THE INFLUENCE OF PAIN SELF-MANAGEMENT EDUCATION ON THE PREVALENCE OF OPIOID PRESCRIPTION AMONG PATIENTS WITH CHRONIC NON-CANCER PAIN: AN AGENT-BASED MODELING SIMULATION

by

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DEDICATION

To my parents Simeon and Veronica Ajala, to my spouse Olusola; and my children Daniel, Joshua and Moyosore

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ABSTRACT

Chronic pain has no cure. It is a lifelong condition presenting a growing concern due to its high occurrence and effects on every facet of life. It cost about $635 billion each year in medical treatment and lost productivity (IOM, 2011). The management of chronic pain using prescription painkiller opioids has increased drastically in the last two decades, leading to a consequential increase in deaths from chronic opioid use. This Plan-Do-Study-Act quality improvement project investigates the problem of the prevalence of opioid prescription using agent-based computational modeling method.

The simulation models the interaction of 50 patient-agents with pain self-management messages in an episode of 50 patient iterations (visits) for 10 simulated years. This interaction generates health benefit and risk outcomes represented by wellness data obtained when messages are processed. As the simulation runs, data are dynamically captured and visualized using wellness charts, time series plots, and benefit and risk regression plots.

The result of the project provides evidence for research and practice on the process of achieving more impact of programs based on administering pain self-management education to patients with chronic non-cancer pain who are currently on opioid therapy and on the process of customizing interventions that might take advantage of the conditions of behavior change driven by pain self-management messages. The tools and the evidences in this project are highly recommended to nurse practitioners primary care providers involve with providing care to the vulnerable groups of patient with chronic non-cancer pain. These evidences might inform the formation of self-management interventions that might lead to a decline in opioid use and prescription and accelerate the acceptance of self-management practices.

CHAPTER 1: INTRODUCTION

Chronic pain presents as a worldwide public health challenge due to its high prevalence and effects on every facet of life. It cost about $635 billion each year in medical treatment and lost productivity (IOM, 2011). There is a continual search for improvement and new treatment modalities in the management of chronic pain. Managing chronic non-cancer pain with chronic opioid therapy has increased drastically in the last two decades, leading to a consequential increase in deaths from chronic opioid use (Sullivan et al., 2008). Based on Center for Disease Control and Prevention (CDC, 2014) data, 46 people die each day in the United States from overdose of prescription painkiller opioids. The use of opioids as a therapy for the management of chronic non-cancer pain, together with the growing number of deaths due to opioid overdose, has become a national health problem. Helping patients with chronic pain achieve wellness has become critical and necessitates the use of evidenced-based interventions in quality improvement projects.

This paper presents a Plan-Do-Study-Act (PDSA) quality improvement project that utilized agent-based computational modeling to simulate the influence of pain self-management education on behavioral change. The simulation exposed 50 patient-agents, each with 50 iteration/visits for over a 10-year period. The simulation utilized computing power and data analysis to understand the impact of health care interventions without costly and time-consuming direct experimentation to anticipate the effects of pain self-management education on chronic opioid usersô choice of continual use or shift to self-management practices. The project studied the influence of pain self-management education on the prevalence of opioid use among patients with chronic non-cancer pain on long-term opioid therapy.

Chronic pain is a lifelong condition with no cure. Therefore, like other chronic disease conditions a long-term plan is required. Self-management is a lifelong task involving daily management of the impact of a condition (Lorig & Holman, 2003). Self-management has become a vital tool in managing chronic conditions because it designates the patient as an active participant in treatment, equipped with the ability to appraise the situation and resources, and to determine the course of action (Lorig & Holman, 2003). Self-management involves a collaborative care approach that enables a patient to acquire skills, confidence and tools to manage his or her condition, and routinely assess problems and accomplishments (Bodenheimer, Lorig, Holman, & Grumbach, 2002). Collaborative care is the integration of physical and behavioral health services, with health-care providers working together with the patient to provide comprehensive care and create a wide range of self-management training and services (Von Korff, Gruman, Schaefer, Curry, & Wagner, 1997).

Education has become a great platform to promote disease self-management. Although traditional patient education provides patients with information and technical skills, self-management education provides patients with skills in domains such as, problem-solving, decision making, taking actions, resource utilization, and establishing a therapeutic patient-provider relationship (Lorig & Holman, 2003).

The purpose of this quality improvement project is to examine the influence of pain self-management education on the reduction in the prevalence of opioid prescription among patients with chronic non-cancer pain on long-term opioid therapy. The efficacy of self-management interventions on reducing pain is supported by evidence-based research (Lorig et al., 1999; Lorig, Hobbs et al., 2001; Lorig, Ritter et al., 2001; Lorig, Sobel et al., 1999; Ory et al., 2014).

Although the efficacy of self-management education interventions has been widely documented, there is limited research to show the efficacy of such interventions in reducing opioid use among patients with chronic non-cancer pain on long-term opioid therapy. Thus, this project explored the reduction in opioid use among the participants exposed to pain self-management education.

Education interventions can be adapted using modern technology to foster patient empowerment for self-management. For this reason, this project explored the influence of participation in pain self-management education on the prevalence opioid prescription using computerized agent modeling simulation technology rather than using real patients. Agent-based modeling (ABM) is a form of computational simulation that has been used to understand complex social processes and dynamics (Gilbert & Troitzsch, 1999).

In an agent-based modeling simulation, the researcher builds an artificial environment that typifies a real-life scenario, and then observes the consequences of manipulating key input variables on attitude and behavior outcomes (Gilbert & Troitzsch, 1999). ABM involves building computer programs known as agents that are programmed to react to a computational environment, interact with each other, or both through information messaging (Gilbert, 2008). The use of ABM eliminates ethical problems that maybe encountered using humans (Gilbert, 2008). ABM has proven useful in understanding interactions between processes and evolving behavior (Bonabeus, 2002; Epstein, 2002; Hegselman, 1996; Macy & Willer, 2002; Penzar & Srbljinovic, 2004). ABM applications in health and related fields have been documented in multiple literature reviews (Barnes, Golden, & Price, 2013; Bruch & Atwell, 2015; Luke & Stamatakis, 2012; Maglio & Mabry, 2011).

This project utilized agent-based modeling simulation because social behaviors are sometimes convoluted and emergent in nature. Thus, understanding the outcome of an education intervention on behavioral changes requires multiple and incremental stages of research. The Institute of Medicine (IOM, 2010) reported on the role of measurement in action and accountability and proposed that the U.S. Department of Health and Human Services (HHS) should use modeling to evaluate intended and unintended outcomes associated with policy, funding, investment, and resources options; as well as to advance the use of predictive and system-based simulation to understand health consequences or underlying determinants of health (IOM, 2010). Computer simulation can help test what might emerge as a probable condition of behavior change in the reduction of the use of opioids in situations that might present ethical difficulties for conducting real-world research. Furthermore, a computer can act as a medium of experience and as a social actor (Fogg, 2003).

This project used computer simulation as an exploratory research methodology to examine whether patient-agents elaborate on the messages of the self-management education intervention without counter-arguing; this response was determined by a change of behavior (Hovland & Weiss, 1951). Hovland and Weiss (1951) described a message as information content that addresses the recipientsô counter-argumentation stances. Messages are the essence of persuasive information. The details of the message formulation are subsequently discussed under the conceptual framework. In this project, pain self-management education is formulated as messages. These messages are transformed into rules and then coded in forms that the computer program can work with.

Background

Reduction of opioid use and opioid safety has become a mandate for this researcher and other healthcare providers at the Veteransô health care system, with the national goal set at 60% in 2015, and the researcher health care facility performance was below the expectation. There is high prevalence of inappropriate use of opioid medications, due to various reasons, including inappropriate prescription of opioids over a long period of time, systemic failure to regulate use and patient preconceived ideas and misconceptions about pain management. Therefore, there is a need for a culture change among providers and patients. There have been various system wide approaches to combat this endemic problem. However, there is the absence of a structured patient education approach or a system-wide method to provide pain education.

Communicating effectively with patients with chronic pain is very challenging for health care providers (Whitten, Evans & Cristobal, 2005). There is great provider variability and inconsistency with any standard measure of effectiveness of such pain education. Education is very pertinent to decrease the potential of opioids overuse, abuse, adverse effects, and opioid prescription escalations. This PDSA improvement project attempts to provide insight and direction for change from the status quo through pain self-management education.

Research Question

How does pain self-management education influence the prevalence of opioid prescriptions in a simulated agent-based model?

Objectives

The following are the specific aims of this quality improvement project:

1. Provide pain self-management education (messages) to simulated patient-agents with chronic non-cancer pain who are currently on opioid therapy.
2. Evaluate whether pain self-management education (messages) leads to changes in self - management behaviors of simulated patient-agents.
3. Evaluate whether this behavior change leads to a decline in opioid prescriptions from providers to simulated patient-agents.

To realize the first objective of providing pain self-management education, pain educational materials were transformed into messages format (as described in the conceptual model). The second objective of evaluating whether the messages led to changes in self -management behaviors was achieved by attaching a weight value to each message to reflect the patientǿs wellness. Wellness was operationalized as the worth of the current state of health of the patient. Fitness was operationalized as the worth of the total state of health for a period of time. Wellness values were used to determine a fitness value.

Patient-agents adapt and improve their wellness by seeking and choosing messages with higher fitness values, having considered the risk of adverse effects of therapy. After observing the interaction of patient-agent with the messages, data collected showed the expected average health wellness, an impact of pain self-management education on patient-agent population currently on opioid therapy. The last objective of evaluating whether the behavior change led to a decline in opioid prescriptions was realized by observing the benefit and risk charts that showed the accrued individual health benefit and the accrued risk incurred in the use of opioids over time.

Significance

Opioid prescriptions have escalated to dangerous levels that pose a concern to the clinicians and the general public. About 90-95% of long-term opioid therapy is prescribed for non-cancer pain and about 3% of the general U.S. population without cancer use opioids regularly for at least one month per year (Sullivan, Edlund, Steffick, & Unutzer, 2005). The increase in the trend of opioid prescriptions does not correspond with new evidence of the efficacy of long-term opioid therapy (Sullivan et al., 2008). Rather, opioid overdoses have increased the mortality rate from opioids to 46 deaths each day (CDC, 2014). One of the suggested methods to reduce opioid prescriptions is providing education to patients (HHS, 2014). However, there were few studies that explore whether this method actually produced the desired effect. Thus, this study provided self-management education and evaluated whether educational messages led to behavioral changes in the self-management practices of patients with chronic non-cancer pain and decline in opioid prescription.

Definitions of Key Terms and Concepts

1. Chronic non-cancer pain, or complex pain, can be defined as pain that is caused by injury, disease, or an unknown cause, that persists longer than 3 to 6 months after injury and has treatment goal of improving quality of life and physical functioning (International Association for the Study of Pain IASP, 2014). Examples of chronic non-cancer pain conditions include: chronic musculoskeletal pain such as neck, shoulder, and back pain; fibromyalgia; whiplash injuries; chronic regional pain syndromes; repetitive

strain injury; chronic pelvic pain; post-surgical pain lasting beyond 6 months; neuropathic pain; neuralgias such as post-herpetic pain and trigeminal neuralgia; and post-stroke and central pain (IASP, 2014). For this project, chronic non-cancer pain also included conditions such as persistent headaches, Crohn's disease, irritable bowel syndrome, diabetic neuropathy, interstitial cystitis, and severe muscular pain due to multiple sclerosis.

2. Agent-based modeling is a form of computational simulation whereby one creates a computer program in which the actors are represented by segments of program codes and then one runs the program, observing what it does over the course of simulated time after a direct communication has occurred between the actors being modeled (patients with chronic non-cancer pain) and the agents in the program (pain self-management education messages) (Gilbert, 2008).
3. Opioids are chemicals that contain morphine or its derivatives and exert pharmacological effects of relieving pain. They reduce the intensity of pain signals by binding to opioid receptors, in the nervous system and gastrointestinal tracts, mediating beneficial, psychoactive, and adverse effects of opioids (IASP, 2014). Classes of drugs include hydrocodone (e.g., Vicodin, Lortab, Norco), oxycodone (e.g., OxyContin, Percocet), morphine (e.g., Kadian, Avinza), codeine, and related drugs (IASP, 2014).
4. Self-management refers to daily decisions about medications, lifestyle, exercises, stress management, and other actions that have significant influence on health and functioning (Lorig & Holman, 2003). Self-management helps patients take control of their lives, which can lead to reductions in pain (Lorig & Holman, 2003). Self-management

programs such as educational interventions can lead to changes in behaviors, health-care status, and health-care utilization (Lorig & Holman, 2003).

5. Wellness is a measure of a value accrued as a result of processing of pain self-management education messages by the patient-agent. Average Wellness is an average of sum of all current wellness of the patient-agents divided by the number of patient-agents (50). Average wellness is determined by the impact of the pain self-management education message on each patient-agent. Wellness parameters include therapy-benefit and therapy-risk, and a higher wellness value indicates a pain self-management education message that conforms to a stronger persuasion. Upon exposure to pain self-management message, each patient-agent has a current wellness value which is calculated using the fitness function in the Netlogo (agent-based modeling software). The value of wellness of individual patient-agent over time is referred to as wellness timeseries.
6. The therapy-risk is the anticipated risk associated with each of the pain self-management education messages. It is the risk quantity associated with each message.
7. The therapy-benefit is a weighted quantity that values the long-term wellness expected from a processed pain self-management education message. It is the benefit quantity associated with each message.
8. The fitness function describes the mathematical expression of the agent-based pain management model. The fitness function is the expression acquired from processing the pain self-management education messages and it is calculated from a patient-agent current wellness, current therapy-benefit and therapy-risk per visit (iteration), as indicated by the patch (pain messages as it appeared on the Netlogo) that the patient-agent is

currently located. The fitness function is expressed in wellness units and it is calculated by the computer. Further descriptions of terms related to the agent-based pain management model are provided in the methodology in chapter three.

Summary

The PDSA quality improvement project utilized an agent-based computational modeling simulation to examine the influence of pain self-management education on the prevalence of opioid prescription among patients with chronic non-cancer pain; and answered the research question regarding whether pain self-management education reduced the prevalence of opioid prescriptions in simulated agents. The simulations exposed 50 patient-agents to messages formulated from pain self-management education for 50 iterations (visits) and simulate behavior changes toward reducing opioids and accepting self-management practices over a simulated period of 10 years. This project prepared a platform for developing clinical practice guidelines for management of chronic non-cancer pain for nurse practitioners.

CHAPTER 2: LITERATURE REVIEW

The literature review presents the results of the literature search that was conducted based on the themes of the research question, which are chronic pain, opioid prescription, self-management education, and the methodology of inquiry, which was agent-based modeling simulation (ABM).

Agent-Based Modeling Simulation

Agent-based modeling (ABM) is one of the three dynamic simulation modeling methods that have been found suitable for healthcare delivery research and interventions; others are discrete event simulation (DES) and system dynamics (SD) (Luke & Stamatakis, 2012). Generally, dynamic simulation modeling methods create mathematical representations of the operations for experimentation to determine effects and advance the understanding of the systems, and influence policies (Sokolowski & Banks, 2011). To differentiate among these three methods, the characteristic feature of ABM is an interaction of its autonomous agents. As a result, ABM is commonly used to model individual decision-making and behavior (Bonabeau, 2002). The more active the object (e.g., people, vehicles & products), the more suitable ABM will apply as a modeling technique (Bonabeau, 2002). Agent-based modeling originated in computer science and it uses algorithms, rule-based formulations, deductive and inductive reasoning (Bonabeau, 2002).

According to Gilbert (2008), ñAgent-based modeling is a computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environmentò (p. 2) ABM is a computer simulation method for modeling ñdynamic processes, adaptive systems and autonomous agentsò (Macal & North, 2014; Marshall et al., 2015a, p. 148). Dynamics indicate that the agents and their environment can change, develop, or evolve over time. Adaptive systems explain how agent interaction exists in structures such as clusters of people in certain locations based on predefined behaviors. Autonomous agents represent objects or individuals such as patients, providers, and staff (Marshall et al., 2015b). Agents are placed in an environment and are allowed to interact with their environment and each other according to common rule-set and emergent behavior (Day et al., 2014). These agents can move through space and time and interact with each other, learn and disseminate new learning to other agents in their social network (Day et al., 2014). Health care delivery consists of multiple complex and fragmented social systems and should adapt to environmental changes and respond to emergent behaviors (Marshall et al., 2015a). The complexity of health-care systems, challenges the stakeholders to evaluate interventions that can improve the effectiveness and efficiency of care delivery (Marshall et al., 2015a). This made ABM an appropriate tool to evaluate health care interventions.

ABM appears to be used widely in studying complex phenomena in social and behavioral sciences (Luke & Stamatakis, 2012; Sawyer, 2005). In ABM, an artificial environment that represents a simplified version of real world interest is created, and the consequences of manipulating key input variables on attitude and behavior outputs are recorded (Gilbert, 1999). It examines the processes underpinning relationships, and the mechanisms through which relationships are generated and outcomes predicted (Hughes et al., 2012). For example, emotions and beliefs of an agent in a simulated world such as fear and grievances can be manipulated; this may not be possible in a real world for ethical reasons (Gorman et al., 2006). Mechanisms through which agent relationships are generated include soup, grid, lattice, 2D/3D space, GIS and networks (Macal & North, 2014).

Agent-based simulation has been found to be effective when there are ethical concerns in conducting real-world research, for testing holistic applications to solve problems in complex systems, examining the impact of change on behavior, and serving as an interactive training tool (Hughes, Clegg, Chris, Robinson, & Crowder, 2012). Wooldridge and Jennings (1995) proposed ABM might be used to study how processes affect outcomes by creating agents (e.g., individuals with chronic non-cancer pain) with adaptive decision rules (e.g., self-management education).

