ORIGINAL ARTICLE

Spatial dynamics of access to primary care for the medicaid population

Nasim Sabounchi^a, Nasser Sharareh^b, Fatima Irshaidat^c and Serdar Atav^d

^aSystems Science and Simulation Laboratory (S3L), Department of Systems Science and Industrial Engineering, Binghamton University - State University of New York (SUNY), Binghamton, NY; ^bPopulation Health Sciences Department, School of Medicine, University of Utah, Salt Lake City, UT; ^cOur Lady of Lourdes Memorial Hospital, Binghamton, NY; ^dDecker School of Nursing, Binghamton University - State University of New York (SUNY), Binghamton, NY

ABSTRACT

Primary care (PC) has always been underestimated and underinvested by the United States health system. Our goal was to investigate the effect of Medicaid expansion and the Affordable Care Act (ACA) provisions on PC access in Broome County, NY, a county that includes both rural and urban areas, and can serve as a benchmark for other regions. We developed a spatial system dynamics model to capture different stages of PC access for the Medicaid population by using the health belief model constructs and simulate the effect of several hypothetical interventions on PC utilisation. The government data portals used as data sources for calibrating our model include the New York State Department of Health, the Medicaid Delivery System Reform Incentive Payment (DSRIP) dashboards, and the US census. In our unique approach, we integrated the simulation results within Geographical Information System (GIS) maps, to assess the influence of geospatial factors on PC access. Our results identify hot spot demographic areas that have poor access to PC service facilities due to transportation constraints and a shortage in PC providers. Our decision support tool informs policymakers about programmes with the strongest impact on improving access to care, considering spatial and temporal characteristics of a region.

ARTICLE HISTORY

Received 28 August 2018
Accepted 15 December 2018

KEYWORDS

Spatial system dynamics; GIS mapping; Medicaid; primary care; health disparities

1. Introduction

Primary Care (PC) and preventive services have been neglected by Americans and the US healthcare system (Asgary et al., 2016; Pecora, 2018; Starfield, Shi, & Macinko, 2005). People who regularly use a PC provider are considered healthier at many levels including lower 5-year mortality rates regardless of their demographics, health status, insurance position, or health perceptions (ODPHP, 2018; Starfield et al., 2005). For every 10 deaths, seven cases are caused by chronic diseases that could be prevented with the appropriate preventive care. These cases account for 75% of health-care spending nationwide (HHS, 2013; O'Grady & Capretta, 2009).

There are several key barriers for access to PC. Unaffordability of care due to the lack of insurance or high cost of healthcare and not having an established relationship with a regular source of care such as a PC provider, negatively impact PC access and utilisation (Asanin & Wilson, 2008; Escarce & Kapur, 2006; Mirza et al., 2014). Also, socio-economic disadvantages such as less education or low income make individuals less likely to undergo preventive care procedures or undertake well-visits on a regular basis (Doubeni, Laiyemo, Reed, Field, & Fletcher, 2009).

The Affordable Care Act (ACA) attempts to make health care more affordable, especially for low-income

Americans through initiatives such as the expansion of Medicaid coverage in 2014. With the promise of health care cost reduction due to disease management, the ACA focuses on improving access to PC services through new insurance coverage (Andersen, Davidson, & Baumeister, 2014; Brown, Polsky, Barbu, Seymour, & Grande, 2016; Fireman, Bartlett, & Selby, 2004). It also enacted new subsidies and cost-sharing protections, and preventive services are more affordable and encouraged (Borelli, Bujanda, & Maier, 2016). Recent studies show that under the ACA, disparities in health care access have reduced significantly (Griffith, Evans, & Bor, 2017), and roughly 20 million new individuals were enrolled in Medicaid by 2016 (Rhodes et al., 2017).

Several states opted out from expanding the Medicaid programme eligibility. As a result, many adults in these states fall into a “Medicaid coverage gap” meaning these individuals fall between eligibility for Medicaid in a given state and the Federal Poverty Level (FPL) for Marketplace subsidies (Garfield, Damico, & Orgera, 2018). Nearly 2.4 million poor Americans, disproportionately represented by minorities, fall into the Medicaid Gap and are excluded from medical insurance coverage. This has implications on efforts to address disparities in health coverage and access to care among minorities (Garfield, Damico, Stephens, & Rouhani, 2016). Studies have shown that those in the Medicaid coverage gap are

more susceptible to serious health problems and expanding eligibility requirements can reduce mortality rates and improve other health-related measures (Artiga, Stephens, & Damico, 2015; Garfield et al., 2016).

Medicaid was expanded in New York State due to the ACA. The main objective of our research was to investigate how the introduction of a government health plan (Medicaid) affected the use of PC services by socio-economically disadvantaged populations that were previously uninsured. We focused on Broome County in upstate New York, a county with nearly two-thirds agricultural or rural residential zones (DMA, 2013), to investigate locations in the county in need of primary healthcare centres. After the expansion of Medicaid in Broome County, the number of uninsured declined and Medicaid Enrollees increased, but surprisingly, the PC visit rate continued to decline. This suggested that insurance coverage by itself did not sufficiently explain utilisation. Other psychological and physical barriers needed to be explored for a full understanding of the dynamics behind the utilisation of PC and preventive health services.

