Artificial Intelligence and Human Behavior

Modeling and Simulation for Mental Health Conditions

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Abstract

Modeling the complexity of individuals with multimorbid physical and mental health problems within a social context is one of the greatest challenges for the post Affordable Care Act era. Stigma associated with mental illness promotes silos that prevent full integration of a person living within a dynamic and contextualized matrix. Traditional regression modeling strategies fail to embrace dynamic health patterns within systems. Synthesizing systems science, agent modeling and simulation, knowledge management architecture and domain theories, we explore the use of Agent-Based Modeling & Simulation (ABMS) for understanding individual, organizational, and societal levels of a hospitalization. In essence, we apply computational science to explore underlying mechanisms that explain medical/surgical hospital outcomes—readmissions—for individuals with comorbid physical and mental illness. In the first section of this chapter, ABMS is conceptualized. Then, a case study serves to demonstrate an ABMS application and gains from knowledge that is unique to this systems social science approach. We conclude with a discussion of strengths and limitations of the ABMS application.

Keywords: agent-based, decision support, community healthcare, systems analysis, readmission, mental health systems.

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Modeling and Simulation for Mental Health Conditions

Background

Chronic illnesses are the leading cause of disability and death and, in the U.S., affect almost half the adult population, or about 133 million Americans (Institute of Medicine, 2012)A recent study places chronic care at 78% of total U.S. healthcare spending, and forecasts costs of over a trillion dollars per year by 2020 (Institute of Medicine, 2012). Among individuals with chronic illness who incur the highest costs are those with mental illness who have multiple layers of physical and/or mental health problems that interfere with their capacity to socialize, plan, organize, and function in their life (Kronick, Bella, & Gilmer, 2009). People with serious mental illness (SMI), approximately 15 million Americans, are in the top 5% of Medicaid beneficiaries for per capita costs and account for more than 50% of all Medicaid spending, with annual per person costs of $43,130 - $80,374 (Coughlin, Waidmann, & Phadera, 2012). Despite this level of investment, the poor health of people with SMI is striking; they die 25 years earlier than the general population from preventable illnesses (Colton CW & Mandersheid RW, 2006). Compared with the general population, persons with SMI are 3.4 times more likely to die from heart disease or diabetes; 3.8 times more likely to die from accidents; 5 times more likely to die from respiratory ailments; 6.6 times more likely to die from pneumonia influenza (Hardy & Thomas, 2012); and 3.8 times more likely to be HIV positive than the general population (Rothbard, Miller, Lee, & Blank, 2009).

The health delivery systems for mental health and medical care are extremely complex, operate independently, communicate with one another inefficiently, and often have different financing arrangements and policies for mental health care (Druss, von Esenwein, Compton, Zhao, & Leslie, 2011). These systems are virtual silos of care and a nightmare for consumers to negotiate (Institute of Medicine, 2006). For individuals with a serious mental illness, an encounter with this fragmented health care system is not only burdensome, but can be perilous, and often results in exacerbation of symptoms and rehospitalizations (Institute of Medicine, 2006). Other consequences of ineffective health systems are devastating and costly – homelessness, victimization, incarceration, repeated hospitalization, and death (Druss et al., 2011). A new study suggests that people with SMI are three times more likely to be in jail or prison than in a psychiatric hospital (Bloom, 2010). These statistics speak volumes about the ineffectiveness of current health systems to care for some of the most vulnerable of populations, and the need for innovative solutions to their care.

The challenges associated with addressing the needs of the most vulnerable populations in our society are related to complex networks of interconnected social, economic, and political systems. One of the best tools for attempting to understand and better manage complex systems is computational modeling and simulation. In this chapter we will model the complexities of individuals with serious mental illness and the environmental factors that influence their health using simulation and agent based modeling technology. None of the current research methods or technology captures the quantity, quality, or breadth of individual and contextual factors used in the simulation and agent based modeling that we will use in the proposed research. The virtual system we will use operationalizes complex patterns and mechanisms of health over the life course including physical environments, sociocultural context, peers and families, coping responses, behavior, biology, and genes, all of which determine the health of individuals within complex environments and social networks (Silverman, 2010).

In the field of healthcare, ABM is already used to analyze a variety of operations and personnel management issues. Examples of such issues are the performance of hospital emergency departments, various resource assignment strategies, and how the decision-processes of doctors and nursing staff impact diagnostic and treatment efficacy (Cil & Mala, 2010; Sibbel & Urban, 2001; Stainsby, Taboada, & Luque, 2009). These models are quite prolific within academic circles but have yet to be included into widely available commercial software packages, which instead tend to rely on purely mathematical or stochastic models (Silverman, 2010). Furthermore, these models are also consistently focused on micro issues without addressing the organizational structure of the healthcare system and the different policy options available to those in the public sector, which is the focus of our project.