The advantages of agent-based modeling stimulation are that it allows for the development of individual-level rules of behavior, captures demographic heterogeneity, enables agent interactions, facilitates the modeling of disease progression, and generates results that are natural representation of a population, which can be synthesized and aggregated to define and understand outcomes (Gilbert, 2008; Macal & North, 2010; Rahmandad & Sterman, 2008; Siebers, Macal, Garnett, Buxton, & Pidd, 2010). Sensitivity analyses demonstrate the usefulness of interpretation of ABM results (Marshall et al., 2015a). These sensitivity analyses enable ñthe modeler to test a range of assumptions about human behavior, how people learn, how they disseminate information to their peers or families and how they change their behavior in response to new information, incentives, or penaltiesò (Marshall et al., 2015a, p. 151). It can address problems that involve both deterministic and probability distribution (stochastic) (Marshall et al., 2015a).

ABM has been used to effectively model population health, large-scale natural disasters, infectious disease outbreaks, public health planning and policy needs, and health-care delivery interventions (Marshall et al., 2015a). ABM provides the opportunity to test assumptions and plan for interventions; anticipate effects in different scenarios and interventions such as disease prevention programs and lifestyle interventions, and predicts the health of large populations over a period of time (Marshall et al., 2015b). It explores how agents respond to their social contexts (e.g., pain self-management education), how others around the agents act, and how the health-care system influences agents through persuasive mechanisms (Bonabeus, 2002).

This project used an agent-based computational modeling method to experiment with a pain management model created from a conceptual framework based on Hovlandôs and Elaborate Likelihood Model of Persuasion (ELM) theories (Hovland, Janis, & Kelley, 1953; Petty & Cacioppo 1984). Computer simulation modeling requires specialized skills in simulation modeling and building models based on mathematical structure. Sometimes the mathematical structures are difficult to communicate, and critics have associated this difficulty with communicating details of modeling to lack of transparency (Marshall et al., 2015b). However, these structures and sophisticated calculations are necessary to adequately represent the problem and obtain accurate result (Marshall et al., 2015b).

Computer simulation studies are relatively new to medical research. ABM has been used for modeling inflammatory response, granuloma formation in tuberculosis, immune response, epidemiological studies; predicting ophthalmic outcomes, and in the field of human behavior. Studies using agent-based modeling simulation to model health outcomes after exposure to self-management education on chronic pain were not found in literature search. However, six relevant agent-based model simulations research in health-care were identified and reviewed.

Li, Kong, Lawley and Pagan (2014) developed an ABM model for cardiovascular health and demonstrate the potential use of the model by assessing the impact of a set of hypothetical lifestyle programs on incidences of diabetes, MI and Stroke. The authors simulated CVD-related health behaviors and health factors of individuals and the emergent health outcomes and mortality for patients age 65 and above. They used a type of agent-based modeling known as the New York Academy of Medicine Cardiovascular Health Simulation model (NYAM-CHS) to evaluate what would happen to short-term and long-term health outcomes, if a primary care practice serving a population of insured patients over age 65 (Medicare-age population) implemented a lifestyle program to improve diet and exercise and reduce weight.

The study assessed the effects of five hypothetical lifestyle interventions that include quitting smoking, promoting healthy diet, improving physical activity, reducing obesity, and other comprehensive efforts aimed at reducing the number of people with diabetes, history of MI or stroke. The simulated population was generated based on the population characteristics obtained from the Behavioral Risk Factor Surveillance System (BRFSS), a nationally representative survey data. Each agent was described as an individual defined by age, gender, history of myocardial infarction (MI) or stroke and seven other behavioral and health factors classified by the American Heart Association: smoking, physical activity, healthy diet, healthy weight, cholesterol, blood pressure and blood glucose. They generated 10,000 hypothetical agents for each population group, and simulated the population for 5, 10, 15 and 20 years.

The results were compared across three key subpopulations of Medicare-age populations with diabetes, hypertension, and high cholesterol. They conducted binomial probability tests and also compared the simulated results with actual statistics estimated from the national survey data

BRFSS 2012 for three major health outcomes. The findings indicated that there were significant reductions in the population of Medicare-age patients with diabetes and high cholesterol for three and five years after implementation of the proposed lifestyle program but there was no significant reduction in the Medicare-age population with hypertension. The obesity intervention was shown to be a more effective intervention in preventing diabetes compared to promoting healthy diet and improving physical activity. The quit smoking intervention was more effective for reducing the incidence of MI and Stroke. The numerical results reveal that improving different behavior and health factors may have different impacts on health outcomes; this information becomes useful when allocating limited resources for disease prevention.

Day, Ravi, Xian, and Brugh (2014) examined the effects of changes to vision screening intervals on the incidence of vision loss in a simulated cohort of veterans with diabetic retinopathy. The authors combined agent-based modeling and discrete event simulation to conduct a simulated randomized controlled trail. As previously mentioned, the agent-based modeling simulation method provides the opportunity to examine potential interventions without putting patients at risk. A population of simulated veterans, using abstracted data from a retrospective cohort of real-world diabetic veterans, and a discrete-event simulation eye clinic where they seek treatment for diabetic retinopathy were used. Using various screening policies, a comparison of vision loss among 5000 simulated agents veterans over 50 independent 10-year simulations were conducted. They found that increasing the screening interval for diabetic patients who have not yet developed diabetic retinopathy from one to two years appears safe, whereas increasing the interval to three years heightens the risk for vision loss.

Day, Ravi, Xian, and Brugh (2013) developed an agent-based model template using the Java-based computer simulation suite AnyLogic Professional 6.6. The model was developed using medical data extracted from a retrospective cohort of patients seen at an eye clinic. Predictors associated with advancing stages of diabetic retinopathy were determined using logistic regression, and the predicted probabilities, obtained from logistic regression were used to generate the stage of diabetic retinopathy in the simulated cohort.

Gorman, Mezic, Mezic, and Gruenewald (2006) designed an agent-based simulation model to examine agent-environment interactions that support the development and maintenance of alcohol use behavior at the population level. Understanding the practical and ethical constraints involved in conducting experimental research on peer group affiliation and neighborhood alcohol outlet density, the authors identified with using ABM simulation which allows for ñwhat ifò scenarios. They used agent-based models to explicitly identify ecological components of the social and environmental processes underlying the movement into and out of drinking states of various severities.

To answer the research question of what happen when people drink at one location and then move about in their environment, coming into contact with both other drinkers and nondrinkers; they modeled the interactions of three types of agents which were current drinkers, susceptible drinkers and former drinkers. They modeled agents to move left or right in single steps at each iteration on a one-dimensional lattice, and toward a bar added to the lattice. The lattice depicted a frequently visited location in the neighborhood that attracts drinkers. There were exchanges of information among the agents about alcohol use. The models demonstrated that the basic dynamics underlying social influences on alcohol use are shaped by contacts between drinkers and the characteristics of the drinking environment.

Rein et al. (2007) studied the cost-effectiveness of vitamin therapy (antioxidants plus zinc) for patients diagnosed with Age-related Macular Degeneration (AMD). The study compared the impact of vitamin therapy to no vitamin therapy among patients with AMD using a computerized stochastic agent-based model. The model, programmed using AnyLogic, created 20 million simulated individuals in both intervention and controlled group who were 50 years old, diagnosed with early AMD, and observed until death or age 100. The model tracked each individualôs cost, incidence, subsequent progression of AMD, if any, visual impairment resulting from AMD, and quality-adjusted life years lived. The findings indicated that vitamin therapy improved visual outcomes by delaying or preventing the onset of advanced AMD at a reasonable health care cost.

Macal et al. (2014) used ABM to model the epidemiology of the community-associated methicillin-resistant staphylococcus aureus (CA-MRSA) bacteria epidemiology in Chicago. They used national survey data and a comprehensive literature search to determine transmission probabilities. Agents were modeled based on variation in socio-demographic characteristics, locations, behaviors, and physical contact patterns. Locations included households, workplaces, schools, gymnasiums, nursing homes, hospitals, jails, and college dormitories. Interaction occurred when multiple agents occupied the same location at the same time. A daily activity profile determined when each agent occupied each location. The geographical trend of CA-MRSA incidence in Chicago from 2001 to 2010 was generated. The study identified that colonized agents, rather than infected agents, were shown to be the source of 95% of transmission events.

These studies demonstrated the effectiveness of agent-based modeling simulation in health care and help to build a case for the use of ABM in self-management education and improving chronic pain management. Experimenting with models instead of real human systems provides information about how the model will behave given a range of inputs as simulated in the real world (Gilbert, 2008). This project utilized agent-based modeling simulation as a novel nursing approach to provide a solution to opioid escalation in chronic pain management.

Is ABM Appropriate?

The International Society for Pharmacoeconomics and Outcomes Research (ISPOR) Task Force report published in early 2015 a checklist to assist researchers and decision makers determine if dynamic simulation modeling method is appropriate to address a specific health system problem. The checklist comprises of eight-point item termed the SIMULATE which means: System, Interactions, Multilevel, Understanding, Loops, Agents, Time, Emergence (SIMULATE), characterized dynamic simulation modeling methods and differentiated them from other modeling approaches such as Markov models and decision trees (Marshall et al. 2015b). Table 1 presents how these characteristics fit into this PDSA quality improvement project.

TABLE 1. *Simulate.*

SIMULATE	Questions	Response
System	Does the problem require modeling multiple events, relationships and stakeholders representing health care delivery processes?	Long-term opioid use in patients with non-cancer pain.
Interactions	Does the problem include nonlinear or spatial relationships among stakeholders and their context that influence behaviors and make outcomes in the system difficult to anticipate?	Patients with chronic non cancer patient, medication adherence, health behaviors and beliefs about opioid use.
Multilevel	Does the problem involves modeling health care delivery problem from strategic, tactical, or operational perspectives?	Opioid escalation is a multifaceted problem that requires effective, efficient and sustainable intervention over the long term.
Understanding	Does the problem involve a modeling complex problem to improve patient-centered care that cannot be solved analytically?	Patientsôbehavior impact on health and disease management and empirical research are unrealistic due to ethical reasons.
Loops	Does the problem involve a modeling feedback loops that change the behavior of future interactions and the consequences for the delivery system?	The project will test how self-management education may influence behavior change, and leads to reduction in pain and decrease opioid use.
Agents	Does the problem involve modeling multiple stakeholders with behavioral properties that interact and change the performance of the system?	Patients with non-cancer pain on long-term opioid medication, interacts with primary care providers, therapists, psychologist with expectation to decrease opioid use.
Time	Are there time-dependent and dynamic transitions in a health care delivery system, either between or within health care system levels or in health status change?	Targeting healthcare benchmarks to decrease inappropriate use of opioids.
Emergence	Are there considerations that the intended and unintended consequences of interventions will address policy resistance and achieve target outcomes?	Anticipate reducing the consequences of opioid use, and decrease opioid-related mortality rate.

The problem identified under the eight characteristics and the appropriate responses generated indicted that this project can be studied using simulation and that ABM is an appropriate method of simulation. ABM was utilized to explore how agents responded to their social contexts and persuasion mechanisms such as pain self-management education messages and to reactions of others agents around them.

Chronic Pain

According to the International Association for the Study of Pain (IASP, 2014), pain is defined as an ñunpleasant sensory and emotional experience associated with actual or potential tissue damage or described in terms of such damage.ò Pain is measured mostly by self-report. Chronic pain is a chronic disease condition that negatively impacts the daily lives of patients. It is a complex life experience resulting from the progression of a patientôs illness and interactions of nociception, suffering, and disability (National Guideline, 2010). Nociception is the biological component of pain that explains the activity of specialized nerves that conveys information about tissue damage. Suffering denotes negative psychosocial experiences such as depression, anger, and anxiety that may accompany pain. Disability characterizes the negative social and behavioral experiences such as isolation, unemployment, inactivity and conflict with providers (National Guideline, 2010). Chronic pain becomes complex when there is a pattern of declining function despite aggressive treatments, accompanied by emotional distress and disability, and dissatisfaction with treatment (VHA, 2014). For this project, chronic non-cancer pain is as defined earlier on page 18.

The primary goal of a chronic non-cancer pain management is to reduce suffering and disability (VHA, 2014). This goal can be achieved by diverting patientsô attention to refocus on the biopsychosocial treatment approach that emphasizes long-term rehabilitation, patient self-management and functional improvement, rather than the focus of immediate relief of pain (VHA, 2014).

In the traditional biomedical pain model, the body and mind are separated and pain is perceived as a symptom of an underlying problem (VHA, 2014). High technological diagnostic modalities may be necessary to obtain diagnosis. Treatments focus on cure and short-term, urgent and complete pain relief, with a goal of treatment placed on medical solutions. In this model patients are helpless and passive while the providers are responsible, expert and in control; this model is suitable for managing acute pain (VHA, 2014).

Whereas, in the biopsychosocial model of pain care, there is a holistic view of the mind and body relationship with pain, and pains is perceived as a complex problem (VHA, 2014). Diagnosis involves comprehensive psychosocial strategies. Treatment focuses on restoring and reactivating function on the long-term. Patients are responsible for creating and maintaining new life roles and coping with the emotional reaction of their conditions. They become active participants in rehabilitation while the providers become teachers or coaches. This model is appropriate for managing chronic pain (VHA, 2014).

To manage chronic pain, health care providers should assess patients for capacities and barriers for self-management. Factors that can interfere with a patient readiness for self-management include extreme belief in the biomedical model, misinformation about treatment efficacy, severe psychopathology that is untreated or undertreated, chronic and severe social instability and competing agendas such as diversion or misuse of opioids, and malingering (VHA, 2014). Resistance to self-management is expected and it indicates patients are ignorant of performing or adopting self-management; when this occurs, reinforcement and adaptive behaviors should be explored (VHA, 2014).

Opioid Prescription and Opioid Use Reduction

Reduction of prescription and use of opioids has become a national priority. Prescription opioids, such as hydrocodone, oxycodone, morphine, and methadone, are commonly used to treat acute and chronic pain. However, there is limited evidence to support the efficacy of long-term use of opioids for chronic pain (Kalso, Edwards, Moore, & McQuay, 2004; Von Korff, Kolodny, Deyo, & Chou, 2011). Opioid use has escalated drastically, with an estimated 201.5 million prescriptions dispensed in 2009, and $8.4 billion spent on opioids in 2010 (IMS 2011; Volkow, Mclellan, Cotto, Karithanom, & Weiss, 2011). Unintended health and social consequences following the increased use of opioids, have increasingly been implicated in drug overdose deaths over the last decade, causing about 37% of all overdose deaths in 2013 (CDC, 2014).

In a press release from March 26, 2015, the U.S. Department of Health and Human Services (HHS) took targeted steps to reduced prescription opioid- and heroin-related overdoses, deaths and dependence. Declaring an opioid crisis, the HHS aimed at significantly influencing those struggling with substance use disorder and saving lives. Current efforts are focused on providing training and educational resources, including updated prescribing guidelines to assist health professionals in making informed prescribing decisions, addressing the over-prescribing of opioids, increasing the use of naloxone, and expanding the use of medication-assisted treatment (MAT). MAT is a comprehensive approach that combines the use of medication with counseling and behavioral therapies to treat substance use disorders. The presidentôs FY 2016 budget allocated $133 million in new funding to address this critical issue. On March 6, 2015, the CDC launched a grant funding prescription drug overdose prevention to provide state health departments the guidance and resources they need to address the problematic opioid prescribing patterns that drive the prescription drug overdose epidemic.

Opioids cause adverse effects including over-sedation; respiratory depression; gastrointestinal effects such as nausea, vomiting, and constipation; opioid-induced hyperalgesia; pruritus; and immunological and hormonal dysfunction (Baldini, Von Korff, & Lin, 2012). The Institute of Medicineôs 2011 report on relieving pain in America, ñA Blueprint for Transforming Prevention, Care, Education and Research,ò discussed the challenges faced by Americans affected by pain (IOM, 2011). While conceptualizing chronic pain as a chronic disease due to its impact on physical function, quality of life, and health outcomes, the IOM report advocated health care providers to improve care by tailoring pain care to individualsô experiences and promote self-management.

The National Action Plan for Adverse Drug Event Prevention for opioids recommended preventing harm in all patients who are prescribed opioids for pain (HHS, 2014). To prevent harm, Jones, Mack and Paulozzi (2013) advocated for safe prescribing and monitoring by providers and providing patient-centered interventions to combat the problems of inappropriate medication use, inappropriate dose, and issues with non-adherence and aberrant medication-related behavior that leads to adverse effects of opioid use. The use of evidence-based prevention tools to assess for patients at risk for adverse effects of opioids and to balance the goals of effective pain management and patient safety were advocated (HSS, 2015). The Current Opioid Misuse Measure (COMM) helps clinicians identify whether a patient, currently on long-term opioid therapy, may be exhibiting aberrant behaviors associated with misuse of opioid medications. Screener and Opioid Assessment for Patients with Pain (SOAPP) predict which patient, being considered for long-term opioid therapy, may exhibit aberrant medications behaviors in the future. Since the COMM examines concurrent misuse, it is ideal for monitor patientsô aberrant medication-related behaviors over the course of treatment.

The National Quality Strategy Priorities identified avenues for advancing opioid adverse drug events (ADE) prevention in outpatient settings priorities as follows:

1. ñSafer care ï This can be achieved by expanding dissemination of evidence-based opioid guidelines and protocols; improving availability and uptake of safe opioid prescribing practices; engaging patients between provider visits at a pain clinic or post-discharge from the hospital; promoting a transition from the biomedical to the biopsychosocial pain management model; developing strategies and tools to facilitate integrated team-based care; specialist consultation and integration with non-pharmacological treatments; promoting the use of Prescription Drug Monitoring Program (PDMPs); and improving communication and data sharing.
2. Patient and family engagement ï This can be achieved by developing and distributing patient education materials and strategies using the principles of health literacy and theories of behavioral change; spreading public health messages promoting safe opioid storage use, and disposal; not sharing opioids with friends or family; and educating patients and their families to recognize early signs of dependence.
3. Effective communication and coordination of care ï This can be achieved by developing more optimal and integrated health opioid management tools; and integrating opioid-specific targets into care transition models.
4. Science-driven prevention and treatment ï This can be achieved by promoting systematic and coordinated care through strategies such as team-based care; and medication

reconciliation; promoting the use of evidence-based strategies for managing risk factors associated with opioid overdoses; increasing availability of mental health and substance use disorder treatment for patients on opioid therapy; and promoting the use of eHealth electronic tools to identify high-risk opioid prescribing practices.

