & D Approach

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- Research health care policy areas and integrate specific focus area data into usable format
  - Based on human decision model
  - Initial focus on human smoking decisions across multiple factors
- Develop ontology models
  - Human decisions
  - Human environmental entities and relationships
  - Cross-domain ontology model of interactions between humans, environment, decisions, and policy
- Develop Agent Based Model (ABM) and methods
  - Document a Design of Experiment (DOE) method
  - Document an approach to analyze ABM output

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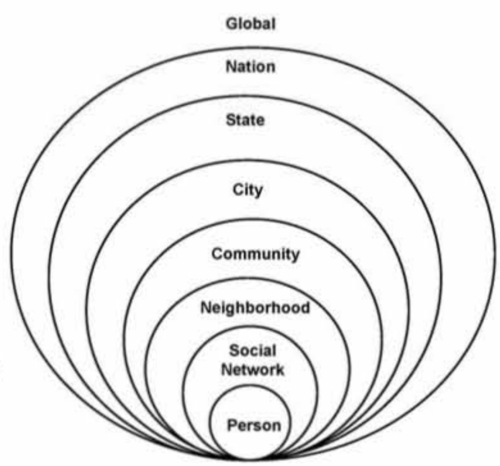
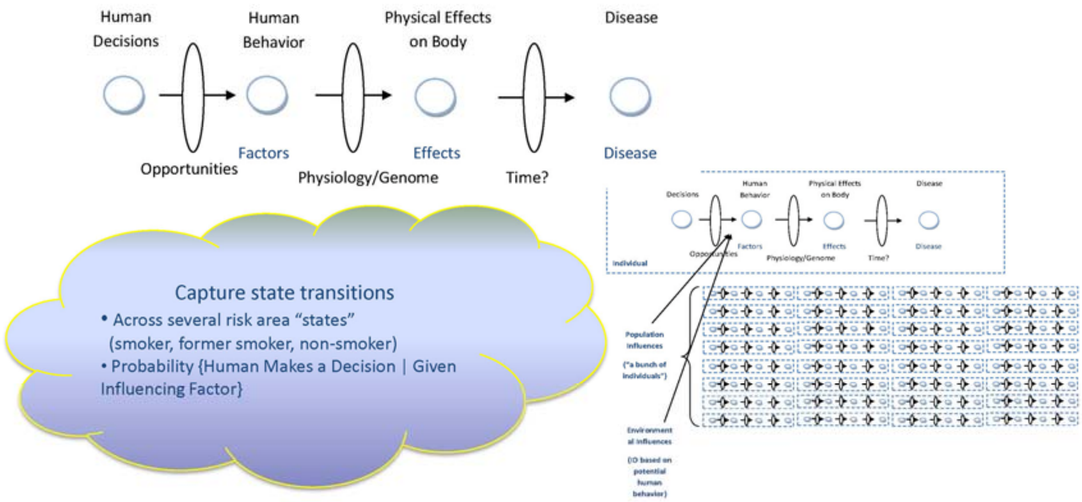
Health Care Research

- Extensive research has been done on individual social risk factors that lead to disease
- Risk factors do not act independently
- This research allows understanding of inter-relationships between environmental influences and social influences on human decisions across many risk factors
- Enable inclusion of many risk factors across many "layers"
- Initial focus on smoking risks



Health Care Policy Focus Area

- impact on human decisions



Agent Based Simulation

- Collection of autonomous decision-making entities (agents)
  - NOT intelligent agents or secret agents
- Allows us to model complexity – multiple system layers and complex interactions
- Discovers "emergent phenomena"
- Becomes a data source for advanced research
- Requires sophisticated methods for:
  - Efficient experimental design
  - Data mining
- Requires computational power

ABS Model Characteristics

- Agent characteristics
  - Age, gender, race, smoker? (never, former, current), prob start or quit
  - Maintain smoking status after age 30
  - Life expectancy based on smoking status
- Population
  - Initially 250 agents
  - Expanded to 1000 agents
- State-based probability of changes on each tick, modified by Odds Ratios (based on interventions)
  - Focus on middle school, high school, and college age
  - Based on informed research using a wide range of journal articles
  - Used chain of conditional probabilities
- Accounts for peers – social aspect of behavior