Health reform is ultimately concerned with social justice and social change. These goals require a sophisticated understanding of the contexts that give rise to social problems and the use of research methods and change strategies that attend to the complexities of social settings. Although researchers dedicate considerable attention to these concerns, ability to understand the intricate and dynamic relationship at the individual, organizational, and societal level still lags behind the considerable need in our society for transformative change in health care delivery. The following section describes the conceptual underpinnings of Agent Based Modeling & Simulation (ABMS), followed by an application of ABMS to explore the hospital trajectory and outcomes for patients with medical and surgical conditions. Our goal is to increase an understanding of ABMS's conceptual and methodological tools available to those involved in designing, implementing, and assessing social change.

Why ABMS and Challenges

Our approach to improving models of care is innovative, as agent-based simulation provides a systems approach that includes attention to the dynamic relationships between individual, social and environment factors. Over the last thirty years, minimal progress has been made on the discriminative ability of traditional risk prediction models, and they are little better than coin flipping at predicting readmissions (Calvillo–King et al., 2013). Most traditional risk models focus on **clinical determinants** of readmission (e.g. severity of illness, prior use of medical services and other comorbidities), while ignoring many higher-level **social and environmental factors** associated with overall health and functional status (e.g. income, insurance status, education, marital status, caregiver availability, access to care, discharge location, crime-rates, walkability and access to transportation services). Traditional risk models are statistical and largely rely on regression to extract cause and effect correlations from large datasets. This is “black box” modeling and it works best on predicting the average behavior, leaving the outliers to error terms. ABMS characterizes the high degree of complexity and uncertainty of health care systems and models underlying processes, sequences of mechanisms, and behavior theories of individual patients and how all these interact to produce emergent macro-effects. In this case, cause and effect are considered circular and dynamic; feedback/feedforward may exist, as can time delays, workflow sequences, and other complex interactions. A challenge is to integrate data from multiple national, community, and health system sources needed to develop such care models.

History of ABMS in Medicine/Mental Healthcare

Brailsford, Harper, Patel, and Pitt (2009) taxonomized the literature on healthcare simulation models into three main groupings: human body level, at the healthcare unit level, and at the system-wide level. Their survey showed numerous excellent models exist for each level separately. A review of ABMS in healthcare by Paraniape and Sandanad (2009) is consistent with this taxonomy. A noteworthy agent model by Schlesinger and Eddy (2012), Archemedes, makes use of both patient clinical factors and clinical cost. However, patient behavioral factors were not included. Our prototype model, further explained in the following sections, complements Archimedes by including mind-body, workflows, and societal factors.

To date, there are no models addressing all three levels as defined by Brailsford et al. (2009). System-wide models tend to be focused largely on the health system facilities alone, not embracing the larger societal issues. As described previously, to effectively model the healthcare ecosystem, the model framework must address all three levels (individuals, organizations, and societal) as important dynamics often lie in the social and behavioral determinants outside the scope of typical clinic services.

Synergies with Other Industries

Over the past decade, the lead author has created multi-tiered ABMSs for the United States Military, Central Intelligence Agency, and the Department of State (Silverman, 2010). These agent-society modeling tools have been applied to hundreds of political events, and these agencies are in various stages of fielding and using these deliverables to support training and decision support of command staffs, reconstruction teams, and country desk people seeking to help communities overseas. The basic approach is open architecture and follows the model driven architecture (MDA) standard that uses a model factory where best practice models of a given component can be added into the suite (or removed) and run with data inputs and outputs going to a publish and subscribe style of data store. A model controller exists that allows one to design ABMS experiments, run Monte Carlo style, or explore sensitivities.

To our knowledge, the system science and artificial intelligence (AI) methods the investigators are using are unique. Their designs are highly scalable, portable, and can be embedded to drive the behaviors of agents in numerous third party simulators. The three levels of the ABMS framework will be further described in the next section.