5. Promotion of best practices within communities ï This can be achieved by using metrics to monitor the use of opioid safety best practices; and promoting effective strategies identified by federal agencies that engage in patient careò (HHS, 2014, p. 143-144).

When long-term use of opioid is warranted, the health-care provider is responsible to provide comprehensive education on risks of adverse effects, potential for misuse, abuse, illicit drug use and diversion; recognize potential for and occurrence of substance misuse, abuse, and addiction; and ensure adherence and safety to opioid use (Manchikanti, Atluri, Trescot & Giordano, 2008). Some effective tools and instruments used to monitor controlled substances use and abuse include Screener and Opioid Assessment for Patient with Pain (SOAPP), Opioid Risk Tool (ORT), Current Opioid Misuse Measure (COMM) and Drug Abuse Screening Test (DAST), Prescription Drug Questionnaire (PDUQ), Screening Tool for Addiction Risk (STAR), and Pain Medicine Questionnaire (PMQ) (Manchikanti et al., 2008). Patient education materials and strategies that are based on the principles of health literacy and theories of behavioral change can be implemented through pain self-management education intervention which is the basis for this quality improvement project.

Self-Management

According to Barlow (2002) self-management is ñthe individualôs ability to manage the symptoms, treatment, physical and psychological consequences and lifestyle changes that are inherent in living with a chronic conditionò (p. 187). The principles of self-management are inherent in the social cognitive theory and self-efficacy theory (Bandura, 2001; Lawrance & McLeroy, 1986; Lorig & Holman, 2003).

Self-management refers to everyday decisions about medications, lifestyle, exercises, stress management and other actions made by patients that will change or reduce the impact of disease on health and functioning (Lorig & Holman, 2003). Self-management allows patients to become active participants of health-care decisions, which may leads to a reduction in pain (Lorig & Holman, 2003). Self-management education is different from traditional patient education because it is involved with skills building and it focuses on the following 8 skills elements: self-efficacy building, self-monitoring, goal-setting and action planning, decision making, problem-solving, self-tailoring, and partnership between the views of patients and health professionals (Lorig & Holman, 2003). Effective self-management intervention or programs should emphasize all the elements as well as make interventions community-based and accessible (Lorig & Holman, 2003). Self-management education should be based on patient perceived problems and a thorough need assessment should be conducted before implementation (Lorig & Holman, 2003).

Pain Self-Management Education

Du et al. (2011) conducted a systematic review and meta-analysis of self-management programs for chronic musculoskeletal pain conditions to evaluate the effectiveness of self-management programs on pain and disability. In a review of 19 randomized clinical trials studies, they found self-management programs had small to moderate effects in reducing arthritic pain, and long-term small effects in improving arthritis-related disability, and insufficient evidence to determine its effectiveness on chronic back pain. The authors advocated for core skills of self-management (self-efficacy building, goal-setting, action, planning, problem-solving, and self-tailoring) to be efficiently delivered in a self-management program and considered delivery of programs using new technological communication media. Although, there are report of exercise related adverse effects in two studies, there is insufficient evidence to conclude that self-management programs are unsafe. This finding was confirmed in another meta-analysis study that concluded that self-management programs caused no harm (Kroon et al., 2014).

Kroon et al. (2014) conducted a systematic review of randomized controlled trials of self-management education (SME) programs in people with osteoarthritis. They included 29 studies that compared self-management education programs to other interventions such as control attention, usual care, and provision of information alone and alternative interventions (e.g., exercise, physiotherapy, social support, acupuncture). The authors found that, SME programs may slightly improve self-management skills, pain, function and symptoms, when compared with usual care. On the contrary, when compared with attention control, SME programs do not improve self-management skills, pain, osteoarthritis symptoms, and function. Similarly, SME programs do not improve self-management skills, positive and active engagement in life, pain, global osteoarthritis scores, function or quality of life in comparison to provision of information alone or alternative interventions.

The discrepancies identified in the SME programs are a mismatch between the aims of the SME and measure of outcomes. The aim of SME program is to educate people about their condition and teach them how best to manage their symptoms. Osteoarthritis is a chronic disease that produces pain which cannot be cured. Therefore, the authors suggested the measure of outcomes should not be pain as found in most of the studies, but rather, outcomes should be measured by self-management skills, indicators of knowledge, and self-efficacy (Kroon et al., 2014).

The authors advocated for new modalities of delivery of SME programs that will target individuals, and provide adequate description of programs to include therapeutic quality assessment, and intended outcomes. To confound biases that would likely favor self-management as they were found across the studies, they advocated for the use of comprehensive and well-validated evaluation tools for SME programs such as the health education impact questionnaire (Kroon et al., 2014).

Health Education Impact Questionnaire (heiQ) is a valid evaluation tool that measures outcomes of self-management programs and patient education in chronic disease management (Osborne, Elsworth & Whitfield, 2007). It is a questionnaire made up of 8 domains and 40 questions. The domains are positive and active engagement in life, health directed behavior, skill and technique acquisition, constructive attitudes and approaches, self-monitoring and insights, health service navigation, social integration and support, and emotional wellbeing. Health Education Impact Questionnaire (heiQ) attempts to operationalize the evaluation of health education (imparting skills), psychosocial impact (empowerment), self-efficacy, self-management and improvement in quality of life (Osborne, Elsworth & Whitfield, 2013).

Gill, Wu and Taylor (2011) evaluated a self-management course (Moving towards Wellness) using the heiQ. The participants that could do things that they werenꞌt prior to attending the course had higher scores with all the eight domains of impact measured by the heiQ. After attending the course they were able to exercise, deal with problems differently, improve interactions with health-care providers and improve quality of life. This revealed that Moving toward Wellness course does have some benefits. The effectiveness of heiQ has also been documented in other settings (Cadhilac et al., 2011; Francis 2009; Greenhalgh 2009; Osborne et al., 2011; Packer et al., 2012; Wanitkun et al., 2011).

Merlin et al. (2015) conducted a qualitative study of pain self-management among HIV-infected individuals with chronic pain. They identified some pain self-management strategies used by the participants. These are physical activity (exercising), cognitive and spiritual strategies (relaxation, meditation, deep breathing, distraction, prayer, music, reading), spending time with family and friends and social support, avoidance of physical and social activity (not exercising, sleeping and staying in bed, medication-centric pain management (pain medications) and substance use (alcohol, illicit drugs). While some of these strategies may lead to worse outcomes, incorporating healthy pain self-management strategies into formal pain self-management interventions to improve pain outcomes was advocated.

Mann, Lefort, and Van Denkerkhof (2013) conducted a review of research of current approaches to self-management interventions for chronic pain in the past five years which was when research in this area began. They found across the studies three models that were commonly used namely Stanford model (Chronic pain arthritis, and chronic angina self-management), acceptance and commitment therapy (ACT) and modified cognitive behavioral therapy (CBT). The findings identified barriers and facilitators of self-management across studies and also concluded that SMIs could reduce both physical and psychological burden of patients with chronic pain.

The ACT helps individuals change behaviors that are motivated by fear of pain to those motivated by a desire to engage in valued activities despite pain. It is conducted by a psychologist and has been found effective in pain groups, among patients who reported high levels of pain distress, disability and/or interference. ACT focuses on principles of pain-avoidance-suffering cycle. These principles involve identifying values/valued activities, and gradually increasing exposure to value-directed behavior instead of pain-directed behavior, cognitive defusion (i.e., identifying and observing negative thoughts without acting on them, and distancing oneself from them), mindfulness, accepting and being willing to engage with pain, commitment to action and identifying obstacles to desire action, planning for future actions and obstacles (Mann, Lefort, & Van Denkerkhof, 2013).

The CBT is delivered by a clinical psychologist, who helps individual identify the relationships between thoughts, emotions and behaviors and encourage positive self-management behaviors. It focuses on cognitive restructuring (i.e., identifying and evaluating catastrophic thinking and constructing realistic alternatives); identifying and restructuring pain avoidance beliefs and behaviors, behavioral activation (e.g., pacing and activity scheduling), understanding biopsychosocial influences of pain goal setting, lifestyle changes (e.g., exercises), self-regulatory skills (e.g., progressive muscle relaxation and breathing exercises), pain management skills (e.g., attention diversion and stress-coping skills, and relapse prevention strategies (Mann, Lefort, & Van Denkerkhof, 2013).

The Stanford model provides individuals with a toolkit of knowledge and skills for managing pain and the physical, social and emotional consequences. It is typically delivered in a community setting, facilitated by trained personnel. The Stanford Chronic Pain Self-

Management Program (CPSMP) is a well-acclaimed evidence-based self-management intervention for patients with chronic disease) in and outside United States. It is a face-to-face group workshop that focuses on frustration, fatigue, isolation, poor sleep, appropriate exercise for maintaining strength, flexibility and endurance, appropriate use of medications, communicating effectively with family, friends and health professional, nutrition, pacing activity and rest and how to evaluate new treatment (Stanford University, n.d). This program has been found to improve participantsô education, coping skills, and overall quality of life (LeFort, Gray-Donald, Rowat, & Jeans, 1998). Limitations to wide spread use of the CPSMP are cost and accessibility.

Conceptual Framework

This study adopted Hovlandös theory as the primary theory of reference, and integrates the Elaboration Likelihood Model of Persuasion (ELM) theory to develop a conceptual framework for pain self-management and an agent-based pain management model (Figure 1). Carl Hovland is a Yale University Professor of Psychology; he is one of the first people to work on communication and persuasion.

Hovland's Theory

Hovlandös message learning theory is a persuasion theory that described how to formulate messages in a way that will persuade people to change their opinion, attitude or behavior. He states, ñThe extent to which a communication is effective in changing opinions depends in part on the extent to which the content of the communication is attended to, understood and remembered (or learned)ò (Hovland, Janis, & Kelley, 1953, p. 114).

Hovlandôs theory states that before a message can persuade, it has to be noticed, understood, and remembered (learned) (Hovland, et al. 1953). The message must provide answers that address the recipientsô counter-argumentation stances, which are internal debates in which the recipients defend their positions against the advocated position (Hovland & Weiss, 1951) (Figure 1). The theory is grounded in stimulus-response learning theory, and assumes that individuals are rational and that source credibility is temporary (sleeper effect). Information that may be factual or nonfactual drives attitudes to change. The influence of a persuasive message on an attitude depends on how well the recipients attend to the message, as well as how well they comprehend and accept it. The variables identified in the theory are the following: ñwhoò (communicator), ñsays whatò (message), ñto whomò (patients with chronic non-cancer pain), ñhowò (written or videotaped message), and ñwith what effectò that is causal relationship between knowledge and attitude, and attitude change unrelated to recall of message arguments (Shrigley & Koballa, 1992 p. 22-26).

In his book ñCommunication and Persuasion,ò Hovland et al, (1953) discussed that what listeners believe about the communicator can also influence the message persuasiveness and subsequent attitude change (p. 92). Basically the communicator tenders a persuasive point of view (the stimulus), and the recipients indicate agreement by yielding to the message (Hovland, et al. 1953). Also, the degree of persistence of opinion changes induced by a communication is determined by the three aspects of communication responsiveness, namely: attention, comprehension and acceptance (Hovland et al., 1953). For acceptance of persuasive communication to occur there must be a relationship between the communicator, the stimuli (message), audience predisposition and opinion change (Hovland et al., 1953). The variable that can be manipulated is the persuasive message (Shrigley & Koballa, 1992). The nature of the message, including how it is presented, to whom, and how the evidence in the message compares with other evidence, determines the level of message persuasiveness (Shrigley & Koballa, 1992).

While the communicatorô s credibility, trustworthiness, intentions and affiliations of the source of information are pertinent to audience perception, the content of the communication and the organization of persuasive arguments should motivate acceptance of new opinions and rejection of original opinions (Hovland et al., 1953). An effective persuasive communication occurs when a change in the individualô s behavior is signified by expressing new opinions, which in turn may have effect on inner acceptance, retention and persistence of the opinion change (Hovland, et al., 1953). In this project, persuasive messages were developed from current evidence-based research and converted to question format messages for the purpose of educating patient-agents in an interactive model simulation.

Elaboration Likelihood Model of Persuasion (ELM)

Petty and Cacioppo (1984) described persuasion as the use of persuasive messages to activate an attitude change that can modify individualsô behaviors. The elaboration likelihood model of persuasion states that, individuals are rational beings who would make decisions that favor their interests when they process received knowledge through a central route entailing thinking and evaluating. Contrarily, individuals are also non-rational beings who would make decisions not because they elaborate received knowledge, but because they attach an emotional meaning to it, which describes processing that occurs via a peripheral route (Petty & Cacioppo, 1986).

The ELM states that attitudes change may occur via two processing route: the central route or the peripheral route (Petty & Cacioppo 1984). Petty and Cacioppo (1984) pointed out that persuasive message can activate an attitude change and modify individualsô behaviors by engendering favorable memory or by provoking counter-arguments. Persuasive message embraces selective memorization, which predicts that receivers will better memorize opinions transmitted by a message if the opinions are comprehensible (Petty & Cacioppo, 1984). Individuals elaborate on the received knowledge, either by thoughtful analyses or by simple decision rule of attaching an emotional meaning to it (Petty & Cacioppo, 1984). Messages follow through a Bartlettôs effect (i.e., a longer message requires more time for the receiver to process), latent effect (i.e., overtime the receiver forgets the source of a message and remembers only the content), and sleeper effect (i.e., source credibility effects are temporary) (Petty & Cacioppo, 1984). Moderate repetition of strong arguments within a message seems to enhance elaboration and printed or written message is predicted to be more persuasive than audio and videotaped messages (Petty & Cacioppo, 1984).

In this project, educational messages are presented in a way to influence patientsô behaviors. The messages include a wealth of information, rational arguments, and evidence-based research to support reduction of opioid therapy and improved self-management in pain care. This provides a high credibility of the information source and reputation for the communicator. The messages attempt to change the belief that opioid use is the only solution to pain, by raising questions, and by modifying the audienceôs values and motives to a mature belief in self-management. The messages are directed toward a selective audience of patients with chronic non-cancer pain with similar exposure and perceptions of opioid therapy.

Counterarguments are expected to generate agentsô internal opinions on the messages. There will be no announcement of an end in the messages; this will be left implicit to generate patient discussions and questions. The benefits of persuasive theory to the project are the ability to reduce resistance and change attitudes and behavior by moving the audience from a negative position on opioid use to a neutral one that considers reducing opioids use in favor of trying self-managements and other alternative therapies.

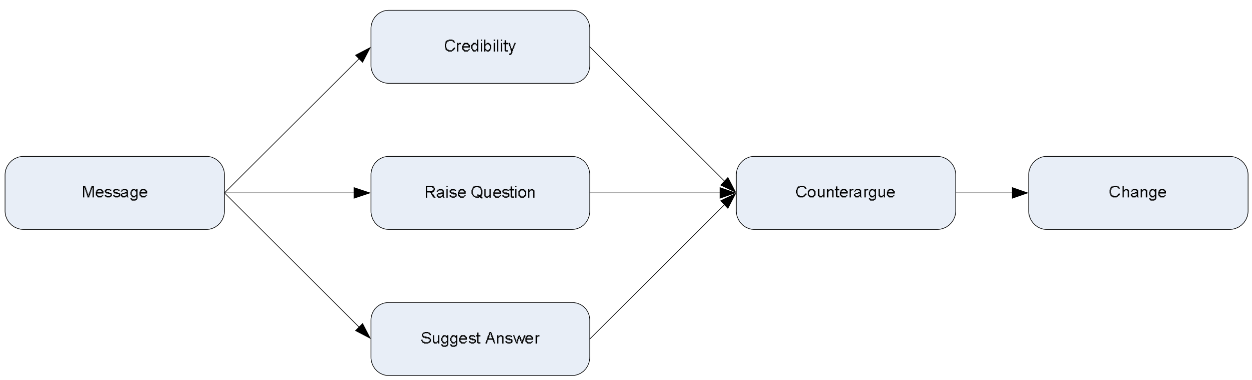


FIGURE 1. Conceptual framework for pain self-management and reduction in opioid prescriptions.

Summary

This literature review section summarized six relevant studies that used agent-based modeling in health-care settings that are similar to the project. The findings substantiate the uniqueness of this method in research with ethical barriers. Chronic pain and opioid prescription and its consequences were discussed, as well as the national initiative to address the growing health concern of reducing opioid use escalations. Self-management and pain self-management education was also discussed. The conceptual framework for this project was developed based on Hovlandôs and elaboration likelihood model of persuasion theories.

CHAPTER 3: METHODOLOGY

The methodology used in this quality improvement project was Plan-Do-Study-Act (PDSA).

PDSA

PDSA is a quality improvement model/tool for documenting a test of change. The PDSA was preferred over other quality improvement programs because it establishes a causal relationship between changes in processes and outcomes (Hughes, 2008). Testing a change involves developing a plan to test the change (Plan), carrying out the test (Do), observing and learning from the consequences (Study), and determining what modifications should be made to the test (Act).

Planning a change involves identifying the problem, conducting root cause analysis, and designing a change, addressing the questions why, what, how, who, where, and when. For this project a needs assessment was conducted relating to opioid escalation and inappropriate opioid use at one of the designated healthcare facility where the researcher practices as a primary care provider. The lack of a pain self-education program was identified and this led to a desire to design a change. The change entails exposing patients to pain self-management education. The desire to explore possible outcomes of pain self-management education in a no risk environment, led to the selection of agent-based computer modeling stimulation. The *Plan* phase entails selecting agent-based modeling, constructing pain self-management education message, defining the patient-agents and environment, and encoding the messages and modeling.

The *Do* phase involves utilizing the improvement strategy, which was to conduct the model simulation, thereby implementing the change on a small scale in a no risk environment.

The *Study* phase involves completing the analysis of data; comparing data to predictions, testing and recording changes, and summarizing what was learned. The *Act* phase of the PDSA cycle involves making changes, interpreting data, evaluating objectives, and integrating findings to real life.