2. Methodology and data

We adopted a system dynamics (SD) approach for developing a simulation model to assess the complex interactions of factors that affect the utilisation of PC services by socio-economically disadvantaged populations. Then, we used the model to investigate two policy scenarios: ACA was not implemented; and perceived barriers to accessing care were reduced. We measured three outcomes under each scenario: total number of Medicaid enrollees (ME); the PC visit rate (PCVR) by Medicaid enrollees; and the number of uninsured population (U). We then combined our SD model with Geographical Information System (GIS) methodology to study the influence of spatial factors on access to PC by Medicaid enrollees.

SD modelling is the process of investigating the feedback structures of a complex system (Ghaffarzadegan, Ebrahimvandi, & Jalali, 2016; Sharareh, Sabounchi, Roome, Spathis, & Garruto, 2017; Sterman, 2000) and can be used to tackle the complexity of healthcare issues. It facilitates the analysis of existing systems and helps policymakers to make predictions and better decisions for the future (Ghaffarzadegan, Lyneis, & Richardson, 2011; Sabounchi, Hovmand, Osgood, Dyck, & Jungheim, 2014). SD modelling can help evaluate the quality of care and system performance and provide policy insights for balancing the trade-offs between access, effectiveness, and efficiency (Milstein, Homer, & Hirsch, 2010; Wolstenholme, 1999). Some SD models were developed to study the socio-economic inequalities in health and to

study the consequences of various healthcare scenarios and design interventions to improve access to care (J. Homer, Milstein, Hirsch, & Fisher, 2016; Mahamoud, Roche, & Homer, 2013).

Additionally, GIS provides useful information about healthcare systems (Shaw & McGuire, 2017; Yasobant, Vora, & Upadhyay, 2016). Specifically, GIS is used to determine PC need and recognise high-need regions based upon different factors including median household income, population, emergency department (ED) patients, insurance coverage, and preventable ED utilisation rates (Dulin et al., 2010). Also, geospatial analysis demonstrates that spatial factors, including the location of healthcare facilities, the distance from patients to providers, and transportation, play significant roles in forming barriers to healthcare access (Edward & Biddle, 2017; Hutson, 2017).

GIS has been used to combine different sources of geographical data to improve population health, reduce health costs, and increase the quality of care (Miranda, Ferranti, Strauss, Neelon, & Califf, 2013) and to have a better understanding of health disparities (Beck, Sandel, Ryan, & Kahn, 2017). Some GIS studies showed the lack of healthcare providers in regions where people with high-needs reside such as the lack of clinics for prenatal care in areas with high-needs mothers (McLafferty & Grady, 2004) or the lack of healthcare providers in populated areas (Rosero-Bixby, 2004). Other studies showed that people living in medically underserved areas had higher preventable ED use (Fishman, McLafferty, & Galanter, 2016).

Xu and Coors (2012) combined the results from their SD model with GIS to study urban residential development. Hovmand and Pitner (2014) showed the potential of integrating SD with GIS to suggest solutions for social problems. We used a similar approach to examine health care access. Using Vensim software, we illustrate the SD simulation results over a 12-year period. Then we combine the SD simulation with ArcGIS Desktop to provide a choropleth map, a dynamic GIS map, to investigate access to PC. There are many other integration techniques (Gharib, 2008; Lowry & Taylor, 2009; Singhasaneh, Lukens, Eiumnoh, & Demaine, 1991) that combine simulation models with GIS maps, including the combination of STELLA with ArcToolbox (Scheffran, BenDor, Wang, & Hannon, 2007) and SIMILE with ArcView (Mazzoleni, Giannino, Colandrea, Nicolazzo, & Massheder, 2003). Although all these techniques are useful and informative, we believe our approach is more straightforward.

For the purpose of validating our SD model, we compiled data from 2008 to 2015 for the total number of Medicaid enrollees (ME), the PC visit rate per 1000 member months (PCVR) and the number of uninsured population (U) for each month. The data are compiled from three government data portals: the New York State Department of Health (DOH, 2014), the New York State Medicaid Delivery System Reform

Table 1. Data sources and details.

Data source	Link	Data extracted	Time period
New York State Department of Health (NYSDOH) (DOH, 2014)	https://www.health.ny.gov/statistics/health_care/medicaid/eligible_expenditures/	Total number of Medicaid enrollees (ME) not disaggregated by age group in Broome County, NY	January 2008 – December 2011
DSRIP dashboards (2015b)	http://dsripdashboards.health.ny.gov/	Total number of Medicaid enrollees (ME) not disaggregated by age group in Broome County, NY	January 2012 – March 2015
US Census Bureau website (USCB, 2015a), the numbers from the 2014 census quick facts (USCB, 2015a)	https://www.census.gov/quickfacts/broomecountynynewyork	Percentage of population under age 65 in the county aged (18–64) = $1 - (\text{percent of people under 18 years} / (100 - \text{percent of people 65 years and over})) = 76.10\%$.	2014
DSRIP dashboards (DSRIP, 2015b)	http://dsripdashboards.health.ny.gov/	PC visit rate per 1000 member months (PCVR) in Broome County	January 2011 – March 2015
New York State Department of Health (NYSDOH) (DOH, 2008)	https://www.health.ny.gov/prevention/prevention_agenda/access_to_health_care/estimates_of_uninsured.htm	Number of uninsured population (U) for each year	2008
New York Uninsured. from County Health Rankings and Roadmaps programme (CHR&R, 2016)	http://www.countyhealthrankings.org/app/new-york/2012/measure/factors/85/data http://www.countyhealthrankings.org/app/new-york/2013/measure/factors/85/data http://www.countyhealthrankings.org/app/new-york/2014/measure/factors/85/data http://www.countyhealthrankings.org/app/new-york/2015/measure/factors/85/data http://www.countyhealthrankings.org/app/new-york/2016/measure/factors/85/data	Number of uninsured population (U) for each year	2012–2016

Incentive Payment (DSRIP) dashboards (DSRIP, 2015a), and the US census (USCB, 2015b). Table 1 lists each data source and each element of data from each data source that was used in our model.