Sociological Inputs into Multi-Tiered ABMS

We used two key sociological theories and a comprehensive systematic review on the social factors impacting hospital readmissions to inform our multi-tiers modeling approach:

Antonovksy's Salutogenesis Model

Antonovsky (1996) developed this model on the principle of a sense of coherence, in gauging how individuals respond to their surroundings and cope with stress. The model has been utilized in a broad array of settings to analyze coping mechanisms in the fields of health psychology, sociology and preventative medicine in Europe. In addition, its close linkages with the field of decision science have also seen its transformation into a heuristic to guide decision making on the fly, healthcare architecture and psychiatry engagements. The model consists of 3 components: <u>Comprehensibility</u> – a belief that things happen in an orderly and predictable fashion and a sense that you can understand events in your life and reasonably predict what will happen in the future. <u>Manageability</u> – a belief that you have the skills or ability, the support, the help, or the resources necessary to take care of things, and that things are manageable and within your control. <u>Meaningfulness</u> – a belief that things in life are interesting and a source of satisfaction, that things are really worth it and that there is good reason or purpose to care about what happens. The Salutogenesis Model's efficacy in connecting psychological stimuli to physiological effects has made it an apt choice for the framework of our value trees, described in the next section. While goals are short term concerns best described by Maslow's hierarchy, standards and preferences are more accurately linked to patient coping styles and perspectives on managing life.

Theory of Reasoned Action

The Theory of Reasoned Action (TRA) suggests that a people's behavior is determined by their intention to perform the behavior and that this intention is, in turn, a function of their attitude toward the behavior and subjective norms *(Fishbein & Ajzen, 1975)*. The best predictor of behavior is intention or instrumentality (belief the behavior will lead to the intended outcome). Instrumentality is determined by three things: their attitude toward the specific behavior, their subjective norms, and their perceived behavioral control. The more favorable the attitude and the subjective norms and the greater the perceived control, the stronger the person's intention to perform the behavior.

Social Factor Impact on Readmission or Mortality

The study by Calvillo-King et al. (2013) provided a comprehensive overview of the factors that affect patient readmissions and mortality, including economic and demographic parameters. Through conducting rigorous magnitude of association and statistical significance tests, factors were ranked according to the degree of correlation that they have with readmission or mortality. The majority of factors analyzed in the study indirectly impacted decision making and were largely demographic in nature, which provided a useful context for identifying behavioral habits that were harmful to health and had a statistically significant correlation.

A Toolbox for Multi-layer Modeling of Social Systems

In terms of the history of this toolbox, we started by modeling individuals from the social psychological and mind-body perspective (deep-narrow) and then added more models that broadened the capability in the economic-political-sociologic dimensions. Specifically, we used two types of models – PMFserv and StateSim – to model the agent, organizational, and societal levels. For further discussion of these tools, see publications by Silverman, Sun, Bharathy, and Weyer (submitted for publication, 2015) and Silverman, BG, Hanarahan, N, Bharathy, (2015, pending). In 2011-2012 we applied these tools to model the community mental health of Philadelphia. In this section, we will illustrate the models with examples from this domain. The section below, Example Application, will then show results from running these models.

Agent Mind/Body Level: The PMFserv Architecture

The basic building block is a model of an agent's bodily needs (physiology, fatigue, hunger, injuries, belonging, etc) and mind. Ortony, Clore, and Collins (1990) stated that the agent mind is where agents apply their moralistic value system, form relationships, appraise the world, and autonomously carry out courses of action. The value system oversees all of this and also regulates level of attending to internal needs. These needs are governed by performance moderator functions (PMFs). A PMF is a micro-model covering how human performance (e.g. perception, memory, or decision-making) might vary as a function of a single factor (e.g. hunger, need for sleep, injury, event stress, time pressure, grievance, and so on). PMFserv culls from the literature dozens of best available PMFs and synthesizes them within a unifying framework and thereby offers a family of models where micro-decisions lead to the emergence of macro-behaviors within an individual. PMFserv includes a plugin architecture that facilitates turning on and off different models and trying new ones. An intel agency, for instance, sponsored us (2000-2005) to implement part of their leader profiling methodology inside of PMFserv. There are too many models to review them all here, but we will sample a few of them.