The conceptual framework suggests that messages should be composed in an interrogative form. Therefore, messages for this project were developed by raising questions and suggesting answers. This chapter discussed how the messages serve as inputs to a computer simulation experiment built from an agent-based modeling method. The details of this modeling method, including the study design, sample and setting, data collection and statistical analysis methods were also discussed.

Study Design

The agent-based modeling (ABM) simulation experiment simulates the influence of change message embedded in the pain self-management education on behavior change from the use of opioid prescriptions to the use of self-management. The simulation involves using a computer as a persuasive medium and social actor to encourage improvement in self-management (Fogg, 2003). The experiment was set up to use computer agents as patients interacting with educational material (messages). The agents are social entities that can interact with themselves and the environment; they have a life span and they follow rules. Rules are step-by-step instructions on how to accomplish a task or make a decision. The rules connect or relate valid input to valid output.

For this project, affirmative and interrogative rules were used to construct messages of pain self-management therapy. Agents were exposed to the messages; they respond to them based on their adaptive traits and accrue certain wellness values. Adaptive traits are rules given to agents for making a decision that produces a behavior change. The patient- agents and messages are then simulated to interact for 50 iterations, which represent 50 visits of each of the 50 patient-agents to the messages for over a simulated 10 year period. At the end of the simulation, data was collected and statistically analyzed. A computer programmer was utilized to code and implement the agent-based pain management model.

The agent-based pain management model simulates how patients achieve behavior change, and how such change leads to reduction in the prevalence of opioid prescriptions. The model explores the conditions of behavior change and the emergent outcome of patient-agentôs adaptive decisions as they process the messages. The model is described in details further in this chapter in line with the protocol commonly used for documenting agent-based models (Grimm et al., 2010). The simulation experiment is conducted using a computer program that implements the model. The computer programs can be written in modeling languages such as MatLab, R, Swam, Repast, Mason, AnyLogic, or NetLogo. NetLogo was chosen as the modeling language for this project because it is free, and has a large user base, as well as a graphical user interface that is easy to use with the ñpoint and clickò actions (Wilensky, 1999). The expected behaviors are self-management behaviors. The dominant independent variable is the self-management pain education and the dependent variable is the prevalence of opioid prescriptions.

Sample and Setting

The project took place on the computer. Pain management model was coded using NetLogo modeling software, which includes codes for a collection of patient-agents and pain education messages. The model inputs are the pain self-management education messages which portrayed self-management and opioid prescription as alternative therapies of pain that vary in benefits and risks. The model outputs are average wellness, and individual agentôs wellness timeseries, mean therapy-benefit and therapy-risk. Computer agents were coded to represent patients with chronic non-cancer pain. Fifty patient-agents were used in this study. These patient-agents were 50 hypothetical patients ages 18 and above, diagnosed with chronic non-cancer pain currently on long-term opioid medications.

The experiment was set up in an environment that has the appropriate input and output variables and parameters required to mirror a real-life learning delivery program. The environments through which the interaction occurs are the wall grids representing the waiting room. The waiting room was 150 x 150 patches in size and has no wrapping at its edges. The screen layout consisted of grid of patches representing a waiting room in an outpatient clinic. The patches have two variables: therapy-benefit and therapy-risk. The therapy-benefit per patch per visit (therapy-benefit, in wellness per visit), and the risk of damages due to the therapy (therapy-risk, in probability per visit) were used to compute a fitness function (fitness, in wellness units) for each patch. The therapy-risk is the anticipated risk associated with each of the pain messages. It is the risk quantity associated with each pain message. The therapy-benefit is a weighted quantity that values the long-term wellness expected from a processed pain management message. It is the benefit quantity associated with each pain message.

The model entities include the patient-agents and their state variables. The patient-agentsô state variables include their location in the waiting room space and their current health wellness (in wellness units). Wellness is an average of current wellness divided by the number of agents. Wellness timeseries is a plot of current wellness for each patient-agent versus time. The model advances in time by a time step of a visit and its simulation runs for 50 visits for a period of 10 years. The model was demonstrated using the Microsoft Windows personal computers.

Data Collection

The patient data were collected after running 50 iterations of the simulation for 10 years using Netlogo World Display. The data elements were defined by the following variables at each time step for each patient-agent: current wellness, current therapy-benefit, current therapy-risk, and current fitness. Then, the mean fitness was computed. These data were plotted to produce charts and timeseries plots and written to an output spreadsheet file for statistical analysis. The model algorithm works as follows:

Patient-agents start out by determining their initial fitness function. When patient-agents are at risk, they reports their poor health and move to the nearest visible message space based on a set radius. When patients have choices, neighboring tiles are scanned for self-management messages for processing. For a rational behavior, patients process messages and then take action based on Hovlandôs theory. For an emotional behavior, patients process messages and then take action based on ELM theory.

The patient-agents decide whether any therapy message offers an answer to their questions on opioid use simulated by a wellness values computed from the fitness associated with its current patch. When answers are available and the risk values were less than the elaborate probability, they repositioned and transferred their wellness to the patch by moving there (i.e., a higher wellness value was occupied). Only one patient can occupy a patch at a time and they execute the reposition procedure randomly. The patient-agents update their wellness state variable and their charts based on their repositioning decision.

Agent-Based Pain Management Model

The following section discusses the agent-based pain management model elements: design theories, initialization, and fitness function. The design theories section covers the theories underlying the model formulation and emergence of behavior change, while model initialization section covers the model state variables and scale. The fitness function describes the mathematical expression of the model.

Design Theories

The underlying theory governing how patient-agents acquire different therapy messages and change attitudes, and decide to alter their behavior after considering the content of the therapies, was based on Hovlandӧs theory, and this process involves a trade-off between increasing wellness and decreasing bodily risk (Hovland, Janis, & Kelley, 1953; Shrigley & Koballa, 1992).

The model also utilizes ELM theory, which states that attitude change may occur via two processing routes: the central route or the peripheral route (Petty & Cacioppo 1984). The central route processing occurs when messages are carefully evaluated (i.e., elaborated) before a decision is made, while the peripheral route processing occurs when a decision is based on value or emotional attachment to the messages with less thoughtful processing.

Patient-agents acquire therapy messages and make their behavior change decisions while balancing the trade-off between therapy-benefit and therapy-risk within the opioid climate (defined by the range of values of therapy-benefit and therapy-risk, and the number of provider patches willing to prescribe opioids). The model outputs expected are average health wellness, and individual agentӧs mean wellness value, mean therapy benefit, and accrued health wellness over time. The patient-agentœs adaptive behaviors are simulated by the decision to move to one of patches within a specified radius. Patches have two variables (therapy-benefit and therapy-risk) that are used in computing a fitness function (fitness, in wellness units) for each patch, displayed at the upper left corner. A random value is generated and if the value is less than the therapy-risk, then the agent repositions by moving to the neighboring patch with the highest fitness; otherwise, the patient-agent chooses one of the eight patches randomly.

The patient-agents do not interact directly with each other, but they do so indirectly through their competition for patches with higher fitness. Patient-agents with higher wellness have no advantage over others in occupying patches. One patient cannot override another who has occupied a patch. The patchœs therapy-benefit and therapy-risk variables are initialized randomly, with certain selected patches assigned to higher fitness values based on their message type.

The future value of the patient wellness variable was obtained by adding a change in the benefit to the current wellness. In this project, the future value of the wellness variable was computed using a fitness function, which was defined as the benefit from the therapy being processed by the patient-agent after, having taken into consideration the potential risk of the pain management message over the time step period. The details of the fitness function were discussed in latter section of this chapter.

Model Initialization

Model initialization assigns initial values to elements of the model. The elements are patient-agent properties, message (tiles) properties, decision state parameter, and experimental variables. The patient-agent properties are wellness, patient-benefit, patient-risk, and visible radius (radius in which a message is visible to the agent). The message properties are therapy-benefit and therapy-risk. The decision state parameter is a probability of elaboration. The experimental variables are simulation length and number of patients.

A higher wellness value represents a patch message that conforms to a stronger persuasion message structure, based on Hovland҆s theory (Hovland et al., 1953; Shrigley & Koballa, 1992). The patient-risk and therapy-risk are represented by probability range of 0.02 and 0.1. Probability values are drawn at random from range 0.02 and 0.1 and then compared with the probability of elaborate processing of 0.04 being the probability that a decision based on processed message will be taken, for it is not often taken based on the elaboration likelihood model (Booth-Butterfield & Welbourne, 2002; Petty & Cacioppo, 1984; Zajonc & Markus, 1982). The patient-agent decides on processing a pain management message if the comparison is less than the threshold of elaborate processing, otherwise the patient-agent will randomly pick any available message with a lower wellness amount. The model initializes 50 patients and places them on patches, one patient-agent per patch, with each patient-agent wellness state variable initialized to zero.

Fitness Function

Under an effective self-management condition, a patient-agent optimizes his or her wellness by processing pain self-management education messages and taking actions that affect the prevalence of opioid prescription. The fitness expression acquired from processing the pain self-management education messages is calculated from a patient-agent initial or current wellness W, current therapy-benefit B per visit, and therapy-risk R, indicated by the patch the patient-agent currently occupies.

The fitness expression defines the future wellness as the predicted wellness (W_{k+1}), which is a function of the current value of wellness, therapy-benefit and therapy-risk, and this is equal to the current expectation E_k (average) that is defined by the deterministic term (W + BT) and stochastic term 〖(1-R)〗 ^T.

$$W_{k+1} = F_k (W, B, R) = E_k\{ (W+ BT) (1- R)\text{^}T \}$$

W is wellness

B is therapy-benefit which is wellness accrued from processing messages

T is a fixed number for valuing future benefit and set at 10 years

R is therapy-risk which is loss of wellness from adverse opioid use

F is linear or nonlinear function

k is discrete time step (i.e. patient visit)

E is statistical expectation (i.e. average)

The deterministic term (W + BT) estimates the patient-agentøs fitness endowment at the end of the time period T. This estimate is obtained by adding the patient-agentøs initial wellness and the wellness obtained, which is therapy-benefit multiplied by the risk due to loss of wellness.

The stochastic term (1 ï R)^T is the probability of not having health loss over the valuing time period T. The expression (1 ï R)^T is the probability of wellness (i.e., no risk). The stochastic term reduces the fitness function as the therapy risk increases. The fitness function formula is encoded in Netlogo and it is automatically calculated when the simulation runs.

The above expression is the simplified form of the general expression for solving optimization problem by processing state information and then taking reward-based decisions, stated as:

$$x_{k+1} - f(x_k, u_k, w_k) - E\left\{g_n(x_n) + \sum_{k-0}^{n-1} g_k(x_k, u_k, w_k)\right\}$$

where f is linear or nonlinear, x is state, k is discrete time step, u is finite or continuous, w is stochastic parameter, n is horizon, g is a function, E is the statistical expectation (i.e., average) taken as the expression is minimized over u (Bertsekas & Tsitsiklis, 1996; Osborne & Rubinstein, 1994).

Pain Management Education Message

Inadequate communication between the patient and clinician regarding treatment and self-management has been identified as one of the major reason for difficulty in treating chronic pain (Whitten, Evans, & Cristobal, 2005). This project offer insights into designing an evidenced-based, easy to present and understand, and individualized pain self-management education tool. The elements addressed by Lorig and Holman (2003) self-management skills, the Stanford model and the health education questionnaire were adapted to formulate interrogative format messages according Hovlandôs theory and ELM. This pain self-management education tool is presented within the domain of eight-message constructs, questions and anticipated responses. The message constructs are self-efficacy, self-monitoring, action planning, goal-setting, decision-making, problem-solving, self-tailoring, and partnership building.

In this project the persuasive messages was developed based on Hovlandôs theory that explained the rationale why participants change their behavior. The theory instructs placing messages in an interrogative format in order to achieve change of behavior. Self-management interventions may also be based on Stanford self-management model, acceptance and commitment therapy or cognitive-behavioral therapy (Mann, Lefort, & Van Denkerkhof, 2013).

The Stanford chronic disease self-management model is an evidence-based self-management intervention for patients with chronic disease (Stanford University, n.d). The health education questionnaire (heiQ) is an evidence-based measure of education program outcomes, for patients with chronic disease (Osborne et al., 2007). Stanford chronic pain self-management focused on frustration, fatigue, isolation, poor sleep, appropriate exercise for maintaining strength, flexibility and endurance, appropriate use of medications, communicating effectively with family, friends and health professional, nutrition, pacing activity and rest and how to evaluate new treatment, while the heiQ addressed the positive and active engagement in life, health directed behavior, skills and technique acquisition, constructive attitudes and approaches, self-monitoring and insight, health services navigation, social integration and support, and emotional wellbeing.

The elements addressed by these interventions were adapted to developed questions and answers in eight categories of message constructs namely: self-efficacy, self-monitoring, action planning, goal-setting, decision-making, problem-solving, self-tailoring, and partnership building. To establish content validity and appropriateness, the self-education message tool was reviewed and validated by two content experts from the College of Nursing University of Arizona, Dr. Heather Coates (PhD, MS, APRN-BC) and Dr. Heather, L. Carlisle (PhD, DNP, RN, FNP, AGACNP).

TABLE 2. *Message Constructs*.

Message Constructs	**Questions**	**Responses**
Decision-making (day to day decisions in response to changes in pain management based on appropriate information on chronic pain)	What is pain? What is causing your pain What do you know about pain? Why change old belief that chronic pain has a cure? Have you noticed any changes (physical, psych, social) since you have been taking opioids? If so, what? If not, have you been told about any of these changes that might occur as a result of long term opioid use? Do you have any safety concerns about your opioid use? Do you think your healthcare provider is concerned about your safety with opioid use? If so why is your healthcare provider concerned? Why would you choose to stop using opioids?	Pain is a universal human experience Define Acute and Chronic pain Describe biology of pain Describe pain pathway Opioid medications and its adverse effects. Too much focus on opioid medication Lasting changes depends on your efforts rather than medical treatments We must change our treatment plan to manage pain rather than cure pain Chronic pain is not curable

TABLE 2 ï *Continued*

Message Constructs	Questions	Responses
Problem-solving (problem definition, and generation of possible solutions)	Do you remember needing to take more medication during or after a stressful event? Do you ever experience fear, depression, anxiety, exhaustion, or disturbed sleep? What do you do during stressful events? Do you ever have loss of strength? If so, does this loss of strength cause you to not be able to exercise? If so, does this loss of strength cause pain when participating in physical activities? Do you lose joint mobility or flexibility? Have you ever felt that you have problems with alcohol use, drug use or tobacco use? Have you ever experienced withdrawal symptoms? If yes, what type of symptoms did you experience? Have you ever had a compulsion to continue taking pain medications for effects other than for pain relief?	Emotional pain can make physical pain worse, but pain medication is not designed to address emotional pain There is need for culture change from focus of pain medications, more tests and more surgeries Recognize deep emotions and distress, stress, anxiety, and depression Chronic Pain like other chronic illnesses has psychological and physical component and a comprehensive approach to treatment will help regain function Pseudo-addiction is judicious increase of opioid medication in order to gain control of pain Addiction is when an individual despite harm has compulsion to taking opioid on an ongoing basis for effects other than pain relief Tolerance is decrease effect of opioids with continued use Dependence is when you develop symptoms because you suddenly stopped your opioid medications. These symptoms are known as withdrawal symptoms, they are normal body physiologic responses to prolonged opioid use Referral to mental health evaluation and counselling
Goal setting (1 to 2 goals at a time, specific realistic and achievable and time limit)	Do you feel that your pain controls your life? If yes, what measures do plan to take to limit or prevent this? Have you thought of other ways of managing your pain in addition to taking medication?	Short-term goal is improved function Long-term goal is quality of life Limit average daily dose of opioids Limit opioid utilization over time Adopt self-management skills and techniques

TABLE 2 ï *Continued*

Message Constructs	Questions	Responses
Action planning (An action plan involves a period 1 to 2 weeks and is very behavior specific, realistic and achievable)	What activities, besides your pain medications, do you do to help your pain? What are three things you do you do to reduce your pain? Are there things you can do that will make you feel better? How can you pace your activity on a typical day? How do you manage pain flare-up? What is one goal you make for yourself to relieve or reduce your pain? What is one pleasurable activity goal you can do while pacing your activities?	Making a short-term action plan Get a goal to begin to manage pain Get active Establish regular physical activity (e.g., walk 10 minutes on Monday and Thursday for two weeks) Increase daily functioning Pacing is start low increase gradually Improve sleep Good nutrition Smoking cessation Limit alcohol
Self-monitoring (physical and emotional response that lead to insights, confidence and actions)	Is there anything getting in the way of your ability to get better? What does your pain level have to be, for you to be as active as you want? How do you prevent overstressing about your pain?	Modern lifestyle of sitting for long time, watching TV or being on computer for longer hours can sensitize the nervous system affecting pain. Catastrophizing pain
Self-efficacy (the capacity to organize and execute action plan)	How certain are you that you can reduce your pain to a small amount without taking extra medications? How certain are you that you could complete an action plan on a 10-point scale from 10 (very sure) to 1 (not all sure)?	Implement your goals and action plan and master and evaluate tasks Interpret your symptoms to include alternative explanations that will lead you to try new self-management behavior Act as model for others Reinforcement, feedback and support from others If score is less than 7 use problem-solving techniques to adapt or change the action plan.
Self-tailoring (applying self-management skills and knowledge to oneself appropriately)	Have you heard about the new opioid safety rules? What do you know about pain self-management? Do you know what would happen if you stopped taking your pain medications?	Opioid prescription must be only from only one provider Each State has prescription monitoring program Read and understand opioid agreement Perform urine drug screen periodically Understand urine drug test result Tapering off opioids Drug-drug interactions Stress-coping skills Attention diversion

TABLE 2 ï *Continued*

Message Constructs	**Questions**	**Responses**
Partnership building (negotiating confidence and establishing communication across health professionals)	Do you have difficulty getting your healthcare provider to understand your symptoms and conditions? Have you ever encountered a situation whereby the healthcare provider does not want to prescribe opioid medications for you? How did you handle the situation? How do you improve communication with your health care provider?	Get support and get into a recovery plan Positive reinforcement Ask your provider about these alternatives: Activity ï physical therapy, water therapy, occupational therapy Stress/Anxiety- Acceptance of the pain condition, mental health therapy, Relaxation therapy, Heat and Cold therapy Depression/PSTD- may need MH therapy and medications Sleeping problems-identify contributing factors, sleep hygiene, avoid sleeping medications Mind and Body Skills programs ï Tai-chi, Yoga, Zumba, Biofeedback etc. Pain clinic- invasive interventions and interdisciplinary approach Nerve stimulation, Chiropractic, Acupuncture, Surgery Pain classes- coaching, counseling, support groups Non-opioid medications- Antidepressants, NSAIDS, Anticonvulsants

Message Encoding

Pain self-management messages were composed and formatted in chapter 3, table 2 Message Constructs. For computer coding, the message constructs are grouped into four categories based on whether they are impactful, easily understood and remembered. The highest valued category takes values from 9,001 to 10,000, followed by 8,001 to 9,000, 7,001 to 8,000, and 6001 to 7,000. These high valued categories of messages are purple color coded on the graphical user interface (GUI) while non self-management messages are yellow color-coded. All non-self-management messages (opioid therapy) are assigned values ranging from 1,000 to 5,000. These values are arbitrary and are chosen to define a means of rating or valuing messages when patient-agents compute fitness function and maximize benefit (Shoham & Leyton-Brown, 2009).