Individuals and States

- Individuals in the simulation have several attributes that describe their state at any given time
  - Smoker or nonsmoker
  - Age
  - Gender
  - Months smoked (total and consecutive)
- Individuals also retain social relationships which affect smoking behavior
  - Parent (single parent, smoking status recorded)
  - Peers (links to "nearby" individuals close to age)

Time Ticks

- Each month (a "tick" of the simulation clock) an individual's state is updated
  - Age and other tracking variables are incremented
  - Smoking is commenced or ceased based on probabilities
  - In the extended model, an individual may develop disease based on probabilities
- Probabilities of changing states are affected by attributes of the individual and their social relationships
  - Parent and peer smoking status affects behavior
  - Age, Gender, prior smoking status has impact on risk

State Transitions

- Baseline transition probabilities for the entire population are derived from the literature

		Next Month	
		Nonsmoker	Smoker
This Month	Smoker	1.024%	98.976%
	Nonsmoker	99.513%	0.487%

- Baseline probabilities are then adjusted based on individual risk factors
  - Literature expresses additional risk as an Odds Ratio (OR)
  - OR > 1 for an attribute means someone with that attribute is more likely to change state, OR < 1 means less likely

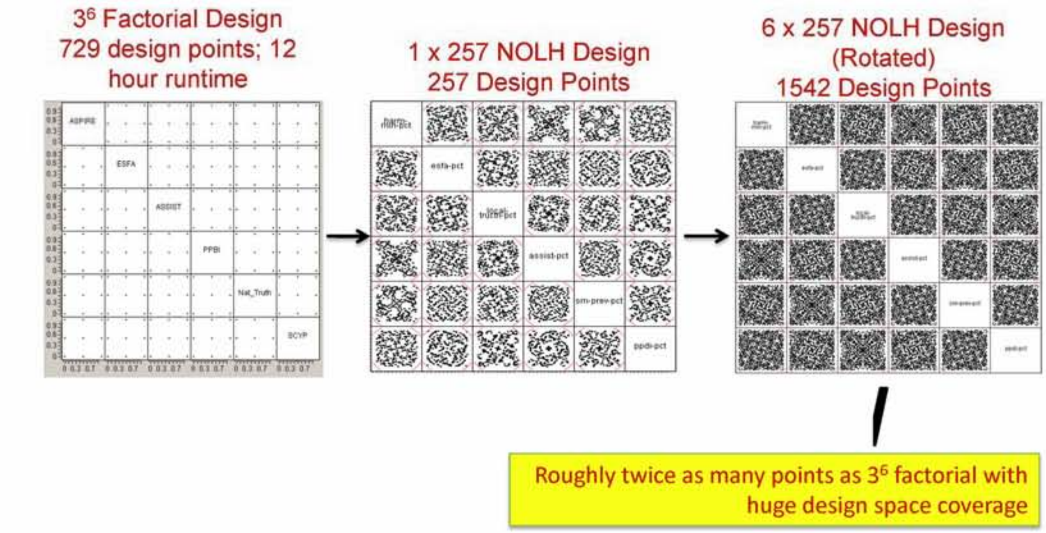
Odds Ratios

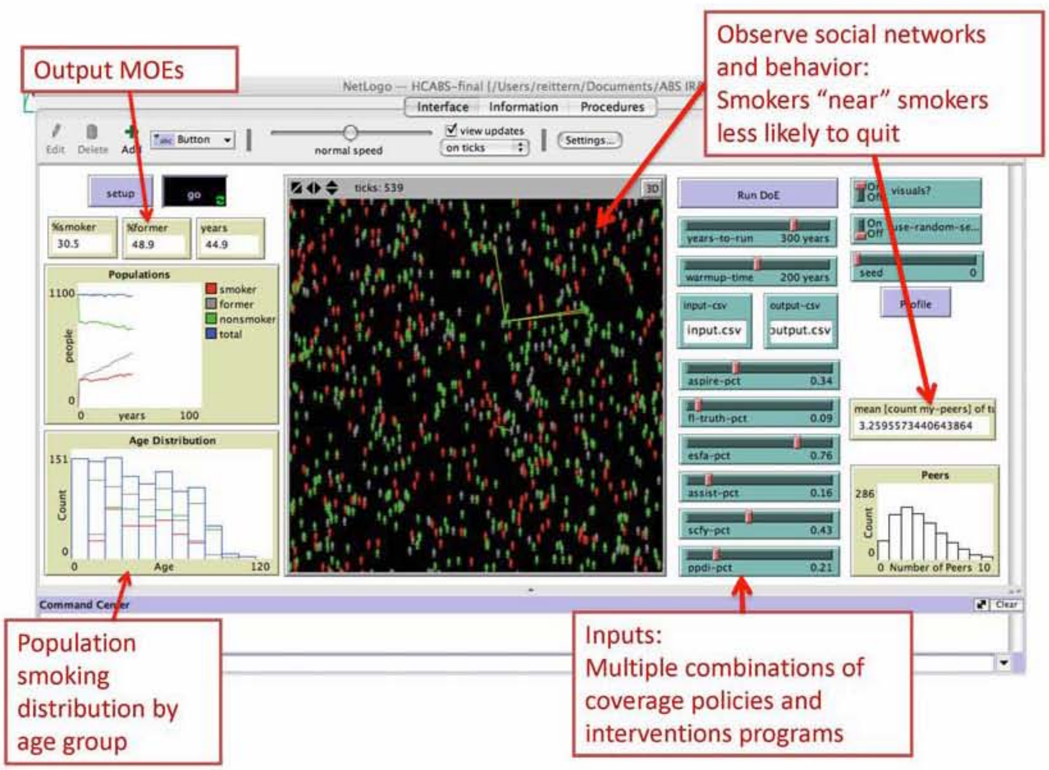
- Simple example
  - Odds of quitting in a month is 1 in 99 (1% chance)
  - If peers smoke, OR is 0.27, which is 3.7 times less likely to quit
  - Odds of quitting are now 0.27 in 99
    - Equivalently, 1 in 99*3.7
- Combining Odds Ratios