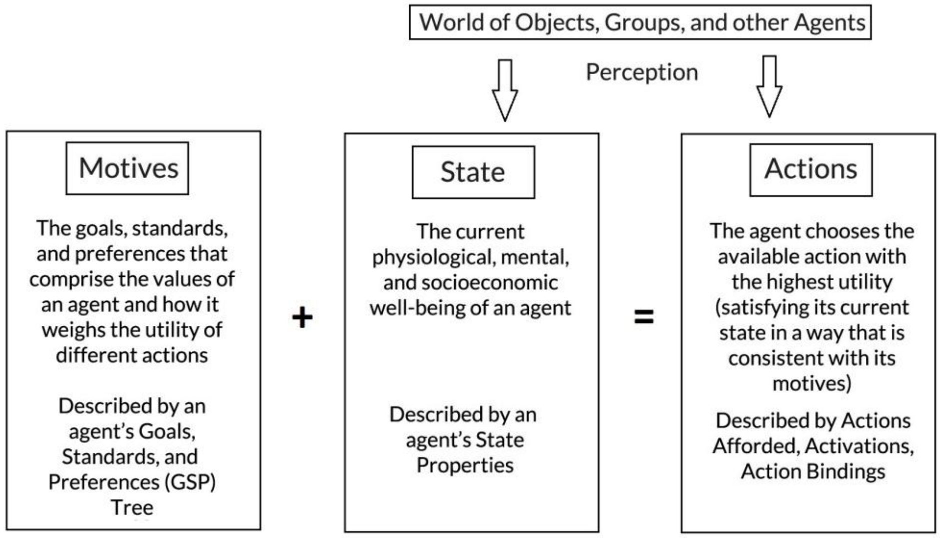

Figure 1: Framework of agent behavior in PMFserv

As an example of just the cognitive appraisal loop, let us examine some agents representing different populations in a large urban setting. The primary components of this framework are Motives, State, and Actions as summarized in Figure 1 and explained in what follows.

Agent motives. In cognitive appraisal, an agent's motives arise based on its value system (Ortony et al., 1990). In PMFserv, this is implemented as Goals, Standards, and Preferences (GSP) Trees, which specify a value system that is based on multiattribute utility theory and Bayesian probability mathematics. In this context, utility refers to the non-monetary measure of satisfaction one derives from various outcomes or situations. These utilities are multi-attribute, meaning that there are several attributes or values (hence, the use of a tree) that are considered when evaluating the utility of a certain outcome. In this case, we embellish the GSP trees with factors from Salutogenesis and Theory of Reasoned Action. Finally, the use of Bayesian mathematics allows a frequency distribution of the past choices of an agent to define the relative important of each branch of the value system to the agent. An example of a portion of such a value system for a cognitive agent is presented in Table 1. There we see that **goals** are the near-term events that an agent wants to happen, **standards** are the socially and morally-imposed guidelines for behavior, and **preferences** are the ideals about the long-term and the desired state of the world. In order to drive its own behavior, an agent evaluates these three dimensions to assess the utility of any potential action it could take as well as those taken by other agents. For instance, an agent with a “negative” patient archetype value system described by Table 1 is apathetic and short term gratification-oriented. It also believes its choices have little impact on outcomes (perceived control) and it views itself as generally ineffective (low efficacy). In the future, we plan to research the branches more fully in terms of what defines a relevant range of patient behaviors, and then based on actual patient histories; we will try to derive important agent archetypes or personas in terms of specific values we assign to each node in a GSP Tree for that personality.

Goals	
Esteem	0.20
Love and belonging	0.20
Physiology	0.30
Safety	0.30
Total	1.00

Standards		
Compliance	0.30	
Gratification horizon	0.30	
Long term		*0.10*
Short term		*0.90*
Perceived control	0.40	
Irrelevant Choices		*0.90*
Perceived Control		*0.10*
Total	1.00	

Preferences		
Instrumentality	0.50	
High efficacy		*0.10*
Low efficacy		*0.90*
Satisfaction	0.50	
Apathetic		*0.90*
Engaged		*0.10*
Total	1.00	

Table 1: Example of Value System for a cognitive agent for a negative patient archetype (based on research by Samuel Lim with inputs from R.Trotta, M. Mikolajczyk)

Agent state properties. In the current prototype, the well-being of an agent is described along three dimensions: their physiological, mental, and socioeconomic state. Each of these three dimensions contains numerous metrics, called state properties, each of which describes a different aspect of the state of an agent. Table 2 shows the state properties that an agent representing a mental health patient in the current version. These states are variously computed by dynamical models in the agent (e.g. hunger, stress, mood), and models and rule sets external to an agent (e.g. employment opportunities, injuries, and social support). Some states are set as initial variables that might be changed stochastically over time (e.g. income, living conditions, psychotic intensity).

A. Physiologic state Properties

State Properties	Description
Fatigue	Level of physical exhaustion
Hunger	Level of hunger and malnutrition
Stress	Level of anxiety and social pressure
Bodily Injury	Amount of personal injury sustained

B. Mental state Properties

State Properties	Description
Psychotic Intensity	Intensity of paranoia and delusions
Mood	Level of depression or anger
Personality	Ability to deal with stress
Substances	Level of influence or withdrawal

C. Socioeconomic state Properties

State Properties	Description
Employment Status	How an individual is employed (if at all) and how they support themselves economically
Living Conditions	Where an individual lives and what kind of atmosphere does it provide
Income (Monthly)	Amount of income an individual is able to spend
Social Support	Amount of support (emotionally and economically) an individual receives from friends and family