Simulation of Agent-Based Pain Management Model

Figure 2 shows the graphical user interface (GUI) of the simulation of the pain management model. The interface shows two variable sliders, three action buttons, one 2D world panel, and three chart panels. The Setup action button initializes the model variables and must be executed before pressing the Go or Go with circle button. The Go button steps through the simulation one step at a time and it helps reveal what an individual agent is doing while the Go with circle button continuously runs the simulation until exit threshold has been reached, a feature useful for quick view of the final outcome of the simulation. The two variable sliders allow model users to vary the values of the number of patients in the model and their visible radius, which determines the number of messages they are exposed to within a time step. They are set before or after pressing the Setup button.

The two dimensional world panels represent a typical waiting room and consist of light yellow and purple tiles, which symbolize all possible pain management messages. These message tiles consist of both opioid messages (yellow tiles) and self-management messages (purple tiles). The human symbols in different colors represent patient-agents and their location corresponds to the current message tile being processed. The lines emanating from the patient-agents show those messages that have already been processed.

The three charts (on the right side of the diagram) plot the wellness, wellness and time, and benefit and risk data. The wellness chart shows the histogram of the expected average health wellness of the population of patients with chronic non-cancer pain who are currently on opioid therapy. It is a useful chart for visualizing the impact of pain self-management education on the population of interest. It also provides the visual for anticipating the average outcome of a health policy intervention based on this agent-based pain management model.

The wellness and time chart shows the accrued health wellness for each patient which is gained from the messages. It reveals the performance of each patient-agent as he or she processes both opioid messages and self-management messages and shows the impact of the pain self-management education on individual patient-agent behaviors over time.

Lastly, the benefit and risk chart shows the accrued individual health benefit and the accrued risk incurred in the use of opioid over time. The chart provides the information for inferring the impact of behavior change of each patient-agent on the prevalence of opioid prescriptions. All the charts are dynamically updated as the simulation runs.

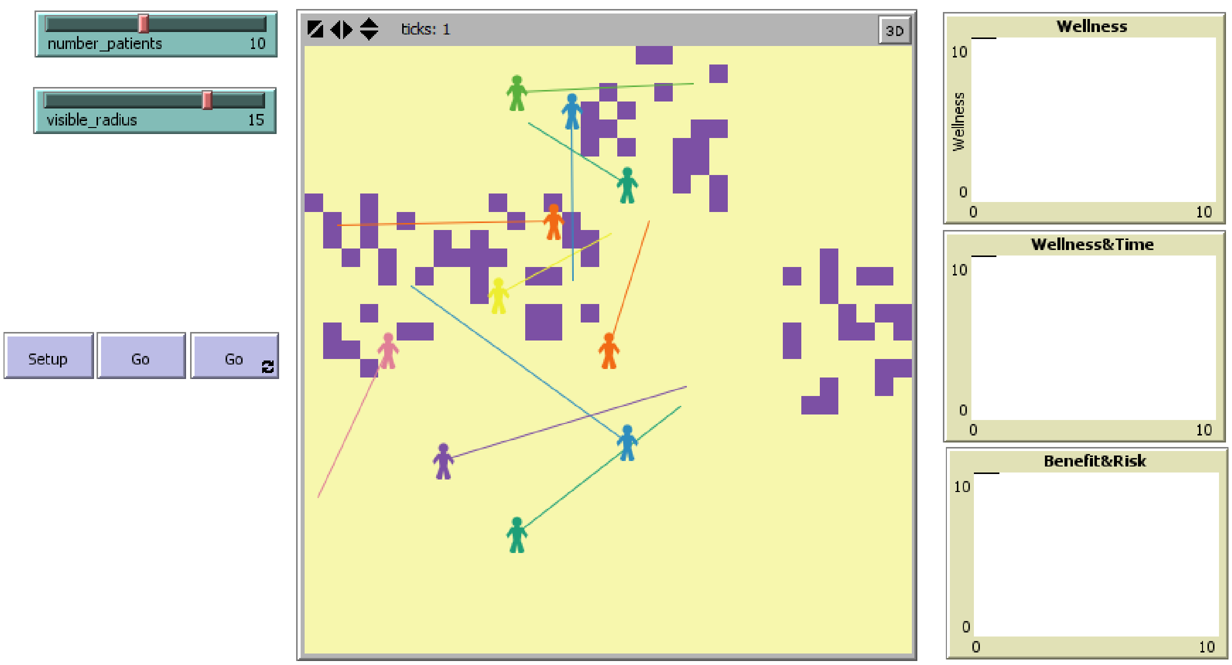


FIGURE 2. Graphic user interface for the simulation of the pain management model.

Statistical Analysis Method

The result of the simulation experiment on the agent-based pain management model was analyzed using descriptive statistics, inferential statistics and non-parametric statistics. Descriptive statistics provide skewness of data distribution, means of distributions together with confidence intervals, and correlation. Inferential statistics include p-value determination and statistical significant test. Non-parametric statistics are used to analyze distributions that are not normal. The non-parametric statistics utilized in this project include Kolmogorov-Smirnov test and Spearman correlation.

Ethical Considerations

This project reports analysis of a computer simulation that involved no data from human subjects. The University of Arizona Internal Review Board (IRB) requirement was waived and an approval to conduct study was obtained. Agent-based modeling (ABM) is commonly used to model individual decision-making and behavior (Bonabeau, 2002). It allows experimentation with models composed of agents that interact within an environment. Using ABM in this project enables the examination of processes underpinning relationships between the patient-agents and pain messages, and how behavior changes are generated and outcomes predicted, which may not be possible in a real world for ethical reasons.

Conducting experiments with vulnerable groups such as patients chronic non- cancer pain in a non-threatening and no risk environment can be achieved effectively with simulation modeling. It is unethical to separate patients into control and treatment groups for real experimentation with health outcome determinant intervention such as self- management education. It is expected that patients with chronic pain will be exposed to educational intervention because of its relevance to health outcomes. However, this project took it further to determine if pain self-management education conducted using interrogative and persuasive messages will produced better outcomes by testing it with simulated agents.

The advantages of ABM identified in this project are, it eliminates the difficulties of human subject selection and ethical problems involves of experimentation, and low cost. Though agent-based models mimic human, and attempt to simulate real world, it is not a panacea. However it is becoming more useful and widely accepted in health care delivery systems intervention research, and population health (Marshall et al., 2015b).

Summary

A simulation of an agent-based computational modeling was used in the proposed project. Patient-agents and messages were programmed or simulated to interact during 50 iterations, which represent 50 visits of each of the 50 patient-agents to the messages over 10 years. The patient data were collected using NetLogo World Display and analyzed based on current wellness, current therapy-benefit, current therapy-risk, and current fitness at each time step for each patient-agent. The patient-agents updated their wellness states based on their repositioning decisions. The data set was plotted to produce charts, timeseries plots and spreadsheets for statistical analysis.

The pain management messages and the conditions of behavior change (understood message, remembered message) were based on Hovlandös model. A computer programmer encoded (assign numerical value) these pain management messages as inputs into the pain management model. The programmer then programs the logic of the conditions of behavior change as the decision algorithm using NetLogo computer language. The agent-based pain management model produces outputs based on the actions of the 50 hypothetical patients. The actions are determined by the fitness value computed by each agent. For example, when agents # 1 is exposed to message A, the agent computes the fitness value of message A using the fitness function. Further details are discussed in chapter 4 and 5 of this project.

CHAPTER 4: RESULTS

The previous methodology chapter discusses the design and implementation of the agent-based pain management model. Responses of 50 patients to pain self-management messages are simulated by experimenting with a model algorithm based on Hovlandôs and Elaboration Likelihood Model theories. The computer algorithm runs 50 iterations of each hypothetical patient-agent, generating 2,500 records. This chapter presents values of variables and parameters, graphical user interface of the model software artifact, charts, and statistics that were produced from these records. The records illustrate the actions taken by patient-agents concerning the processing of the messages and their continued use of opioids and self-management education.

Simulation Implementation

Patient-agent move actions are illustrated on the graphical user interface (GUI) by track lines. When a patient-agent moves and occupies a message tile, it processes the associated message therapy-benefit and therapy-risk values associated with that message patches. All messages are assigned therapy-risk values from 0.02 to 0.1. The cumulative wellness value of a patient-agent at a particular tile location (i.e., message location) is obtained by computing the fitness value using the fitness formula and substituting the values of the therapy-benefit and therapy-risk of the current location. Once the agents decide to read the values of the therapy-benefit and therapy-risk assigned to the tiles of the 2D environment, they update their own benefit and risk properties, termed patient-benefit and patient-risk, by the values of the therapy-benefit and therapy-risk. It should be noted that the therapy-benefit and therapy-risk (properties associated with messages) are different from the patient-benefit and patient-risk (properties associated with patient-agents). The therapy-benefit and therapy-risk becomes patient-benefit and patient-risk only when patient-agents have read the messages.

Graphical User Interface

The graphical user interface (GUI) depicted below (Figure 3) illustrates how the modelôs algorithm works. The GUI shows four clusters of the distribution of the self-management messages in the color purple while non-self-management messages are in the color yellow. The patient-agents are color coded so that their individual tracks in the GUI and their curves in the wellness timeseries chart are identifiable. Each patient-agent represents a typical chronic non-cancer pain patient.

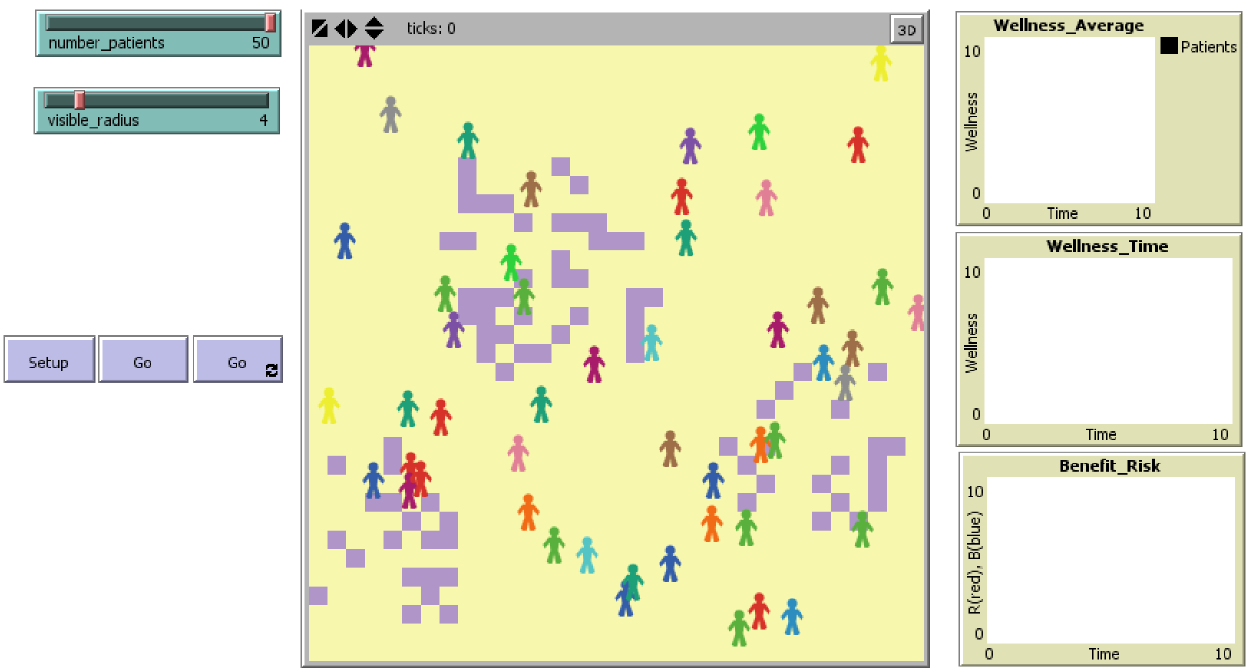


FIGURE 3. Graphical user interface (GUI) of the pain management model.

As the model runs (for 50 iterations), some patient-agents will consume more self-management messages (illustrated by their network of tracks) in Figure 4.

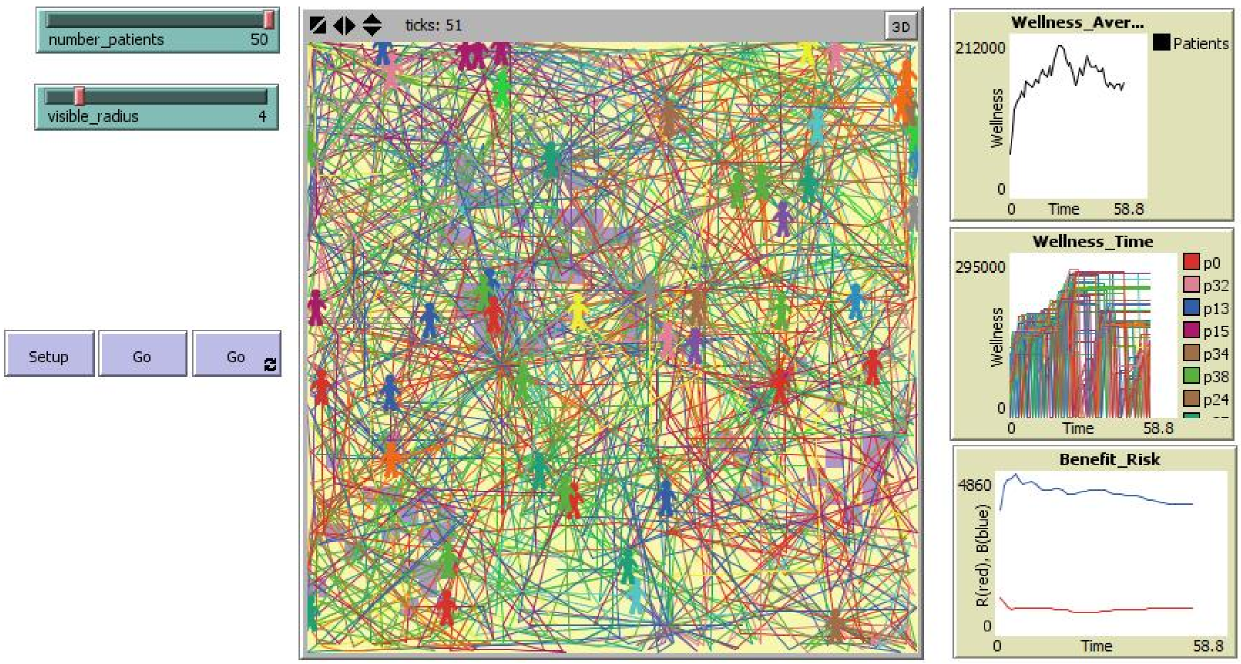


FIGURE 4. Graphical user interface after 50 iterations of 50 patient-agents.

The algorithm allows patient-agents to start out by determining their preference for pain self-management (i.e., whether they favor self-management or not by the virtue of their initial placement on the tiles, similar to assigning participants to treatment and control groups randomly). The patient-agents read the encoded values of benefit and risk assigned to their current tile message. Then they compare the risk value with a randomly generated number. If the result of the comparison is less than the current tile risk value, then the patient-agent will not favor self-management, otherwise if the comparison is higher than the current tile risk, the patient-agent will favor self-management. The wellness value of patient-agents that do not favor self-management will be set to zero. The zero wellness enables exposure to self-management messages in order to determine if there will be a behavioral change. On the next time step (i.e., next iteration) the patient-agent scans or reads the nearest visible message space within a visible radius of four tiles. The radius can vary from 1 to 20 tiles, by setting the value using the visible radius slider on the GUI. Each patient-agent scans for self-management messages within their visible radius for elaboration and processing. For those patients choosing a rational behavior, they process messages and then take action based on Hovlandŝ and ELM theories whereas others process messages and then randomly take action. The model is iterated for 50 simulated time visits or time steps and data are automatically collected after each iteration.

Average Wellness

Fifty patient-agents were simulated by experimenting with the agent-based pain management model algorithm in an environment modeled as tiles in a two dimensional geometric space. The computer algorithm runs 50 iterations of each hypothetical patient-agent, generating 2,500 records. This 2,500 records dataset was summarized into 50 records dataset by finding the average of each iteration. The aggregated dataset is shown in Appendix A.

The 50-record dataset has a mean (typical value) of 155,400 wellness units. The 95% confidence interval for the mean is between 148,282.4 and 162,454.2. The p-value of the 95% confidence interval is less than $2.2*10^{-16}$ (< 2.2e-16). With a chosen significance level of 0.05, the p-value for the mean is significant. This implies there is a significant impact and confidence in the mean value of the analyses.

The average wellness dataset presents a multimodal distribution shape as shown in Figure 5. This shape suggests nonparametric statistical analysis.