We estimated Medicaid enrolment by age using the US census parameters for Broome County. The data series for total number of Medicaid enrollees not disaggregated by age group in Broome County, NY, between January 2008 and December 2011 is downloaded from the New York State Department of Health (NYSDOH) (DOH, 2014). Also, the data series for number of Medicaid enrollees between January 2012 and March 2015 is downloaded from DSRIP dashboards (2015b). The NYSDOH website (DOH, 2014) provides Medicaid programme statistics at county level and also serves as the source database for DSRIP dashboards (DSRIP, 2015a). In order to estimate the number of enrollees between the age of 18 – 64, the total enrollees are multiplied by the percentage of population aged 18–64 in the county. The following assumptions are made to approximate the required data series.

*Number of Medicaid unique members aged (18–64) in the county = the number of Medicaid unique members aged (0–64) * percentage of population aged (18–64) in the county*

The “percentage of population in the county aged (18–64)” was calculated according to the available data of demographics on the US Census Bureau website (USCB, 2015a). We adopt the numbers from the 2014 census quick facts (USCB, 2015a) which are the

most updated numbers on demographics. Since the percentage of population under 18 years old and the percentage of people aged >65 is available, hence, the “percentage of population in the county aged (18–64)” is equal to $1 - (\text{percent of people under 18 years} / (100 - \text{percent of people 65 years and over}))$. The resultant percentage of people aged 18–64 among the group aged 0–64 years old in Broome County, NY is equal to 76.10%.

Furthermore, the data series for PC visit rate per 1000 member months (PCVR) in Broome County is available for every month between January 2011 and March 2015, which is the time of the data download. Member months represents the total number of Medicaid enrollees multiplied by the total number of months that they are enrolled in the Medicaid plan (DSRIP, 2015b). Also, a year by year data series for Total Number of Uninsured Population in Broome County disaggregated by age group was found (CHR&R, 2016) and added as a third data series for model calibration.

3. The simulation model

The simulation model was designed for Broome County in upstate New York, which is one of the eight counties of the Southern Tier Region that aligns with the northern border of Pennsylvania. We used the model to assess complex interactions of factors that affect the utilisation of PC services by the Medicaid

population. The model allowed us to examine the effect of policy scenarios on our outcome variables.

The model consists of a detailed stock and flow diagram that captures the navigation of Medicaid enrollees through the health care delivery system (Figure 1). Stocks represent accumulations of the difference between the inflow and outflow of the process elements over time (Sterman, 2000). The supplementary material includes all the formulas and equations for our simulation model.

The initial stock measures the number of “Uninsured and not Qualified for Medicaid” (Figure 1). A major portion of this group became qualified for Medicaid after two policy changes: the enactment of the ACA in 2010 followed by Medicaid expansion in the state of New York in 2014 (KFF, 2014). However, a small proportion does not get qualified for Medicaid due to income ineligibility or undocumented immigrant status, and so flow into the stock of “Uninsured and Not Qualified for Medicaid after ACA”. Also, a proportion of the uninsured can be eligible for a government subsidy scaled by their income and leave through the flow of “Rate of Enrollment for Private Insurance” (Sommers & Rosenbaum, 2011) (Figure 1).

Among the newly qualified for Medicaid, a fraction gets enrolled in Medicaid and flow into the stock of “Medicaid Enrollees not Utilizing PC”. Another fraction who are eligible for Medicaid hesitate to enrol in the programme due to their desire to stay out of the government system, lack of knowledge of their eligibility, or the belief that their health status is good or will improve and hence, they do not need any health insurance (Moody, 2016). Consequently, this population flows into the other stock “Qualified and not Enrolled”. Before Medicaid expansion, these individuals would have never enrolled in Medicaid, but after the ACA, due to the open enrolment and obligated penalty systems for non-insured (Andrews,

2016), a proportion ended up enrolling in Medicaid and moving to the stock of “Medicaid Enrollees not utilizing PC” (Figure 1).

Later, the Medicaid enrollees move to the stock “Medicaid Enrollees Intend to Utilize PC” (Figure 1). Their intention of utilising PC depends on their perceptions of barriers to access PC services “Average Perceived Barriers” that we define based upon the Health Belief Model (HBM) constructs (Glanz, Lewis, & Rimer, 1997) (Figure 1). HBM is a psychological model that explains various psychological and physical barriers that affect patient health actions and behaviours (Glanz et al., 1997). We can use HBM to facilitate the creation of incentives to improve attitudes with respect to PC utilisation.

Once Medicaid beneficiaries have the readiness to start accessing the care they move into the stock “Medicaid Enrollees Start Utilizing Care” (Figure 1). At this point, the beneficiaries have experienced direct contact with a healthcare provider. Staying in this loop for 2 years qualifies this population to be Permanent Utilizers. This is represented in the stock “Medicaid Enrollees Utilize PC on a Permanent Basis” which reflects a continuous relationship between Medicaid beneficiaries and their healthcare providers (Figure 1). This is proved by their follow up appointments, yearly well visits and continuous monitoring of their chronic health issues. However, those who fail to adhere to provider’s recommendations and quit their follow up appointments are considered non-compliers and are included in the stock “Medicaid Enrollees Never Complying” (Figure 1).