Table 2: Categories of state properties in an agent

Organizational Level: StateSim

This toolset introduces a model of a state (or cross state or sub-state) region including all the important organizations, the relevant portions of government and its institutional services, economic and security conditions, political processes, domestic practices and external influences. StateSim adds plugins and models atop FactionSim including a population model, economic services models, and the actual institutional agencies that allocate public goods and services (or not) to the factions in that region of interest. StateSim was originally built for three DARPA programs. To date, it has been applied in Afghanistan, Iraq, Palestine, Africa, Sri Lanka, Bangladesh, Thailand, and the Koreas (as well as for UK soccer hooligans and USA crowds) to model (forecast) emergence of state instabilities (insurgency, rebellion, domestic political violence, repression, etc.) which are macro-behaviors that emerge from the micro-decisions of all the participants, including the diverse leaders and followers. In tests run during 2010, DARPA indicated StateSim was better than 80% accurate in over 240 backcast trials they put it through. One can use this model to experiment on and study operations that might influence a region's instabilities and to assess the primary, secondary, and tertiary effects of different courses of action on the stakeholder groups and actors. In an extension for the Army in 2011-12, we scaled up this capability so that StateSim now also includes a module that permits many 10,000s of less-cognitive, follower agents. These exist in networks that carry out the workflows of their daily lives. They also execute the cognitive leader agents' courses of action decisions in a spatial and temporally realistic fashion.

The goal of our analysis is to utilize StateSim to represent the behavioral health care services of a community in a large urban setting, though it also minimally portrays other governmental and non-governmental services (e.g. police, courts and justice system, private hospitals, social service agencies, places of employment, and so on) that might impact the lives of the individuals being modeled. Briefly, in terms of Medicaid healthcare services, *Pre-Admission* represents the periods when individuals do not interact with hospitals or psychiatric resources. Depending on the status of income level and mental stability, individuals will attend regular checkups or take prescribed medicine. *Admission* to a hospital requires physician approval and physicians are accessed in many different ways. Health providers attending patients, policemen, and family or significant others may present patients to a hospital for a physician evaluation. Individuals can also present themselves for a hospital admission. In some cases, individuals seek hospital admission for shelter and meals for the night, or "three hots and a cot," an inefficiency for hospitals. This leads to *Assessment*, or the different ways patients are redirected to receive the care they need. Inpatient *Treatment* or services can be divided into four general categories: ER/Intensive Care – immediate care is required; Acute Treatment – urgent, short-term treatment required; Sub-acute Treatment – in between acute and chronic treatment; slightly urgent, medium-term treatment required; 24-Hour Bed – patient is provided with food, bed and is released following day. The *outpatient* stage is crucial in assessing relapse rates, which are, as noted above, very high in Philadelphia.

An important capability of this tool is that it captures, represents, and runs the workflow of individual agents in all of the groups and organizations one is interested in modeling. In the current prototype, we authored 43 workflows for the residents' daily life activities (e.g. sleep/wake up, get dressed, take medication, do errands, etc.) and for workers in such as those in Hospitals, Homeless Shelters, and Jails. Each of these workflows involve steps that the agent must take, participant roles that must be filled and carried out for the workflow to succeed, various inputs/resources that get consumed (e.g. facilities, space, medicines, supplies, equipment, and so on), and specific outputs or outcome possibilities.