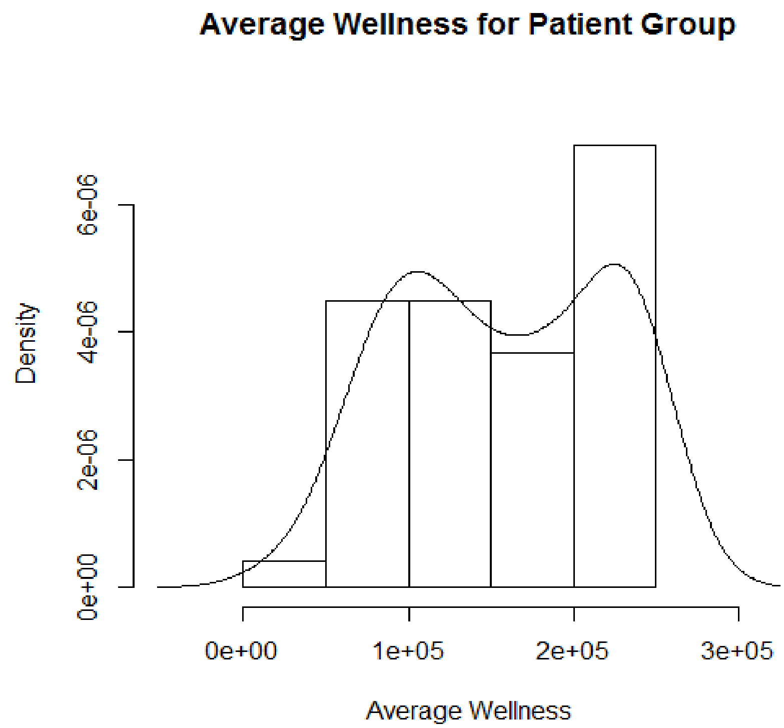


FIGURE 5. Average wellness for patient group dataset.

The distribution of the dataset was tested against randomness by performing a nonparametric statistics termed Kolmogorov-Smirnov test (Zar, 2010). Kolmogorov-Smirnov test compares two distributions to determine whether they belong to the same underlying distribution. The test is appropriate for the dataset because it is multimodal (i.e., non-normal) as discussed in the section on wellness timeseries in the later part of this chapter. The test starts out by assuming that the two distributions in comparison are from the same underlying distribution. Here the aggregated dataset distribution was compared with a random dataset distribution using One-sample Kolmogorov-Smirnov test. The result produces a D = 1, p-value < 2.2e-16. The p-value is less than a significant level of 0.05, indicating that the aggregated dataset and random dataset come from differing underlying distribution. Thus, the average wellness dataset is not random.

Figure 6 provides the dynamic plot for the average wellness curve. The curve plot is updated as the simulation runs. It illustrates an expected typical wellness value or impact of providing education messages over time.

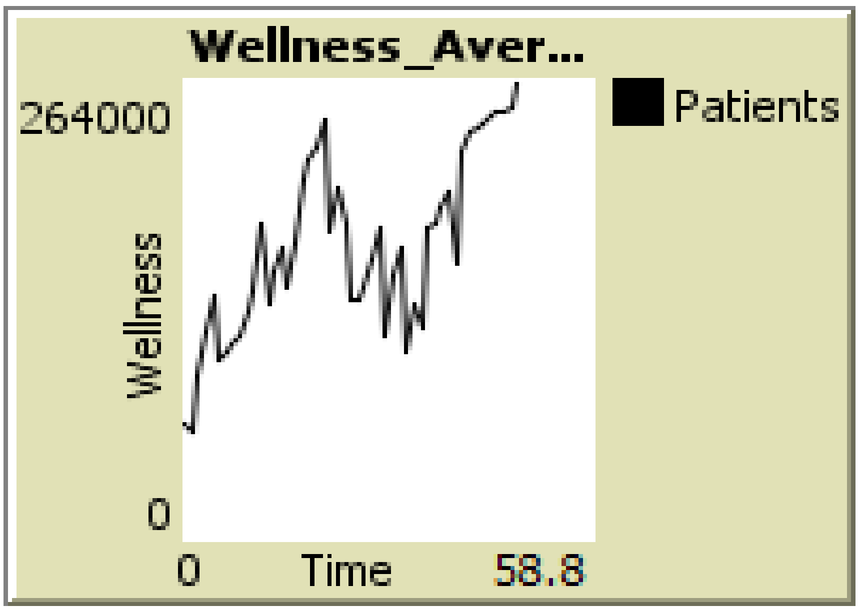


FIGURE 6. Dynamic chart for average wellness.

Even though the agents execute a stochastic (random) expression while optimizing the system state presented to them by the messages, their results illustrate an underlying impact distribution that is not random based on Kolmogorov-Smirnov test. Average wellness is computed using fitness function, and it determines the impact of the message. The processing of the messages results in an impact on patient-agent behavior over time. The higher the value of the fitness function is the more the impact of the message on behavior. The impact of the messages indicates that messages are being elaborated and processed, a probable condition of behavior change (Petty & Cacioppo, 1984). This behavior change exhibits high resistance to counter-argument (Petty, Haugtvedt & Smith, 1995) and is likely to accelerate the reduction in opioid prescription and acceptance of self-management practices based on ELM theory.

Wellness Timeseries

The wellness timeseries is a data table that collects the values of wellness of individual patient-agent over time (i.e., simulated time step). In order to conduct an in depth analyses to evaluate a self-management behavioral change of individual simulated patient-agents a sample of four patients were selected (objective 2). Those selected agents are labeled patient 0, patient 1, patient 2, and patient 3. An abridged version of the dataset (data table) is shown in Appendix B.

A dynamic chart for wellness average is implemented and displayed as part of the GUI. Figure 7 shows the selected patient-agents plotting their decision chart as they decide which tile message to process based on the benefit value of the message and its associated risk. Thus, a failed wellness is simulated stochastically by generating a probability and checking if the probability is less than the risk probability of the current occupied tile message. The agentös accrued wellness value is set to zero when self-management is not favored, causing the curve to spike down to zero and then back up in the next time step. So the downward spikes are instances when self-management messages are not favored.

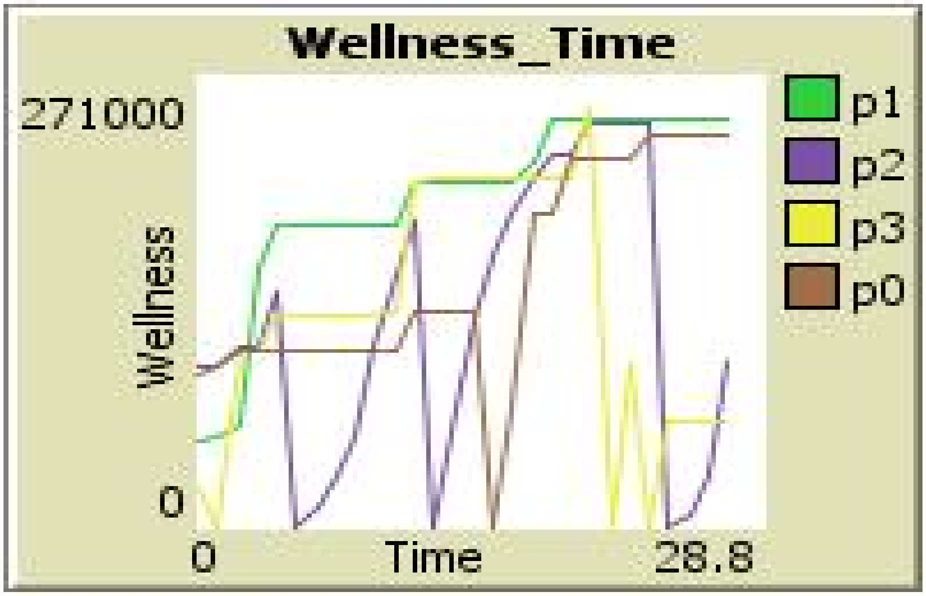


FIGURE 7. Dynamic chart for wellness timeseries for patient-agent Patient 0, 1, 2 and 3.

Figure 8 shows histograms overlaid with a density curve. The histograms show the frequency distribution of wellness data for each of the patient-agent Patient 0, 1, 2, and 3. The area under the histogram is proportional to the number of observations that lies within the width of the rectangle. The density curve estimates the proportion of the sample values per unit interval. It shows the shape of distribution and where the majority of high values and low values are clustering.

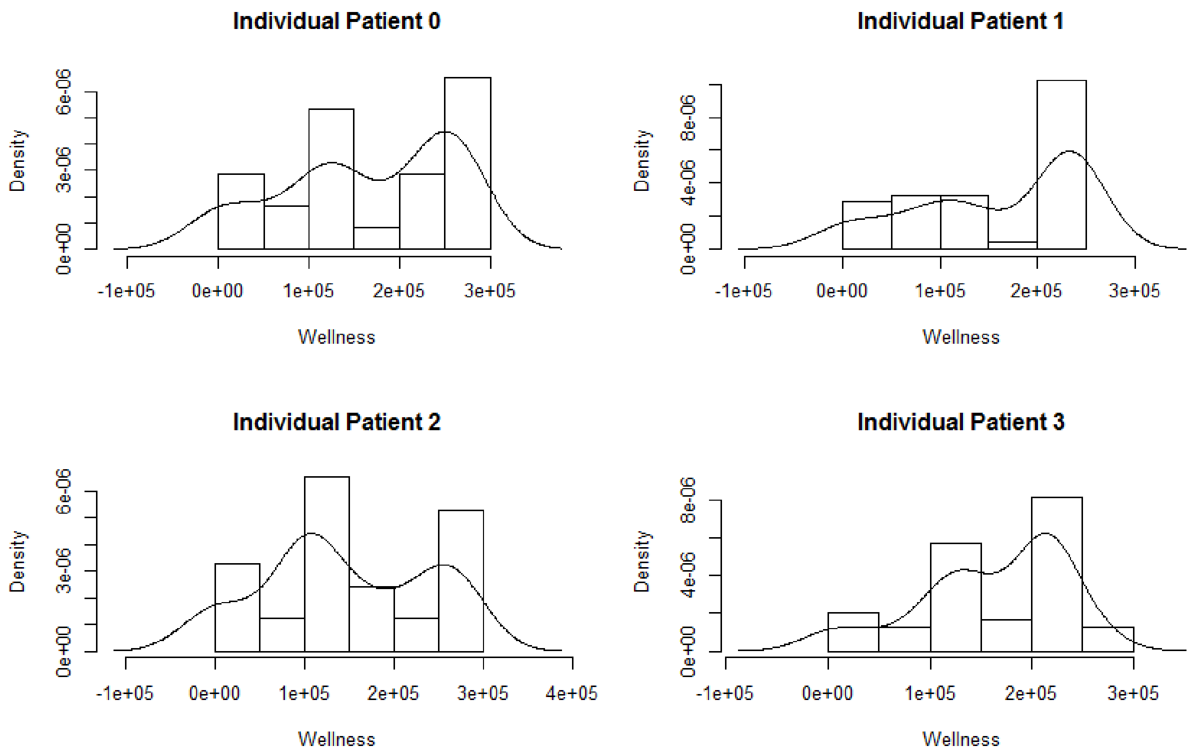


FIGURE 8. Histograms of wellness data overlaid with a density curve for patient-agents 0, 1, 2 and 3.

The e+/e- symbols indicate scientific notation for representing real numbers. The density axis represents frequency of wellness, and the wellness axis represents individual patient-agent wellness (discussed in model initialization section in chapter 3).

As shown in Figure 8, the density curves generally depict non-normal distributions (i.e., distribution with multiple peaks), suggesting analysis by nonparametric statistics (see statistical analysis method section in chapter 3). Density curves of Patient 0, 1 and 3 in particular show that the majority of high values are clustering at the right tail, around 2e+05 to 3e+05 (i.e., positively skewed) along a continuum. Therefore, the sample shows that the majority of patient-agents engage in processing high-valued messages.

Analysis of Behavior Change and Decline of Opioid Prescriptions

Correlations and scatter diagrams were constructed to explore the projectôs third objective of evaluating whether the behavior change will lead to a decline in opioid prescriptions from provider to simulated patient-agents. The chart in Figure 9 shows the dynamic plot of the average patient benefit and risk resulting from the processing self-management messages by patient-agents over time. On the benefit curve (blue), message processing initially dips before rising. It then levels around 6,980 units. The risk curve (red) starts off at about 0.07 and gradually reduces.

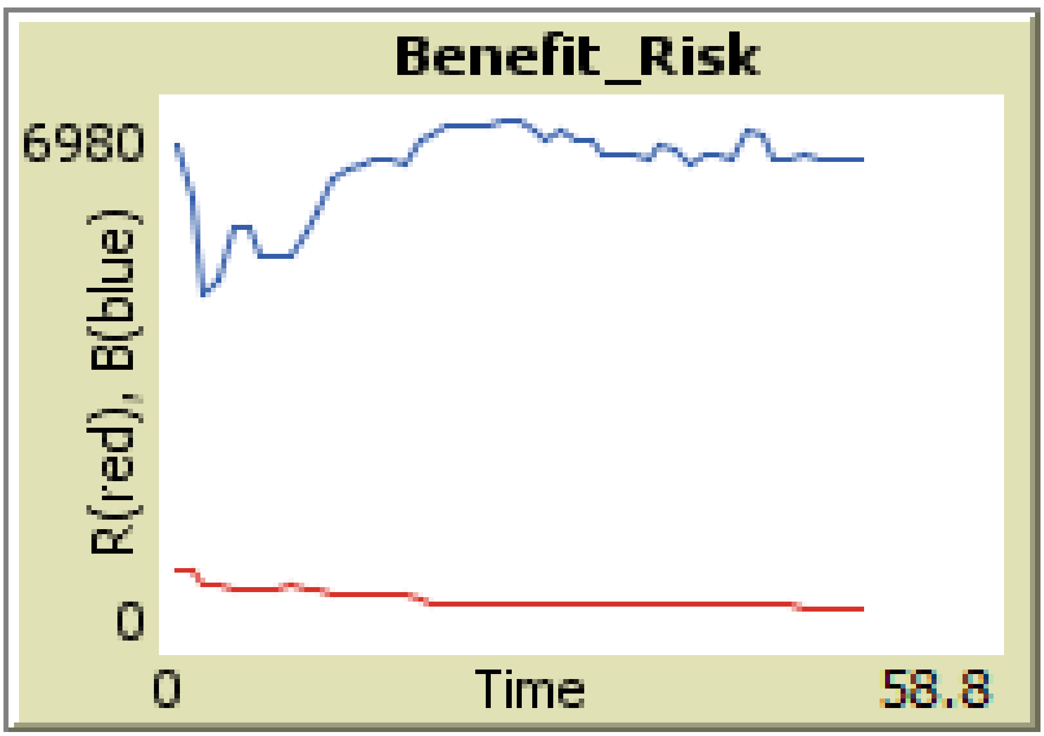


FIGURE 9. Dynamic curve of the average patient benefit and patient risk.

Correlations among the dataset columns of selected patient-agents were computed using the Spearman correlation values. The researcher employed Spearman correlation instead of the conventional correlation because the distributions are non-normal. Spearman correlation is a nonparametric correlation statistic that provides a p-value (Wackerly, Mendenhall, & Scheaffer, 2001). A p-value $\leq$ 0.05 indicates that the correlation is significant whereas p-value > 0.05 indicate it is not. See Appendix C, the scatter diagram shows little visual association.

From the scatter diagram of benefit and risk for selected patient-agents (Appendix C), the Spearman correlation between patient benefit and patient risk for:

Patient 0, is -0.13 with a p-value = 0.36.

Patient 1, is -0.46 with a p-value = 0.00067.

Patient 2, is -0.17 with p-value = 0.24.

Patient 3, is -0.29 with a p-value = 0.04.

The association between patient benefit and risk is negative and statistically significant for Patient 1 and 3. This implies that Patient 1 and 3 are favoring self-management messages. As the decision choice of Patient1 and 3 for higher patient benefit increases, their patient risk decreases. That is as they favor self-management messages; the use of opioid prescription reduces.

From the scatter diagram of wellness and benefit for selected patient-agents (Appendix C), the correlation between wellness and patient benefit for:

Patient 0, is 0.04 with a p-value = 0.80.

Patient 1, is 0.12 with a p-value = 0.42.

Patient 2, is 0.10 with a p-value = 0.51.

Patient 3, is 0.07 with a p-value = 0.65.

The association between patient-agent wellness and patient benefit is positive but not statistically significant.

From the Scatter diagram of wellness and risk for selected patient-agents (Appendix C), the spearman correlation between wellness and patient risk for:

Patient 0, is 0.07 with a p-value = 0.65.

Patient 1, is -0.13 with a p-value = 0.36.

Patient 2, is -0.10 with a p-value = 0.49

Patient 3, is 0.01 with a p-value = 0.93.

The association between patient-agent wellness and risk is negative (i.e., as wellness increases, risk decreases) but not statistically significant.

In evaluating whether this behavior change leads to a decline in opioid prescriptions from providers to simulated patient-agents, simulation analysis identifies no significant relationship between patient-agent wellness and patient risk, and between patient-agent wellness and patient benefit. However, there is a negative association between patient benefit and patient risk for some patient-agents. That implies some patient-agents favored self-management messages. According to ELM theory, their favorable position for self-management constitutes a strong resistance to counter argument of self-management, and with a behavior change that favors self-management, opioid prescription is likely to decline. Strong resistance to opioid therapy is likely to lead to actions that will decrease their requesting for opioid prescription.

Sensitivity Analysis

The sensitivity analysis was performed with respect to what might happen as a program based on this model continues to run for a very long duration. The researcher utilized NetLogoôs BehaviorSpace tool to explore the parameter space of the model. This space exploration is important in order to eliminate the randomness or chances from the result.

In ABM studies, one way of abstracting the complexity of the real world when building models is to build in some randomness (Barabási & Albert 1999). There is always a high tendency for collecting inconsistent data because most ABM models employ randomness or random decisions in their algorithms (Wilensky 1998; Wilensky 1999). These random decisions occur at least once for each patient agent in this project for each time step. Clearly one set of observation is not adequate to characterize the behavior of this model (or any other ABM model). The need to eliminate the effect of randomness or chances is met by performing parameter space exploration (Klemm et al. 2003).