  - Can multiply multiple odds ratios together (e.g., female, high school age, peers smoke, exposed to Truth Campaign)
  - For computational efficiency, take log(OR) and add
  - To combine multiple estimates of the same OR, from different literature sources, use least squares regression on log(OR)
  - For any given individual state, add up log(OR) of applicable risk factors

Experimental Design

- Various types of intervention programs (factors)
  - **ASPIRE**: Computerized smoking prevention curriculum: school-based self-study
  - **ESFA**: European Smoking prevention Framework Approach: integrated classroom with teacher, advertising, journalism
  - **ASSIST**: A Stop Smoking in Schools Trial - school based, peer-led
  - **PPBI**: Pediatric Practice-Based intervention - healthcare provider and peer-based
  - **National Truth** Campaign - Advertising campaign and youth advocacy
  - **SCYP**: Smoking Cessation for Youth Project
- Levels (for each intervention)
  - Percent coverage from 0 to 100%
  - Length of interventions, from 0 years to 128 years (evaluated, but no need to implement)
- Responses (% of total population)
  - % Smokers
  - % Former Smokers

Evolution of Design





Initial Analysis Results

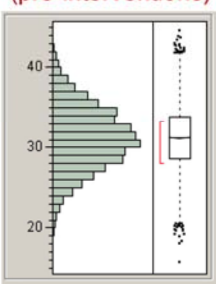
- Multivariate Regression analysis
  - All 6 interventions as dependent variables, with all 2-way interactions
  - Decrease in % smokers as independent variable (positive is good)
  - Expected results:
    - positive coefficients for each intervention
    - Negative coefficients for interactions due to diminishing returns
  - Actual results:
    - SCYP * PPDI positive interaction
    - Using both together better than each one separately