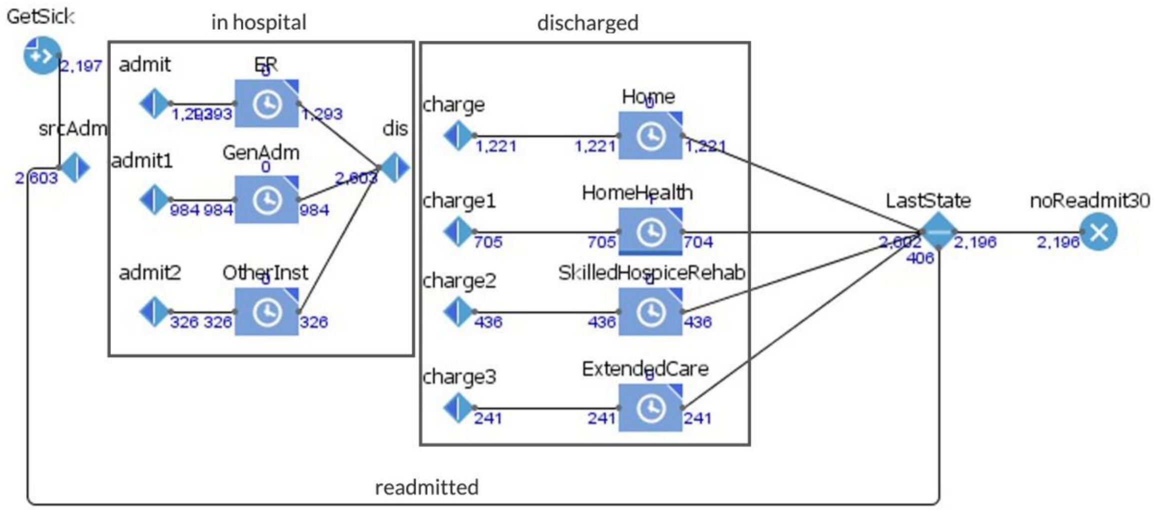

Figure 2: High-level view of patient daily life/health activities for the baseline scenario

Societal Level: StateSim

This level of PMFserv adds in a model of the social and organizational roles that exist in a community of interest (e.g., multi-state, state, sub-state, or region/neighborhood) and that may be played by the PMFserv agents. Developed under a 3 year grant from AFOSR, FactionSim implements a number of recognized scientific theories from sociology (mobilization, leader-follower theories, motivational congruence, social norms, etc) and political-economy (developmental economics). To apply it to a region, one adds neighborhood factors; activities of home, social, and work life; the role of added institutions; and public/private goods and services. We use this technology in the ABMS to model neighborhood issues, living arrangements (housing quality, safety, support), income, payments, and so on.

In our urban community mental health case study, we organized the groups according to the widely used four-quadrant clinical integration model (Bartels, 2004). The groups categorize those who have low mental and physical health problems (Quandrant I), high mental health problems and low physical health problems (Quandrant II); low mental health and high physical health problems (Quandrant III); and, high mental and physical health problems (Quandrant IV). Thus, individuals in Quadrants I& II function well with few medical and mental health problems; in contrast to those who have greater functional limitations from physical health problems with high mental health comorbidities—Quadrant III or greater functional limitations from mental health problems with high medical comorbidities—Quadrant IV. Individuals categorized in Quadrant III & IV often have major social needs due to poverty, unemployment, unstable housing. These people are often insured by Medicaid or Medicare or both. The population with serious mental illness (SMI) and comorbid medical problems represents one of the most complex social problems for public health administrators. Druss, Zhao, Cummings, Shim, Rust, and Marcus (2012) show that two thirds of people with SMI do not access timely physical or mental health care and do not receive adequate treatment.

Causes and consequences of wellbeing are woven in a complex web of social–cultural–technological conditions and associated human decisions. For instance, belonging to a group (quadrant), sets up social norms such as what such a member is expected to be capable of performing. However, behavior is tempered by a number of other factors as well. For example, do they have family supports and live in a safe area? Or are they living in dangerous neighborhoods where they might be preyed upon resulting in loss of their payment checks and medications, or exposed to drug dealers and become dependent on substances. The agent state properties are also used to capture and represent further variability such as, among other factors: acuity and risks of disease levels in each quadrant, age, income, gender, race, migrant status, social support system, and social class.

Data and Privacy Constraints for ABMS in Mental Health Modeling Applications

This chapter has shown the data points needed for designing agent-based models. However, there are a number of challenges to obtaining data useful for such analyses. The federal Health Insurance Portability and Accountability Act (HIPAA) protects health information privacy and requires de-identification of data prior to release to researchers. The de-identification process involves removing 18 types of identifiers, including geographic information, such as city, county, and precinct, as well as date elements (except year), including admission and discharge dates. The strength of agent-based models comes from being able to simulate individuals in their local environments. Models utilizing de-identified data cannot be truly correlated with any geographic information system data, thus limiting their value.

Data availability presents another challenge to agent-based modeling. In the case of our model, hospital readmission data was only available at the summary level, thus preventing us from conducting a regression analysis for comparison with the model results. Key risk factors associated with hospital readmissions, such as co-morbidity, ability to perform activities of daily living, socioeconomic status, and environment and support were also not available in publically available data sets.

In what follows, we review some ways that researchers might overcome some of these challenges and utilize data that are available from national and local sources.