In parameter space exploration, the experiment is replicated to get multiple observations (i.e., multiple runs are performed) because one observation is not always enough to characterize the behavior of systems. With multiple replications over parameter space of the model, distinct regions do emerge despite the use of randomness (Axelrod 1997; Axelrod & Dawkins 1990). Therefore, the research performed multiple runs using NetLogoȏs tool for performing parameter space exploration called BehaviorSpace.

Summary

This chapter has presented the results of the responses of 50 patients to the self-care management messages concerning their action on continued use of opioids in a computer-simulated experiment of 50 patient visits or iterations. It also demonstrates the probable conditions of behavior change by computing a typical wellness value (mean value), determining impact of messages, and evaluating the association or correlation of wellness, patient benefit and risk, for probable adoption and use of self-management education.

Data produced by individual patient-agent were collected (2,500-record dataset) and an average for each iteration was also collected, yielding 50 records as the group dataset. The datasets were tested for impact using Kolmogorov-Smirnov test. The result produces a statistically significant result, indicating that the datasets are not random. Even though the agents execute a stochastic (random) expression for optimization, their results illustrate an underlying distribution is not random. The wellness timeseries and their density curves generally describe non-normal distributions (i.e., distribution with multiple peaks), suggesting analysis by nonparametric statistics. Most density curves are right skewed, indicating that the majority of high values are clustering at the right tail, meaning more patients are processing high valued therapy messages. Thus, the processing of the messages resulted in an impact on patient-agent behavior over time.

Furthermore, the correlation or association among wellness, patient benefit and risk was computed. The association between patient-benefit and patient risk-is negative. This implies some patients favored self-management messages. According to ELM theory, their favorable position for self-management constitutes a strong resistance to counter argument of self-management, and with a behavior change that favors self-management, opioid prescription is likely to decline.

The next chapter, the discussion chapter will highlight important points from the facts presented in this result chapter and then delve deeper into their implications for nursing practice and research.

CHAPTER 5: DISCUSSION

This discussion chapter focuses on the explanations of the facts presented in the result chapter. It discusses how the purpose and the three objectives of this study have been met including the limitations of the study and implications for research and practice.

Relationship and Implication of Results on Practice

The purpose of this quality improvement project is to examine the influence of pain self-management education on the prevalence of opioid prescription among patients with chronic non-cancer pain on long-term opioid therapy. Using agent-based computer simulation method to develop a pain management model, 50 patient-agents were exposed to pain self-management education messages for 50 iterations over a period of 10 simulated years, and their behavior and interaction with the message were simulated and statistically analyzed. The simulation was conducted successfully. Under the three aims (objectives) of the study, the answer to the research question (how pain self-management education influences the prevalence of opioid prescriptions in a simulated agent-based model), the relationship of results to practice, aims and other evidence, and the implications of results to practice are presented below.

Aim 1: Provide Pain Self-Management Education

The first aim is to provide pain self-management education to simulated agent patients with chronic non-cancer pain who are currently on opioid therapy. This aim is accomplished by using agent-based modeling simulation to expose patient-agents to pain messages. This PDSA quality improvement project achieves this aim by formulating self-management education using different format of interrogative messages based on Hovlandȏs and ELM theories and by encoding those messages using real numbers. Because chronic pain is a disease that has no cure, it is pertinent that patients with chronic pain be equipped with self-management skills to improve their clinical outcomes. The development of this new methodology of message formulation that presents education in ways that it is easily understood, learned and remembered is a valuable contribution of this project to nursing practice, research and management of patients with chronic pain.

Aim 2: Behavior Change and Self-Management Pain Education

The second aim is to evaluate whether pain self-management education (messages) lead to changes in self-management behaviors of simulated agent patients. The formulation of the messages according to Hovlandôs guidelines facilitates an increased chance of elaborate processing and presents probable conditions of behavior change of patients, which is shown by the average wellness values calculated by fitness function (page 73 and Appendix A). The statistical analysis establishes that the generated aggregated dataset is not random despite being computed from a stochastic expression as established by Kolmogorov-Smirnov test (page 74).

The agents execute a stochastic expression while optimizing the messages presented to them by the environment, thereby producing results that illustrate an emergent interaction which is not random. Therefore, it is inferred that the processing of the messages results in an impact on patient-agent behavior over time. The wellness timeseries of each patient-agent shows the trend of their accrued wellness gained from the messages and the impact of their decision to process self-management pain education over time (page 76 and Figure 7). The findings are significant for the density curves of Patient 0, 1 and 3. The majority of high values are clustering at the right tail, (i.e., positively skewed) along a continuum (Figure 8). Therefore, the wellness timeseries results show that the majority of patient-agents engage in processing high-valued messages that produce high wellness values more than the mean, a finding that is corroborated by the clustering at the right tail (page 78 and Figure 8). Since self-management messages yield high wellness values, having the majority of values in the right tail implies that more processing of self-management messages is being done; more elaboration is being undertaken. Elaboration of a well-composed message has a high likelihood of inducing a changed attitude and behavior according to the ELM theory. Thus, the processing of the messages results in an impact on patient-agent behavior over time. This supports earlier findings that elaboration or processing of a well composed message has a high likelihood of inducing a changed attitude and thus a changed behavior (Petty & Cacioppo, 1984; Petty & Wegener, 1999; Booth-Butterfield & Welbourne, 2002).

Achieving the second objective demonstrates the PDSA quality improvement project tested the impact of the pain messages on the behavior simulated patient-agents. Therefore, the majority of patient-agents engage in processing high-valued messages. For nursing practice, the adoption of formulating self-management education based on elaboration and persuasion theories will improvement patient engagement and lead to changed attitude and changed behavior. The elements of message formulation, elaboration and persuasion theories should be included in the curriculum of nursing education to enhance structured nursing communication. These education elements are highly likely to have great impact in planning patient education for health promotion, disease prevention and chronic disease management intervention programs.

Aim 3: Behavior Change and Decline in Opioid Prescriptions

The third aim is to evaluate whether this behavior change leads to a decline in opioid prescriptions from providers to simulated agent patients. This aim is achieved by using correlation and scatter graphs to show the dynamic result of processing self-management messages by patient-agents over time (pages 79-81, and Appendix C). The association between patient-benefit and patient-risk is negative and statistically significant for Patient 1 and 3. This implies that Patient 1 and 3 are favoring self-management messages. As some patient-agents make decision choices for higher value messages, their therapy-benefit increases (i.e., they are adopting self-management messages) and their patient-risk decreases (i.e., they are demanding less of opioid therapy). The association between wellness and patient-benefit is positive, which means as patient-benefit increases, wellness also increases. Whereas wellness is negatively associated with patient-risk, that is, as wellness increases patient- risk decreases; though this is not statistically significant, it is a pertinent finding. It implies that as patient wellness increases (increased adoption of self-management messages), patient- risk decreases (reduced demand of opioid therapy) without serious relapse effect in the short term. In the long term, the relapse effect is likely to become serious and patients will need to persistent on self-management so that their health gains are sustained.

Furthermore, the existence of impact of messages in the aggregated wellness dataset suggests that the behavior change impact will lead to a decline in opioid prescriptions from provider. Therefore, with this PDSA quality improvement project, the researcher argues that as benefit increases and risk decreases, the demand for opioid prescriptions decreases.

Limitations and Further Research

Computer simulation modeling requires specialized skills in model building and computational simulation based on mathematical structures. Sometimes the mathematical structures are difficult to communicate, and critics have associated this difficulty with communicating details of modeling to lack of transparency (Marshall et al., 2015b). Agent-based modeling (ABM) is insufficient to completely replace real-world clinical trials, but it is capable of simulating realistic scenarios and test ideas that are plagued with uncertain outcomes.

In this project the findings cannot be generalized to larger population without a real-life implementation and calibration. Patient-agents are simulated to exhibit similar decision traits based on the assumptions that agents are rational and strategic and will attempt to maximize returns while preventing taking actions that are dominated (Osborne & Rubinstein, 1994; Shoham & Leyton-Brown, 2009). These assumptions are explicit in this project as all the agents behave in a similar fashion and their interaction does not require deep heterogeneity as guided by the research questions of this study. Further research might introduce more agent heterogeneity to explore other interaction emergence, thereby increasing the accuracy of the model and confidence in its predictions.

A system of patient-agents with sensors was implemented for interacting with their environment depicted as messages. The agent process messages by moving to a better message location based on the locationô message benefit and risk. Further research might implement incentive schemes for agents toward the goal of accelerating adoption self-management practice.

Implications for Practice

The outcome of this PDSA quality improvement project will be used to improve the current process of providing self-education for patients with chronic pain on opioid therapy at my practice setting. Specifically, the interrogative pain messages will be incorporated into the current pain education module. The next PDSA cycle will be focused on testing the educational tool on real humans in a pilot study and evaluating the outcome in real-life. The plan is to use the framework of the eight-message constructs of pain self-management education to develop a brochure that will be available to patients with chronic non-cancer pain.

This project will influence policy change to provide goal oriented self-management education for patients with chronic pain and inform nurse practitioners and primary care providers of how to integrate structured self-management education into the care for patients with chronic non-cancer pain. This project prepares the platform for developing clinical practice guidelines for management of chronic non-cancer pain for nurse practitioners. The experience of developing an evidenced-based and theoretical driven pain self-management education tool has increased the researcherôs confidence and step-wise approach to conducting self-management education to patients on chronic opioid therapy. The researcher has improved her communication style, a style that has endowed her with the ability to reach out and communicate effectively with patients with chronic pain. This tool will be highly recommended to nurse practitioners and primary care providers involved with providing care to the vulnerable groups of patients with chronic non-cancer pain.

Conclusion

Chronic pain continues to be a lifelong condition presenting a growing concern due to its high occurrence and effects on every facet of life. This PDSA quality improvement project has investigated the problem of the prevalence of opioid prescription using agent-based modeling simulation. The simulation modeled a large number of patient computer agents and simulated their interaction with pain self-management education, referred to as messages. These messages are formatted and composed based on Hovlandôs theory of persuasion. They are coded and presented to the agents via the agent environment modeled as tiles in a two dimensional geometry. The experiment captures the responses of 50 patient-agents to the pain self-management messages in an episode of 50 patient iterations (visit) over 10 simulated years.

As the simulation runs, data are dynamically captured and visualized using dynamic wellness charts and timeseries plots. Summaries of the expected health wellness and accrued health wellness for individual patient-agent are collected. Data are stored on files as agents interact with the messages and process them being guided by the elaboration likelihood model theory. Though the agents execute a stochastic expression while optimizing the system state presented to them by the messages, their results illustrate an emergent interaction, which is not random. Thus, the processing of messages impacts patient-agent behavior over time.

This project has helped to contribute a unique body of knowledge to self-management education to patients with chronic non-cancer pain. Specifically, the education tool and the use of agent-based modeling to examine the influence of pain self-management education on patient with chronic non-cancer pain on opioid therapy, show potential for aiding evidence-based research and quality improvement in self-management education.

APPENDIX A:

AVERAGE WELLNESS DATA SET

Time Step	Average Wellness	Average Patient Benefit	Average Patient Risk
0	57689.96243	3708.280561	0.055590516
1	88690.68351	4419.899931	0.047672333
2	113464.3943	4597.222963	0.042870837
3	126031.5682	4636.467546	0.038392294
4	131658.496	4772.356251	0.040675524
5	138287.2194	4543.572164	0.040840312
6	130934.1261	4487.149566	0.039966775
7	151148.7105	4532.661345	0.039765215
8	147803.6129	4577.880221	0.039692534
9	144544.4989	4460.291716	0.040222242
10	143673.6832	4412.709988	0.040947778
11	152316.1106	4318.691231	0.040691128
12	149250.0173	4324.475939	0.040502734
13	158938.9068	4310.723116	0.039522745
14	165914.6505	4333.526064	0.038473807
15	160984.5696	4368.297097	0.037228634
16	157212.2575	4291.120059	0.037673145
17	172044.2337	4182.036944	0.037054091
18	158239.4771	4181.973868	0.036105705
19	179322.585	4194.655397	0.034258427
20	192604.8955	4226.018051	0.034612952
21	197779.3024	4249.353122	0.034368649
22	196643.858	4281.924879	0.034094872
23	192223.6951	4296.333194	0.034247671
24	179828.7247	4312.062305	0.034279638
25	171339.0055	4306.110491	0.034485689
26	175651.1628	4299.909204	0.035170781
27	162177.8876	4295.313844	0.035788607
28	145890.938	4217.838048	0.036865307
29	151802.7651	4176.445935	0.037433474
30	167504.4872	4179.634971	0.038121089
31	158586.3133	4188.532483	0.038489266
32	166891.3904	4152.272769	0.038344734
33	184555.239	4123.22054	0.037760067
34	174100.1836	4128.879699	0.038192055
35	170397.0387	4125.721667	0.038117576
36	170426.877	4084.016117	0.038458691
37	171674.1827	4042.131926	0.039053676
38	164064.701	4024.193305	0.03930831

Time Step	Average Wellness	Average Patient Benefit	Average Patient Risk
39	164021.5752	3995.418328	0.03929971
40	166995.9222	3959.262432	0.039743726
41	150084.8696	3945.273674	0.039975461
42	144352.4332	3935.316079	0.040199996
43	148970.7628	3908.113281	0.040285236
44	144989.5334	3893.489038	0.040860406
45	142866.9655	3886.693469	0.040954697
46	146756.0984	3892.418322	0.040794127
47	147971.057	3891.215279	0.040596989
48	140265.5092	3870.640689	0.040793526
49	148846.3178	3873.124689	0.040807577

Aggregated Dataset of Average Wellness Value of 50 records

APPENDIX B:

INDIVIDUAL PATIENT-AGENT WELLNESS DATA SET

Agent	Time Step	Wellness	Patient Benefit	Patient Risk
(patient 0)	0	61171.4033	8109.708924	0.036982452
(patient 1)	0	0	8842.147303	0.029842201
(patient 2)	0	65988.7762	7475.557466	0.022469396
(patient 3)	0	114661.054	7475.557466	0.022469396
(patient 4)	0	90213.2016	4353.923023	0.022010169
(patient 5)	0	69161.493	9301.572059	0.037241654
(patient 6)	0	54826.9512	3492.214645	0.062090008
(patient 7)	0	87993.6752	4610.2078	0.026634523
(patient 8)	0	81971.3111	3480.446109	0.023489148
(patient 9)	0	61698.2376	1156.968059	0.026528706
(patient 10)	0	65599.1269	2914.558829	0.039646053
(patient 11)	0	68761.6867	8634.674912	0.078364254
(patient 12)	0	126285.33	9324.99029	0.024845026
(patient 13)	0	46929.8003	2019.13548	0.062364524
(patient 14)	0	31070.2127	6334.289962	0.07985446
(patient 15)	0	63044.6361	7269.181017	0.024462416
(patient 16)	0	94139.6358	4679.305478	0.02062622
(patient 17)	0	64481.4362	4289.395785	0.053762465
(patient 18)	0	48036.1057	4714.333819	0.084629307
(patient 19)	0	95696.4014	4948.222776	0.021265077
(patient 20)	0	29303.9006	2850.800809	0.021929663
(patient 21)	0	24993.2703	2639.441764	0.031622397
(patient 22)	0	57607.9988	8411.95181	0.045930646
(patient 23)	0	61931.8102	1394.623714	0.028982101
(patient 24)	0	91068.1688	9108.619958	0.054944134
(patient 25)	0	26109.5696	4254.899706	0.068084077
(patient 26)	0	41538.0783	3924.71977	0.091472181
(patient 27)	0	34007.0511	9301.572059	0.037241654
(patient 28)	0	30376.9971	1699.75543	0.099000821
(patient 29)	0	67072.525	3333.030922	0.041514488
(patient 30)	0	56550.4648	3989.606895	0.063564133
(patient 31)	0	13646.9896	2216.263694	0.076460365
(patient 32)	0	50032.2425	2283.3766	0.059089203
(patient 33)	0	87669.302	4211.714675	0.02356447
(patient 34)	0	46118.8127	4726.029568	0.088441836
(patient 35)	0	61221.1762	2560.151317	0.042747996
(patient 36)	0	37906.8474	4815.475228	0.038656224
(patient 37)	0	56837.3243	1846.357959	0.042363869
(patient 38)	0	49530.553	1574.668977	0.052471322