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-5.192125	0.062685	-82.83	0.0000*
SCYP	0.4832354	0.049809	9.70	<.0001*
ESFA	1.4631586	0.049813	29.37	<.0001*
Truth Campaign	6.3315738	0.04981	127.12	0.0000*
ASSIST	0.4912404	0.049809	9.86	<.0001*
ASPIRE	5.1580737	0.049809	103.56	0.0000*
PPDI	1.3071909	0.049809	26.24	<.0001*
(SCYP-0.50006)*(ASPIRE-0.50001)	-0.552469	0.179475	-3.08	0.0021*
(SCYP-0.50006)*(PPDI-0.49999)	0.3496265	0.178338	1.96	0.0499*
(ESFA-0.50009)*(ASPIRE-0.50001)	-1.614977	0.158925	-10.16	<.0001*
(ESFA-0.50009)*(PPDI-0.49999)	-0.406185	0.178849	-2.27	0.0231*
(Truth Campaign-0.4995)*(ASPIRE-0.50001)	-1.115554	0.179431	-6.22	<.0001*
(ASSIST-0.49997)*(ASPIRE-0.50001)	-0.469038	0.178315	-2.63	0.0085*
(ASPIRE-0.50001)*(PPDI-0.49999)	-1.179963	0.178747	-6.60	<.0001*

Sampling of Model Response

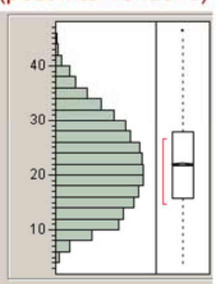
% Smokers (pre-interventions)



Quantiles

100.0%	maximum	44.800
99.5%		41.201
97.5%		38.843
90.0%		36.170
75.0%	quartile	33.871
50.0%	median	31.174
25.0%	quartile	28.571
10.0%		26.210
2.5%		23.770
0.5%		21.338
0.0%	minimum	15.789

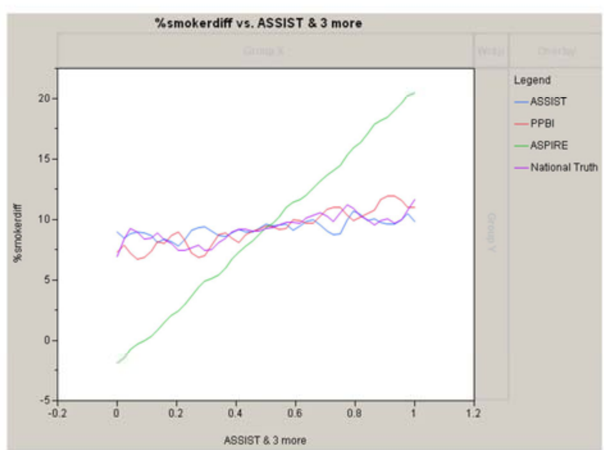
% Smokers (post interventions)



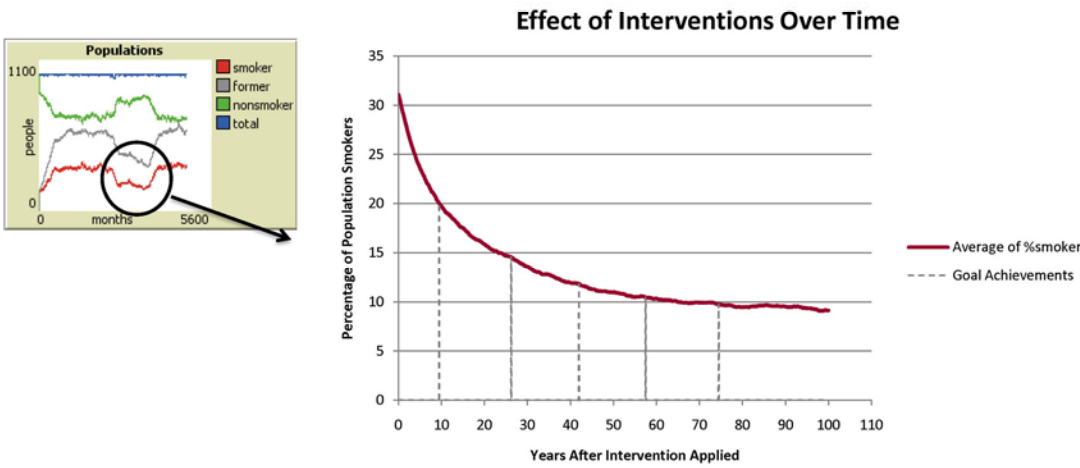
Quantiles

100.0%	maximum	46.748
99.5%		41.559
97.5%		37.600
90.0%		32.773
75.0%	quartile	27.823
50.0%	median	21.656
25.0%	quartile	15.702
10.0%		11.489
2.5%		8.434
0.5%		6.024
0.0%	minimum	3.252