National Data Sources. There are few national data sets dedicated for mental health. The following two data sets are the most comprehensive sources for mental health researchers:

National Survey on Drug Use and Health (NSDUH). This survey, sponsored by the Substance Abuse and Mental Health Services Administration (SAMHSA) and U.S. Department of Health and Human Services, constitutes the primary source of data on the use of illicit drugs, alcohol, and mental health. The target population for this survey is non-institutionalized civilians, 12 years old or older. Homeless persons, active duty military personnel, residents of institutional group quarters, such as jails and hospitals, are excluded. For the 2013 survey, 160,325 addresses were screened and approximately 67,500 interviews were completed. All data has been de-identified (United States Department of Health and Human Services Substance Abuse and Mental Health Services Administration Center for Behavioral Health Statistics, and Quality, 2014). In our case study, detailed in the Example Application section below, the NDUHS data set measures for SMI related to functional status and safety were derived from survey data from 2012.

Local data sources. National data sets do not contain all the data needed for constructing agent-based models, especially those that seek to model SMI. Other potential sources of data include local health systems databases. However, due to privacy and HIPAA constraints, the utility of this data for modeling is limited as well. Consider these examples:

Penn data warehouse. The University of Pennsylvania Health System hosts a data warehouse that contains clinical and encounter data. Data on patient demographics, encounter/visits, diagnosis and procedures, and medical history are available in de-identified form. A recent study by Hanrahan et al., utilized this data to examine the impact of SMI on all-cause hospital readmissions. The authors constructed a variable for SMI by using a 12-month look-back from index hospitalization and patients who had a comorbid psychiatric diagnosis. The final sample yielded 70,858 without SMI and 3,221 patients with SMI. This is useful for examining SMI vs non-SMI readmission differences, and this was the source of the statistics cited in the case in Sect. 4. However, due to de-identification, there is no easy way to equate these patients to the further data available about SMI individuals in the national datasets above.

U.S. census and geographic information systems (GIS) data. One can obtain US Census Bureau data for 2010. Geocoded data cannot be matched directly with de-identified data, so one must make inferences about census tract and block group that a de-identified patient might live at. GeoLytics, a public provider and repackager of US Census Bureau data (10 year census, annual American Community Survey, ACS, etc). The data that one could obtain from GeoLytics at the block-group level is the Census 2010, the American Community survey (ACS) 2010 and 2011 (and newer ones as they come out). With a lot of work and effort, one could possibly compute block averages for data elements, such as form of income, race/ethnicity, total population, poverty, age, sex, occupation, language isolation, immigration, labor force participation, home structure type, structure age, expenditures, educational attainment, ability to speak English, health insurance coverage, time leaving home to go to work, travel time to work, poverty status, school enrollment and type of school, social security income, journey to work, facilities, homeowner vacancy rates, mortgage status. These summary stats could then be linked with the local patient data in an effort to further understand the impact of living environment, SES status, and neighborhood on readmissions of SMI vs non-SMI individuals.

Example Application

In this section, we present a prototype that illustrates both of these issues – construction and data. The goal of this example application was to explore factors affecting readmission rates of patients with SMI compared to patients without a SMI. In order to bridge disconnects between the national and local datasets, de-identified patient archetypes are identified. One patient archetype represents the population with SMI and the other archetype, no SMI. We used the University of Pennsylvania Hospital System dataset from 2011-2013 to extract patient demographic and clinical data from 3 urban hospitals. We used this data to study patterns of rehospitalization, comparing 74,079 patients with and without an SMI (no SMI, n=71,080 and SMI, n=3,230).

National datasets contribute to understanding behaviors and intentions of these archetypes. For the sake of illustration, we took just two variables from the NDUHS data set for the prototype model: MHSUITRY (suicide attempt), a binary variable used to model safety; WHODASC2, which is the World Health Organization Disability Assessment Schedule (WHODAS) that covers 6 domains of functioning including cognition, mobility, self-care, getting along, life activities, and participation. We use these as proxies for safety and instrumentality, which represent the goals and preferences categories, respectively, in the agents' motivational structure (Table 1). The database provides different probability distributions for these two properties depending on the two sample populations (SMI or no SMI), each of size greater than 35,000.

The application of this input in each layer of the model is summarized in descriptions below at the individual, organizational, and population level.

Agent/Individual Modeling

The model of the individual profiles lifestyle and compliance behaviors that lead to being at home, in the hospital, in the process of discharge, or "NoReadmit30," which in the simulation represents that the patient will not be readmitted within the next 30 days. According to the TRA an individual is at higher risk for return to the hospital if decisions about adherence to medication, diet, and exercise are poorly managed. For instance, a patient may have short-term goals and low adherence level under standards (Table 1), making the patient at higher risk for readmission. As already mentioned, based on the NSDUH, we were able to derive a probability distribution of safety and instrumentality and apply these to the two archetypes to inform this model.