4. Model calibration and simulation results

Since most of the parameters in the model are not found in any of the related references, we used model calibration to estimate these parameter values by using the

Figure 1. Overview of the simulation model.

maximum likelihood estimation approach to minimise the difference between historical time series data with the simulated data series (Dogan, 2004). Parameter values can be calibrated using a calibration module built in the system dynamics simulation software (Vensim) (Ventana, 2015). The calibration module in the modelling software calculates the optimum values of model parameters within the range defined according to literature review and experts' opinions.

The goal of calibration is to minimise the objective function which is represented by the summation of the “difference between each historical time series and the corresponding simulated time series” multiplied by the weights and squared (Dogan, 2004). For each calibration round, a weight (w) is calculated and inputted in the calibration module. The weights are calculated by finding reciprocal of the standard deviation of the error terms (σ) that corresponds to the maximum likelihood estimation method (Dogan,

2004). We stopped at the third iteration since the changes in weight values became negligible from second to third iteration (Dogan, 2004). The following equation represents the objective function for this calibration.

$$\begin{aligned} \text{Minimize} \quad & \left(\int_{t=Jan.2008}^{t=March\ 2005} (w_1(ME(t) - ME_{data}(t)))^2 \right. \\ & + \int_{t=Jan.2008}^{t=March\ 2005} (w_2(PCVR(t) - PCVR_{data}(t)))^2 \\ & \left. + \int_{t=Jan.2008}^{t=March\ 2005} (w_3(U(t) - U_{data}(t)))^2 \right) \end{aligned}$$

The final calibrated parameters along with confidence intervals are summarised in [Table 2](#). Constraints on plausible values of the calibrated parameters listed in [Table 2](#), were formulated from literature and discussions. Then we validated the calibrated

Table 2. Final calibrated parameter values along with estimates from primary care providers.

Parameter [Unit of Analysis]	Value in the Model	Confidence Interval	Provider 1	Provider 2	Provider 3	Provider 4	Provider 5	Provider 6	Estimation Interval
Fraction of Uninsured who become Qualified for Medicaid (<i>after ACA</i>) [%]	75.13	79.13–75	75	75	90	90	90	75	75–100
Average Time Delay for Enrollment in Medicaid [<i>Months</i>]	10.50	9.95–11.07	2	0.25	1	0.5	0.5	3	1–70
Average Time Delay for Uninsured to Become Qualified (<i>Before ACA</i>) [<i>Months</i>]	1.73	1.70–1.76	2	0.5	N/A	1.5	1	3	1–25
Average Time Delay for Uninsured to Become Qualified (<i>After ACA</i>) [<i>Months</i>]	1	0.30–1	2	0.5	N/A	1.5	1	3	1–25
Average time to Decide to Utilize PC [<i>Months</i>]	2.30	2.74–3.24	1	1	1	2	1	3	1–100
Average Time Delay for Medicaid Enrollee, once Decided to Utilize PC to make a Visit to Provider's office [<i>Months</i>]	25.39	22.86–27.94	3	0.25	1	2	1.5	2	1–70
Average Time Delay for Medicaid Patient, once made a visit to Provider's office to Continue Utilizing PC, quit, or Delay Further Utilization [<i>Months</i>]	17.21	16.73–17.71	1	6	24	5	6		1–300
Fraction of Medicaid Enrollees who Started to Utilize PC, become Permanent Utilizers [%]	14.82	14.82–44.47	20	30	90	10	10	90	10–30
Fraction of Medicaid Enrollees who Started to Utilize PC, Quit Utilizing PC [%]	68.71	53.03–74.11	20	30	10	40	30	50	10–80
Fraction of Medicaid Enrollees who Started to Utilize PC, Delay Utilizing PC [%]	16.47	14.82–21.79	20	30	10	25	25	25	10–30
Number of visits that a Medicaid Patient who permanently Utilizes PC, Makes to Provider's Office [<i>Visit per Month</i>]	0.08	0.08–0.15	1	1	0.33	1	1	1	0.08–2
Number of visits that a Medicaid Patient who started to Utilize PC, Makes to Provider's Office [<i>Visit per Month</i>]	2	1.96–2	1	0.3	0.33	1	1	1	0.08–2
Fraction of Medicaid Enrollees who become Unqualified [% <i>per Month</i>]	0.0001	0.0001–0.004	25	30	2	1	1	50	0.0001–1

Other calibrated parameter values

Parameter [Unit of Analysis]	Value in the Model Confidence Interval		Estimation Interval
Fraction of Uninsured who become Qualified for Medicaid (<i>before ACA</i>) [%]	5.62	5.52–5.72	0–9
Fractional Rate of Uninsured Purchasing Private Insurance (<i>After ACA</i>) [% <i>per Month</i>]	24.96	10–90	10–90
Rate of Newly Uninsured [<i>People per Month</i>]	125.23	122.18–128.28	1–300
Average Time Delay for Enrollment in Medicaid after ACA, for late enrollees [<i>Months</i>]	12	5.50–12	1–12
Fraction of Qualified who enrol for Medicaid (<i>before ACA</i>) [%]	55.18	54.83–55.52	50–100
Fraction of Qualified who enrol for Medicaid (<i>after ACA</i>) [%]	94.52	90.84–97.90	1–100
Fraction of Qualified who enrol late for Medicaid (<i>after ACA</i>) [%]	1	1–2.18	1–100
Fractional Rate of Medicaid Enrollees who Decided to Utilize PC, but Quit before going to a Provider's Office, [% <i>per Month</i>]	1	1–1.39	1–70
Initial Perceived Barriers (IPB) for a Medicaid Enrollee to Utilize PC [%]	90.40	89.52–91.14	0.1–99.99