Effects of Interventions

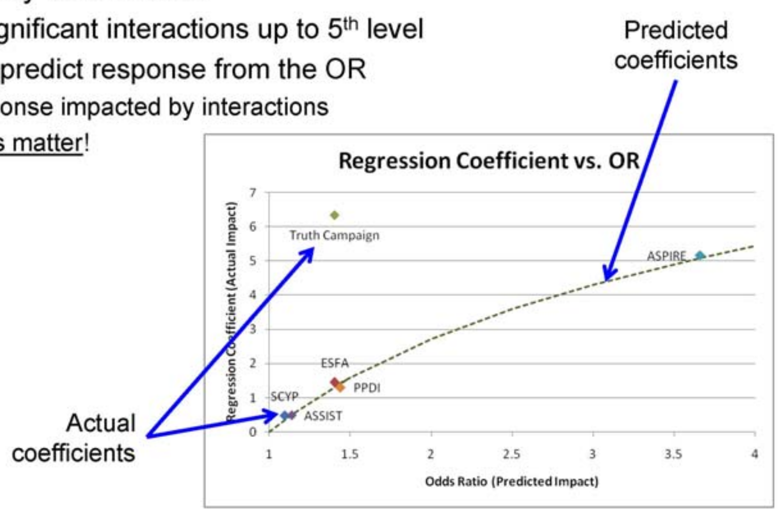


(Zooming in on timeframe when interventions took effect)



Impact of interactions on predictions

- Tested up to 6-way interactions
  - Statistically significant interactions up to 5th level
  - You can't just predict response from the OR
    - Actual response impacted by interactions
    - Risk factors matter!



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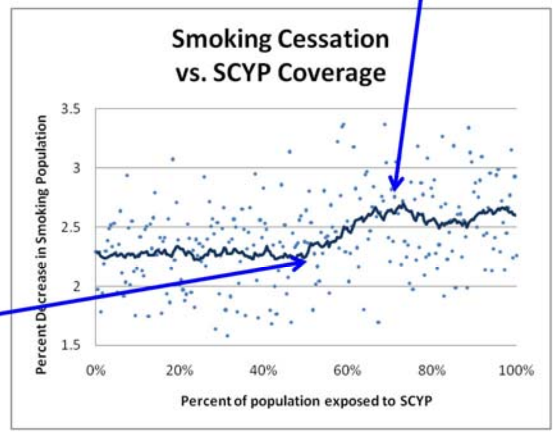
A closer look at SCYP

- SCYP shows a clear "threshold effect"
  - PPDI Interaction highlighted this sensitivity to other interventions
  - Minimum and maximum effective level
  - Dependent on which other interventions are employed



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Potential next steps – just for smoking

- Simulation results used to populate "response surface"
  - Lots of threshold effects for other interventions at various combinations
    - 7-dimensional, so we can't show you here
  - Given costs of each intervention, along with cost constraints, can use optimization methods to find best mix at each investment level
  - Pareto frontier of optimal intervention mixes can inform decisions on overall investment level
- Additional simulation exploration of "non-overlapping" multiple interventions
  - Each individual might only experience one intervention, but peers may experience others
  - Potential to mitigate negative interactions due to "over-intervening"

Potential next steps – bigger picture

- More complex behavior and physical interactions
  - Exercise and food choices impacted by peers
  - All these choices add to risk factors for various diseases
  - Explore impact of "wellness programs"
    - Particularly relevant to analysis of health insurance costs
    - Insurance provider may invest (with potential government subsidy) in wellness programs to lower costs (healthier customers)

Questions?