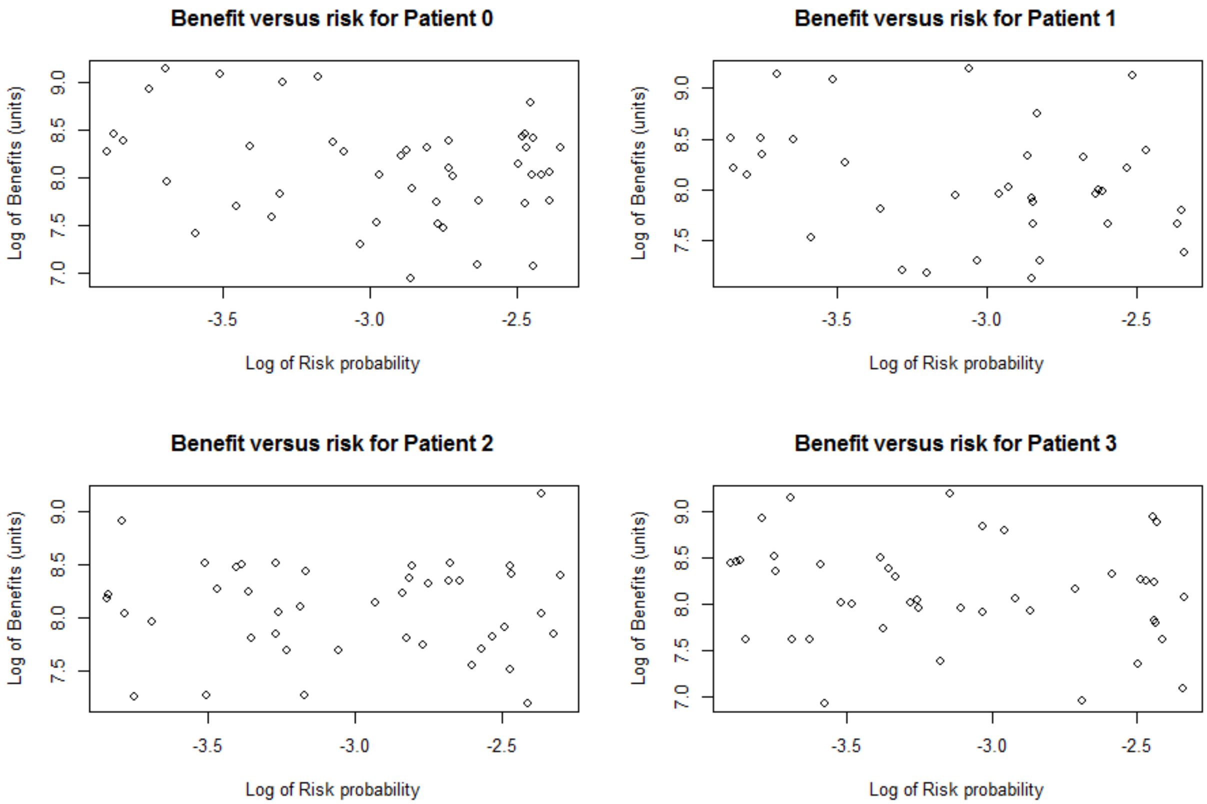
Agent	Time Step	Wellness	Patient Benefit	Patient Risk
(patient 39)	0	0	2535.819309	0.099958913
(patient 40)	0	42911.313	3837.872164	0.087778948
(patient 41)	0	50821.7675	4666.124874	0.07907218
(patient 42)	0	35836.6208	1548.554232	0.082361704
(patient 43)	0	114661.054	7475.557466	0.022469396
(patient 44)	0	42026.2567	1724.967397	0.069545622
(patient 45)	0	39328.5858	1049.809267	0.068147813
(patient 46)	0	63244.8833	4610.535788	0.058257659
(patient 47)	0	36564.6007	3387.089628	0.098410788
(patient 48)	0	95782.8631	8411.95181	0.045930646
(patient 49)	0	48066.6197	2477.735838	0.064810045
(patient 0)	1	0	2327.723317	0.072075939
(patient 1)	1	76909.8812	3041.529198	0.053624959
(patient 2)	1	65988.7762	1319.483349	0.089739527
(patient 3)	1	0	4005.482014	0.035687734
(patient 4)	1	90213.2016	3623.833015	0.053552888
(patient 5)	1	103044.167	9352.46335	0.044639482
(patient 6)	1	128568.189	9684.995949	0.04317316
(patient 7)	1	87993.6752	1778.786908	0.065543113
(patient 8)	1	121647.85	4679.305478	0.02062622
(patient 9)	1	65689.1186	4666.124874	0.07907218
é	é	é	é	é
(patient 0)	49	189252.105	2354.944647	0.091805276
(patient 1)	49	113231.223	9836.11778	0.046952417
(patient 2)	49	193248.605	4208.448894	0.068302359
(patient 3)	49	109328.643	2700.165426	0.048318666
(patient 4)	49	124733.846	8109.708924	0.036982452
(patient 5)	49	100723.183	3917.103186	0.031088152
(patient 6)	49	235611.817	2733.328844	0.044203314
(patient 7)	49	117438.346	8149.334148	0.042045587
(patient 8)	49	248171.948	2763.345446	0.083029209
(patient 9)	49	0	1737.443164	0.053718929
(patient 10)	49	170299.532	1087.993458	0.047278935
(patient 11)	49	109432.116	4534.649144	0.027283414
(patient 12)	49	91750.5578	3496.218205	0.080148282
(patient 13)	49	92775.1934	2449.683249	0.034938016
(patient 14)	49	193248.605	3607.600707	0.069849614
(patient 15)	49	191547.52	3781.188955	0.087487496
(patient 16)	49	205652.497	3102.597826	0.093679979

Agent	Time Step	Wellness	Patient Benefit	Patient Risk
(patient 17)	49	138400.872	7475.557466	0.022469396
(patient 18)	49	93177.0112	3159.824404	0.033168211
(patient 19)	49	205652.497	3764.1726	0.030655692
(patient 20)	49	173524.626	4635.761142	0.042109004
(patient 21)	49	73654.7101	3284.682156	0.05653296
(patient 22)	49	123078.725	9836.11778	0.046952417
(patient 23)	49	164049.435	2700.358298	0.060788246
(patient 24)	49	210882.06	2394.782923	0.058755135
(patient 25)	49	235154.646	2082.187012	0.036556447
(patient 26)	49	166057.518	4548.419454	0.092880744
(patient 27)	49	230300.273	1556.063725	0.074194594
(patient 28)	49	161637.857	9524.668404	0.024314212
(patient 29)	49	133993.844	2749.768259	0.082358168
(patient 30)	49	149454.483	3283.761405	0.096872022
(patient 31)	49	71751.2871	4586.311738	0.067820372
(patient 32)	49	107153.085	3558.175124	0.023776383
(patient 33)	49	202983.77	1461.566675	0.054905608
(patient 34)	49	119730.321	4948.222776	0.021265077
(patient 35)	49	171173.514	1686.63494	0.083786855
(patient 36)	49	143099.523	1471.851752	0.059483528
(patient 37)	49	118876.581	1734.971929	0.095699811
(patient 38)	49	193248.605	3479.746446	0.050545807
(patient 39)	49	132553.06	9301.572059	0.037241654
(patient 40)	49	109328.643	3808.88966	0.088564487
(patient 41)	49	0	1485.476751	0.04816142
(patient 42)	49	110663.361	4558.294455	0.027534654
(patient 43)	49	170299.532	3159.824404	0.033168211
(patient 44)	49	126842.396	3190.644085	0.098587429
(patient 45)	49	259873.69	4656.746767	0.060493678
(patient 46)	49	126245.115	7668.061899	0.032481419
(patient 47)	49	232562.375	3226.791924	0.06944243
(patient 48)	49	174221.625	3507.105009	0.061070715
(patient 49)	49	126245.115	8634.674912	0.078364254

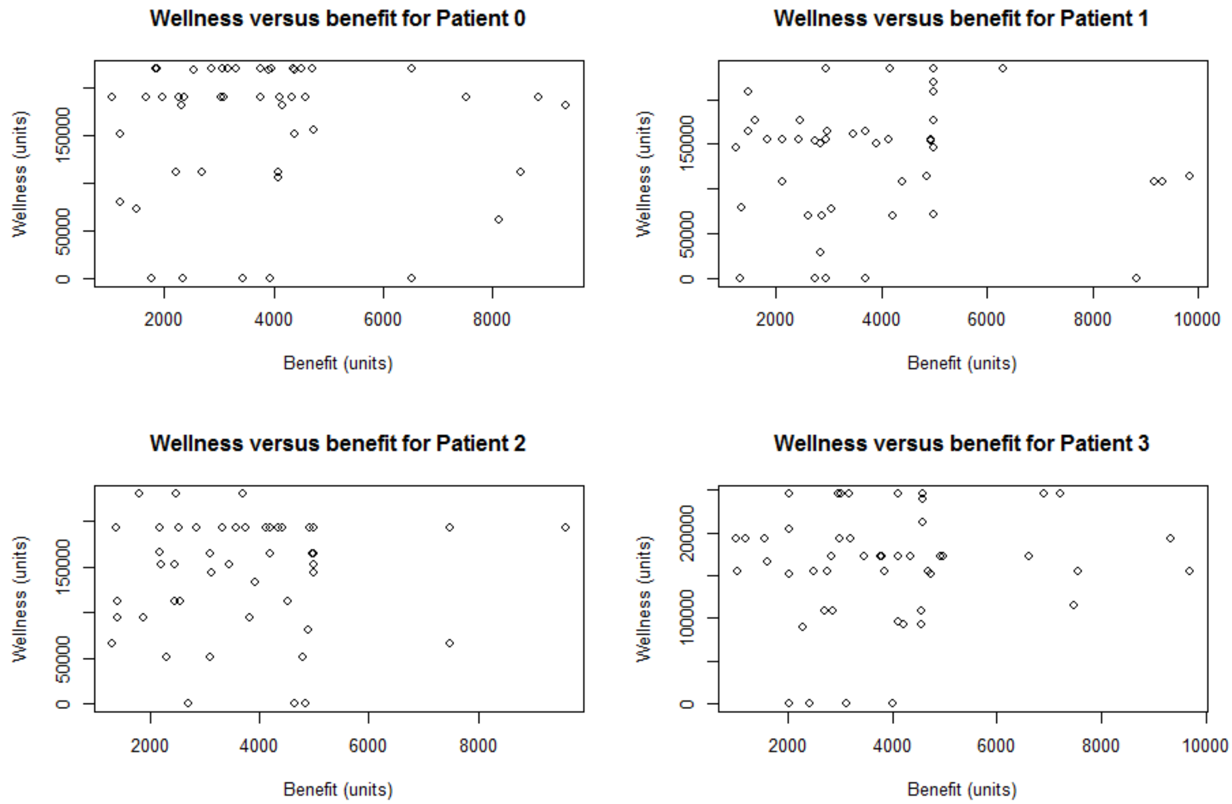
Abridged Dataset of 2500 records of individual patient-agents

APPENDIX C:

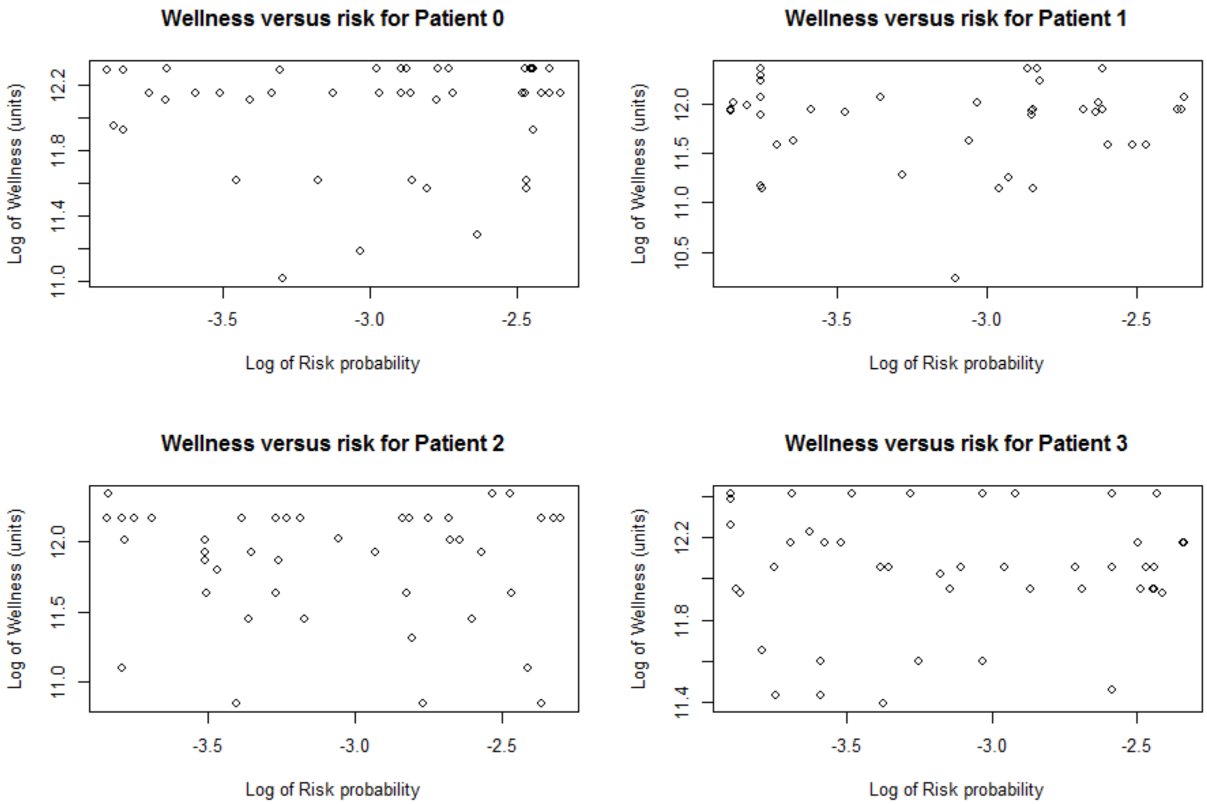
CORRELATIONS AND SCATTERED GRAPHS



Scatter diagram of benefit and risk for selected patient-agents.



Scatter diagram of wellness and benefit for selected patient-agents.



Scatter diagram of wellness and risk for selected patient-agents.

APPENDIX D:

PAIN SELF-MANAGEMENT EDUCATION MESSAGES

Message Constructs	Questions	Responses
Decision-making (day to day decisions in response to changes in pain management based on appropriate information on chronic pain)	What is pain? What is causing your pain What do you know about pain? Why change old belief that chronic pain has a cure? Have you noticed any changes (physical, psych, social) since you have been taking opioids? If so, what? If not, have you been told about any of these changes that might occur as a result of long term opioid use? Do you have any safety concerns about your opioid use? Do you think your healthcare provider is concerned about your safety with opioid use? If so why is your healthcare provider concerned? Why would you choose to stop using opioids?	Pain is a universal human experience Define Acute and Chronic pain Describe biology of pain Describe pain pathway Opioid medications and its adverse effects. Too much focus on opioid medication Lasting changes depends on your efforts rather than medical treatments We must change our treatment plan to manage pain rather than cure pain Chronic pain is not curable
Problem-solving (problem definition, and generation of possible solutions)	Do you remember needing to take more medication during or after a stressful event? Do you ever experience fear, depression, anxiety, exhaustion, or disturbed sleep? What do you do during stressful events? Do you ever have loss of strength? If so, does this loss of strength cause you to not be able to exercise? If so, does this loss of strength cause pain when participating in physical activities? Do you lose joint mobility or flexibility? Have you ever felt that you have problems with alcohol use, drug use or tobacco use? Have you ever experience withdrawal symptoms? If yes, what type of symptoms did you experience? Have you ever had a compulsion to continue taking	Emotional pain can make physical pain worse, but pain medication is not designed to address emotional pain There is need for culture change from focus of pain medications, more tests and more surgeries Recognize deep emotions and distress, stress, anxiety, and depression Chronic Pain like other chronic illnesses has psychological and physical component and a comprehensive approach to treatment will help regain function Pseudo-addiction is judicious increase of opioid medication in order to gain control of pain Addiction is when an individual despite harm have compulsion to taking opioid on an ongoing basis for effects other than pain relief Tolerance is decrease effect of opioids with continued use Dependence is when you develop symptoms because you suddenly stopped your opioid medications. These symptoms are known as withdrawal symptoms, they are normal body physiologic response to prolonged opioid use Referral to mental health evaluation and counselling

Message Constructs	Questions	Responses
	pain medications for effects other than for pain relief?	
Goal setting (1 to 2 goals at a time, specific realistic and achievable and time limit)	Do you feel that your pain controls your life? If yes, what measures do plan to take to limit or prevent this? Have you thought of other ways of managing your pain in addition to taking medication?	Short-term goal is improved function Long-term goal is quality of life Limit average daily dose of opioids Limit opioid utilization over time Adopt self-management skills and techniques
Action planning (An action plan involves a period 1 to 2 weeks and is very behavior specific, realistic and achievable)	What activities, besides your pain medications, do you do to help your pain? What are three things you do you do to reduce your pain? Are there things you can do that will make you feel better? How can you pace your activity on a typical day? How do you manage pain flare-up? What is one goal you make for yourself to relieve or reduce your pain? What is one pleasurable activity goal you can do while pacing?	Making a short-term action plan Get a goal to begin to manage pain Get active Establish regular physical activity (e.g., walk 10 minutes on Monday and Thursday for two weeks) Increase daily functioning Pacing is start low increase gradually Improve sleep Good nutrition Smoking cessation Limit alcohol
Self-monitoring (physical and emotional response that lead to insights, confidence and actions)	Is there anything getting in the way of your ability to get better? What does your pain level have to be, for you to be as active as you want? How do you prevent overstressing about your pain?	Modern lifestyle of sitting for long time, watching TV or being on computer for longer hours can sensitize the nervous system affecting pain. Catastrophizing pain
Self-efficacy (the capacity to organize and execute action plan)	How certain are you that you can reduce your pain to a small amount without taking extra medications? How certain are you that you could complete an action plan on a 10-point scale from 10 (very sure) to 1 (not all sure)?	Implement your goals and action plan and master and evaluate tasks Interpret you symptoms to include alternative explanations that will lead you to try new self-management behavior Act as model for others Reinforcement, feedback and support from others If score is less than 7 use problem-solving techniques to adapt or change the action plan.
Self-tailoring (applying self-management skills and	Have you heard about the new opioid safety rules? What do you know about pain	Opioid prescription must be only from only one provider Each State has prescription monitoring program

Message Constructs	**Questions**	**Responses**
knowledge to oneself appropriately)	self-management? Do you know what would happen if you stopped taking your pain medications?	Read and understand opioid agreement Perform urine drug screen periodically Understand urine drug test result Tapering off opioids Drug-drug interactions Stress-coping skills Attention diversion.
Partnership building (negotiating confidence and establishing communication across health professionals)	Do you have difficulty getting your healthcare provider to understand your symptoms and conditions? Have you ever encountered a situation whereby the healthcare provider does not want to prescribe opioid medications for you? How did you handle the situation? How do you improve communication with your health care provider?	Get support and get into a recovery plan Positive reinforcement Ask your provider about these alternatives: Activity ï physical therapy, water therapy, occupational therapy Stress/Anxiety- Acceptance of the pain condition, mental health therapy, Relaxation therapy, Heat and Cold therapy Depression/PSTD- may need MH therapy and medications Sleeping problems-identify contributing factors, sleep hygiene, avoid sleeping medications Mind and Body Skills programs ï Tai-chi, Yoga, Zumba, Biofeedback etc. Pain clinic- invasive interventions and interdisciplinary approach Nerve stimulation, Chiropractic, Acupuncture, Surgery Pain classes- coaching, counselling, support groups Non-opioid medications- Antidepressants, NSAIDS, Anticonvulsants

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