parameter with six different nurse practitioners in primary care settings. These providers have PhD or a Doctorate of Nursing Practice (DNP) degree and provide PC services for Medicaid patients on a regular basis for more than 10 years. We oriented each provider to our model concepts and requested them to examine the parameter values based on their professional experiences. Estimations from different providers and the final calibrated values for parameters are provided in Table 2. Overall estimates by providers and calibrated values match. A major discrepancy was observed for the average time it took for a Medicaid patient decided to utilise care, to get an appointment and make the visit to a PC office. The calibrated value was 25.4 months while the estimate from various providers was on average 1.6 Months. This demonstrates that contrary to general beliefs, it takes much longer on average for Medicaid patients to make a visit to the PC Provider's office. Also, Fraction of Medicaid Enrollees who became unqualified per month was calibrated as 0.0001%, whereas estimates by providers were on average 18% per month.

According to the historical time series, there were 40,555 adults between the ages 18 and 64 in Broome County who were enrolled in Medicaid in March 2015. The simulation result for "Medicaid Enrollees" projects that by the end of the simulation period (ie, July 2020), the number of Medicaid enrollees would reach 46,840 for Broome County (Figure 2).

The simulation results for PC visit rate per 1000-member months for the Medicaid population in

Broome County fit the historical data and declined between January 2011 and March 2015 and never pick up in the future (Figure 2).

For the uninsured population, we utilised a yearly data series (Figure 2) that was available until January 2016. The uninsured population encountered a decline starting in 2008 in all southern tier counties according to the historical data (CHR&R, 2016). Also, the number of uninsured declined sharply after the ACA and Medicaid expansion. The model's simulated trend matches the decline of the uninsured data and continues this behaviour (See Figure 2). Uninsured numbers kept on declining since the population qualified for Medicaid and Medicaid enrolment rates increased significantly after the ACA. Then due to slower growth in Medicaid enrolment, the number of uninsured started to increase after 2017.

5. Discussion and policy analysis

During the first few years of the ACA, higher enrolment in Medicaid occurred due to expanded eligibility. However, the simulation results show that growth in Medicaid enrolment slowed down after May 2016 and began to stabilise and reach a new equilibrium level (Figure 2). This empirical result indicates that qualifying more of the population to enrol in Medicaid will not necessarily lead to a respective increase in enrolment. Ongoing intervention programmes are needed to

Figure 2. Results for policy test 1: Effect of ACA implementation: a) uninsured individuals b) Medicaid enrollees c) PC visit rate per 1000 member months.

improve knowledge of the benefits of the Medicaid insurance plan and the enrolment process.

Furthermore, PC visit rate per 1000-member months for the Medicaid population is declining (Figure 2). This is not favourable since a higher PC access rate will promote better community health, reduce chronic disease severities, decrease ED visits, and reduce health-care costs. A decline in the PC visit rate indicates poor access to PC service facilities due to time, cost, and transportation constraints, or an actual shortage in PC Providers that do not align with the influx of new enrollees. If policies to reform healthcare allow more people to enrol in Medicaid without addressing existing accessibility issues, then the proportion of Medicaid patients utilising PC services will not increase respectively. Consequently, we need to design policies and interventions to improve access to PC.

5.1. First policy scenario: not implementing ACA

In the first policy scenario, we looked at various measures if the ACA was not implemented. Results show a 41.2% increase in the number of uninsured individuals by the year 2022 compared to the base run (Figure 2(a)). As well, the Medicaid population would decrease by 10.05% by June 2022 (Figure 2(b)). Additionally, the PC visit rate for Broome County declines 11.6% by the year 2020 (Figure 2(c)).

Some argue that if PC is offered freely, all beneficiaries will pursue these services. Our simulation indicates that with Medicaid expansion, PC visit rates do not notably increase (Figure 2(b)). In addition to increasing the number of PC Providers, more programmes that aim to improve access are needed.

The simulation model did not explain why the increase in Medicaid enrollees did not yield a growth in PC visit rates. We hypothesised that this might be due to the lack of access to PC in some regions; therefore, we adopted GIS methods to investigate this hypothesis.

5.1.1. GIS map

The “PC Visit Rate per 1000 Member Months” is dependent on the county’s demographics, number of PC provider’s facilities and resources, spatial accessibility and educational programmes regarding enrolling in Medicaid. Thus, our simulation results show variations in both space and time. Our GIS map highlights the regions with low access to PC similar to some other GIS studies (Brown et al., 2016; Xu & Coors, 2012). It is also dynamic and uses the simulation results from our calibrated model. This approach enabled us to demonstrate the Medicaid enrollees’ growth and the PC visit rate decline within each census tract of Broome County from 2008 to 2020.