Organization Modeling

The model on the organizational level is the work flow diagram presented earlier (Figure 2) of discrete event processes which include: (1) admittance to the hospital through the ER, General Admission, or Other Institutions, (2) discharge to Home, Home with Health or home with care, a skilled nursing facility, hospice, or rehab, and extended care. And (3), after being discharged to a center or staying at home for 30 days, an agent either leaves the system ("NoReadmit30") or may be readmitted. The time spent in each node and the likelihood of going to one of the others has been derived as frequencies or probability distributions corresponding to statistics taken from the 3 local hospitals data. For example, admittance to the hospital through the ER, General Admission, or Other Institutions relies on randomization using these distributions. The emergency department is the top source of 61.52% of admission sources for patients with SMI, while routine admits is the major source of 48.42% of patients without SMI. Likewise, length of stay in any of the hospital or other care facilities and discharge destination relies on similar distributions. In a future version, these could be informed by decision criterion that a model user inputs and rely on agent parameters like socio-economic status, age, illness severity, co-morbidities, functioning, and environment.

Population Modeling

Lastly, at the population level the prototype integrates the individual and organizational layers by illustrating important statistics about readmission. These include the percentage of the population susceptible for readmission or in the hospital, 30 day readmission rates for agents with SMI or no SMI over time, and the average individual parameters for the readmitted population. The left most graph (Figure 3a) shows the ratio of patients who are at home at that time of the simulation and therefore at risk for readmission compared with the population percentage currently in the hospital. The model outcome for readmission rates for the agents with SMI or no SMI, shown in Figure 3b, reasonably reflect the readmission averages for each group at approximately 17% and 11% respectively. Given the appropriate individual data input for a population's distributions, the model predicts with general accuracy the type of individuals who are readmitted. This statement is explained by an example in the following paragraph.

The next two graphs (Figures 3c & d) show the parameter levels for safety and instrumentality, respectively, of the agent population that gets readmitted. For instance, data that compares patients with or without SMI, a simulation run of 2,608 patients processed (among those 412 patients readmitted) shows an average functionality (WHODAS score) of patients readmitted at 10.15 and an average functionality of patients not readmitted at 8.81, and this difference is significant with p value 0.03 (see Figure 3d). Thus, the model reveals how differences in patient parameters—functionality—correlates with distinctions in readmission probability. Furthermore, because certain characteristics like poverty (using Medicaid insurance status as a proxy) can be correlated with patients with SMI, the model predicts whether those characteristics are correlated with readmission. These live-feed graphs (Figure 3), captured during a simulation, provide insights into the hospitalization process and time-correlated statistics that previous statistical analysis do not.

Figure 3: Population analysis graph

An important limitation is that the data used in these models did not have a high level of specificity. Additionally, we provide only one example of how parameters are tested. As we develop the models and add more specific metrics at the individual, organization, and population level, our ABMS becomes more sensitive and accurate.

Future prospects

The multi-tiered framework we used readily supports fuller modeling of patient physiology, cognition, and socio-economic determinants, as well as the workflows and caregiving of providers. Adding depth into these dimensions will allow fuller assessment of interventions and their impacts. Further research is thus warranted to add flesh to the component models. As one example, the underlying PMFserv agent framework allows one to replace the physiologic state properties with a model of physiologic dynamics. Also, we hope to extend agent cognition to the point where they use individualized value trees (goals, standards, and preferences, or GSPs) as described in the section describing model tools. Indeed, this is consistent with the theory of reasoned action (Fishbein & Ajzen, 1975), which presumes that people’s behavioral intention are based on their attitudes about that particular behavior and the current subjective norms based on societal influence. PMFserv supports quantifying of attitudes via the GSP approach, though we are interested in adopting more formal instruments for profiling these in the future. As to the social norms, the current prototype clusters agents into heterogeneous categories based on disease type, severity quadrants, and social property levels (family support, neighborhood, lifestyle). The underlying agent models exist for dynamically modeling activities of daily life. Adding all these models to a future version would more fully inform the analysis and be more useful for assessing the impact of interventions.

Conclusion

This chapter presents a roadmap to using ABMS and three level architecture to overcome the limitation of black box modeling (e.g. regression based). We have demonstrated the use ABMS using three levels of models of the health of a community – the individual population members, the healthcare "system" including the various practices and services that comprise its "parts", and the overall "containing society". The first and last are critical since the decision making of individuals in the population and societal determinants are the primary drivers of living well. ABMS supports decisions about and management of SMI facilities and care decisions. The section on tools for multi-tiered modeling (A Toolbox for Multi-layer Modeling of Social Systems) outlined the types of parameters that would help in the construction of such models, while the Data and Privacy Constraints section delineated a number of privacy related obstacles to getting the data to parameterize those models.

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