In the first exhibit (Figure 3(a)), the darker the colour is, the higher the number of Medicaid enrollees living in that census tract. The yellow circles show the geocoded PC providers’ locations based on their latitude and longitude data. In Broome County, the number of hospitals that Medicaid members utilised for PC services in 2014 is three and the number of PC providers, women’s health centres, walk-in clinics and retail clinics that Medicaid members accessed to receive PC is 299 (DSRIP, 2015a). We illustrated the major roads and districts in the county to distinguish urban and rural areas. The left panel shows measures for Broome County in 2008 and the right one shows the simulated measures in 2020. The simulation model runs for each month from 2008 to 2020 but we are just showing the first and the last month of simulation. The simulation video is available at <https://figshare.com/s/7a4ba83b7034b2a9f296>. The dynamic GIS map shows that the number of Medicaid enrollees grows significantly in different regions. However, the number of PC providers remains almost the same during this 12-year period.

As the map shows, many PC providers practice in Vestal, which is one of the more affluent areas in the Broome County, NY, based on household income (USCB, 2017). Relatively few Medicaid enrollees live in this district. Conversely, in the poorer region of Whitney Point with lower median household income (USCB, 2016), just three PC providers practice, and in Harpursville, one of the areas with the highest number of Medicaid enrollees, there are no PC providers. This map explicitly displays the discrepancies among regions and highlights hot spots that are high-need areas and that should be a priority to establish PC health centres.

In the second exhibit (Figure 3(b)), the PC visit rate per 1000 members is illustrated. Interestingly, the regions with a high number of Medicaid enrollees including Whitney Point and Harpursville have the lowest PC visit rate which indicates the lack of access to PC providers. This explains why the PC visit rate decreased from 2008 to 2020. We speculate that the reason for the low PC visit rates in those areas with many Medicaid enrollees is due to barriers in accessing PC providers. Our approach can be further developed by considering more variables to be shown on the map and expanding the scope of the map.

5.2. Second scenario: reducing perceived barriers on accessing PC

Reducing perceived barriers can be accomplished through educational campaigns, having community role models to promote PC utilisation, distributing information regarding the importance of preventive care tests, and locating PC providers in those areas where Medicaid patients reside. In order to simulate this scenario, we

Figure 3. Dynamic GIS maps for Broome County, NY: a) Medicaid enrollees b) PC visit rate (simulation video available at <https://figshare.com/s/7a4ba83b7034b2a9f296>).

gradually reduced the base-line “Initial Perceived Barriers (IPB)” value on accessing care for the Medicaid enrollees, within the simulation model, by 50% between September 2014 (ie, 12 months after the open enrolment period for the ACA) and September 2016.

As a result of this scenario, the number of individuals overcoming barriers for PC utilisation increases. Since more patients are seeking care due to lower perceived barriers to care, the PC visit rate initially shows an increase when compared to the base run (Figure 4(a)).

However, a decline in the PC visit rate starts to occur around October 2018. The model calculates the PC visit rate by dividing the product of “the total individuals in preventive care” and the “average PC visits” (numerator), by the “total Medicaid enrollees” (denominator). Since the numbers of Medicaid beneficiaries increases more than the total individuals in preventive care, the PC visit rate drops (Figure 4(b)).

Although the scenario shows effectiveness in raising the PC visit rate in early stages, it loses

Figure 4. Results for policy test 2: reduction in the initial perceived barriers (IPB): a) PC visit rate per 1000 members b) PC Permanent Utilizers.

its effect by the fourth years. This is why such programmes need to be re-invigorated to counteract the steady-state behaviour people exhibit in their care-seeking behaviour. The interventions should also address the individuals that quit accessing care and do not stay in the loop of care. Additional policies could be tested using the simulation model.

6. Conclusion

SD modelling is a suitable technique to investigate the dynamic nature and complexity of health care problems (Atkinson, Page, Wells, Milat, & Wilson, 2015; Newman, Velasco, Martín, & Fantini, 2003). SD modelling takes into account a complex set of factors at both the individual and community level (Homer & Hirsch, 2006; Sharareh, Sabounchi, Sayama, & MacDonald, 2016), and offers a more comprehensive approach than other

regression-based methodologies (Ghaffarzadegan et al., 2011; Srijarinya, Riewpaiboon, & Chaikledkaew, 2008). It can be a powerful tool for programme evaluators and policy makers by enabling a variety of future predictions and behaviours (Atkinson et al., 2015; Fredericks, Deegan, & Carman, 2008).

In this study, we investigated the utilisation of PC services by Medicaid enrollees. The main goal of this study was to create a model that could replicate the trends of PC access for Medicaid enrollees and to assess how these trends were reflected in geographic areas. We used the model to explore initiatives and interventions to improve access to PC. The model can be further utilised by programme evaluators and policy makers for a variety of policy predictions.

Since the simulation results of our SD model are associated with geospatial factors in demonstrating healthcare access, combining the SD methodology with GIS mapping allows for the simulation of

dynamic geospatial factors and the conceptualisation of complex systems. Integrating data from our simulation model within GIS maps helped us to assess the needs of different regions for healthcare providers, identify underserved regions, and propose interventions to improve the health of communities.

Our unique contribution was to extend the SD and GIS methodologies, by integrating the simulation data generated by the SD models into GIS maps to incorporate the geospatial factors to assess PC provider shortages in different regions. It is evident from the dynamic GIS maps that establishing PC health centres for high-need areas should be a priority. Combining the SD toolbox with GIS mapping allows us to incorporate dynamic and spatial factors to explore policy scenarios to improve health care access.

Our model is focused on Broome County in upstate New York. Our results would lead discussions on thinking about policies that State of New York could implement to try to encourage providers to move to these locations. Using our approach and method, others can test the reliability of the approach and develop a model that can be recalibrated for other county and location if similar data is available for them. However, the generalisability of the approach is unknown and is a limitation of our study. Further research is needed to test whether the same kind of results and analysis can be pursued for other locations, to investigate hot spot areas in need of primary care providers and interventions to improve primary care access.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Nasim Sabounchi <http://orcid.org/0000-0002-8027-8779>
Nasser Sharareh <http://orcid.org/0000-0001-9552-2028>

References

- Andersen, R. M., Davidson, P. L., & Baumeister, S. E. (2014). *Improving access to care*. In G. F. Kominski (Ed.), *Changing the US health care system: Key issues in health services policy and management* (pp. 33–69). San Francisco, CA: Jossey-Bass.
- Andrews, M. (2016). What are the penalties for not getting insurance? *Kaiser Health News*. Retrieved from <http://khn.org/news/what-are-the-penalties-for-not-getting-insurance/>
- Artiga, S., Stephens, J., & Damico, A. (2015). The impact of the coverage gap in states not expanding medicaid by race and ethnicity. *Disparities policy*. The Henry J. Kaiser Family Foundation. Retrieved from <https://www.kff.org/disparities-policy/issue-brief/the-impact-of-the-coverage-gap-in-states-not-expanding-medicare-by-race-and-ethnicity/>
- Asanin, J., & Wilson, K. (2008). “I spent nine years looking for a doctor”: Exploring access to health care among immigrants in Mississauga, Ontario, Canada. *Social Science & Medicine*, 66(6), 1271–1283.
- Asgary, R., Alcades, A., Feldman, R., Garland, V., Naderi, R., Ogedegbe, G., & Sckell, B. (2016). Cervical cancer screening among homeless women of New York City shelters. *Maternal and Child Health Journal*, 20(6), 1143–1150.
- Atkinson, J.-A., Page, A., Wells, R., Milat, A., & Wilson, A. (2015). A modelling tool for policy analysis to support the design of efficient and effective policy responses for complex public health problems. *Implementation Science*, 10(1), 26.
- Beck, A. F., Sandel, M. T., Ryan, P. H., & Kahn, R. S. (2017). Mapping neighborhood health geomarkers to clinical care decisions to promote equity in child health. *Health Affairs*, 36(6), 999–1005.
- Borelli, M. C., Bujanda, M., & Maier, K. (2016). The affordable care act insurance reforms: Where are we now, and what’s next? *Clinical Diabetes*, 34(1), 58–64.
- Brown, E. J., Polsky, D., Barbu, C. M., Seymour, J. W., & Grande, D. (2016). Racial disparities in geographic access to primary care in Philadelphia. *Health Affairs*, 35(8), 1374–1381.
- CHR&R. (2016). New York Uninsured. from County Health Rankings and Roadmaps program. Retrieved from <http://www.countyhealthrankings.org/app/new-york/2016/measure/factors/85/data>
- DMA. (2013). DMA 2000 Hazard Mitigation Plan Update – Broome County, New York [Disaster Mitigation Act of 2000]. Retrieved from http://www.gobroomecounty.com/files/planning/_pdf/Hazard%20Mitigation/Final%20Draft%20For%20Approval/Section%204%20b-%20General%20Information%20County%20Profile%20February%202013%20low%20Res.pdf
- Dogan, G. (2004). Confidence interval estimation in system dynamics models: Bootstrapping vs. likelihood ration method. *Paper presented at the 22nd International Conference of the System Dynamics Society*, Oxford, UK.
- DOH. (2008). 2008 Census Bureau Estimates of the Uninsured. Retrieved from https://www.health.ny.gov/prevention/prevention_agenda/access_to_health_care/estimates_of_uninsured.htm
- DOH. (2014). Medicaid Enrollees and Expenditures by County. Retrieved from https://www.health.ny.gov/statistics/health_care/medicaid/eligible_expenditures/
- Doubeni, C. A., Laiyemo, A. O., Reed, G., Field, T. S., & Fletcher, R. H. (2009). Socioeconomic and racial patterns of colorectal cancer screening among Medicare enrollees in 2000 to 2005. *Cancer Epidemiology, Biomarkers & Prevention*, 18(8), 2170–2175.
- DSRIP. (2015a). The Delivery System Reform Incentive Payment (DSRIP) Performance Data - New York State Department of Health [NYS Medicaid DSRIP Dashboards]. Retrieved from <https://dsripdashboards.health.ny.gov>
- DSRIP. (2015b). Trend of Primary Care Visit Rates per 1000 Member Months [NYS Medicaid DSRIP Dashboards]. Retrieved from <http://dsripdashboards.health.ny.gov/SDM/Publish.aspx?dashboard=DSRIP+++C4+Trend+of+Primary+Care+Visit+Rates+per+1000+Member+Months&categoryId=0#SID=fa085afb406948e6b6efdb68e056899>
- Dulin, M. F., Ludden, T. M., Tapp, H., Blackwell, J., de Hernandez, B. U., Smith, H. A., & Furuseth, O. J. (2010). Using geographic information systems (GIS) to

- understand a community's primary care needs. *Journal of the American Board of Family Medicine*, 23(1), 13–21.
- Edward, J., & Biddle, D. J. (2017). Using geographic information systems (GIS) to examine barriers to healthcare access for Hispanic and Latino immigrants in the US south. *Journal of Racial and Ethnic Health Disparities*, 4(2), 297–307.
- Escarce, J., & Kapur, K. (2006). Access to and quality of health care. In M. Tienda & F. Mitchell (Eds.), *National Research Council (US) Panel on Hispanics and the future of America* (pp. 410–415). Washington (DC): National Academies Press (US).
- Fireman, B., Bartlett, J., & Selby, J. (2004). Can disease management reduce health care costs by improving quality? *Health Affairs*, 23(6), 63–75.
- Fishman, J., McLafferty, S., & Galanter, W. (2016). Does spatial access to primary care affect emergency department utilization for nonemergent conditions? *Health Services Research*, 53(1), 489–508.
- Fredericks, K. A., Deegan, M., & Carman, J. G. (2008). Using system dynamics as an evaluation tool: Experience from a demonstration program. *American Journal of Evaluation*, 29(3), 251–267.
- Garfield, R., Damico, A., & Orgera, K. (2018). The Coverage Gap: Uninsured Poor Adults in States that Do Not Expand Medicaid. Retrieved from <https://www.kff.org/medicaid/issue-brief/the-coverage-gap-uninsured-poor-adults-in-states-that-do-not-expand-medicaid/>
- Garfield, R., Damico, A., Stephens, J., & Rouhani, S. (2016). *The coverage gap: Uninsured poor adults in states that do not expand medicaid—an update*. Menlo Park, CA: Kaiser Family Foundation.
- Ghaffarzadegan, N., Ebrahimvandi, A., & Jalali, M. S. (2016). A dynamic model of post-traumatic stress disorder for military personnel and veterans. *PloS one*, 11(10), e0161405.
- Ghaffarzadegan, N., Lyneis, J., & Richardson, G. P. (2011). How small system dynamics models can help the public policy process. *System Dynamics Review*, 27(1), 22–44.
- Gharib, S. (2008). Synthesizing system dynamics and geographic information systems in a new method to model and simulate environmental systems (Doctoral Thesis). The University of Bergen, Norway.
- Glanz, K., Lewis, F. M., & Rimer, B. K. (1997). *Theory at a glance: A guide for health promotion practice* (2nd ed.). Bethesda, MD: U.S. Dept. of Health and Human Services, Public Health Service, National Institute of Health, National Cancer Institute.
- Griffith, K., Evans, L., & Bor, J. (2017). The affordable care act reduced socioeconomic disparities in health care access. *Health Affairs*, 36, 1503–1510.
- HHS. (2013). *Affordable care act rules on expanding access to preventive services for women*. US Department of Health Human Services. Washington, DC.
- Homer, J., Milstein, B., Hirsch, G. B., & Fisher, E. S. (2016). Combined regional investments could substantially enhance health system performance and be financially affordable. *Health Affairs*, 35(8), 1435–1443.
- Homer, J. B., & Hirsch, G. B. (2006). System dynamics modeling for public health: Background and opportunities. *American Journal of Public Health*, 96(3), 452–458.
- Hovmand, P. S., & Pitner, P. (2005). Combining system dynamics, social networks, and geographic information systems. Paper presented at the 23rd international conference of the system dynamics society, Boston, USA. <https://www.systemdynamics.org/assets/conferences/2005/proceed/papers/HOVMA404.pdf>.
- Hutson, S. N. (2017). *Understanding social, legal, economic, and spatial barriers to healthcare access in El Paso County*. Texas Colonias: An Examination of Structural Violence Using Mixed Methods: University of Colorado at Denver.
- KFF. (2014). How Will the Uninsured in New York Fare Under the Affordable Care Act? Retrieved from <https://www.kff.org/health-reform/fact-sheet/state-profiles-uninsured-under-aca-new-york/>
- Lowry, T., & Taylor, R. (2009). Visualizing spatial and temporal dynamics in google earth using powersim. Paper presented at the 27th International Conference of the System Dynamics Society, Albuquerque.
- Mahamoud, A., Roche, B., & Homer, J. (2013). Modelling the social determinants of health and simulating short-term and long-term intervention impacts for the city of Toronto, Canada. *Social Science & Medicine*, 93, 247–255.
- Mazzoleni, S., Giannino, F., Colandrea, M., Nicolazzo, M., & Massheder, J. (2003). Integration of system dynamics models and geographic information systems. Paper presented at the the european multidisciplinary society for modelling and simulation technology (Eurosis-Eti). http://www.ecoap.unina.it/doc/staff/francesco_giannino/Integration%20of%20System%20Dynamics%20Models%20and%20Geography%20Information%20Systems.pdf.
- McLafferty, S., & Grady, S. (2004). Prenatal care need and access: A GIS analysis. *Journal of Medical Systems*, 28(3), 321–333.
- Milstein, B., Homer, J., & Hirsch, G. (2010). Analyzing national health reform strategies with a dynamic simulation model. *American Journal of Public Health*, 100(5), 811–819.
- Miranda, M. L., Ferranti, J., Strauss, B., Neelon, B., & Califf, R. M. (2013). Geographic health information systems: A platform to support the 'triple aim'. *Health Affairs*, 32(9), 1608–1615.
- Mirza, M., Luna, R., Mathews, B., Hasnain, R., Hebert, E., Niebauer, A., & Mishra, U. D. (2014). Barriers to health-care access among refugees with disabilities and chronic health conditions resettled in the US midwest. *Journal of Immigrant and Minority Health*, 16(4), 733–742.
- Moody, K. (2016). 6 Million Americans qualify for Medicaid but don't sign up [Fierce Health]. Retrieved from <http://www.fiercehealthcare.com/payer/6-million-americans-qualify-for-medicaid-but-don-t-sign-up>
- Newman, J., Velasco, M. A., Martín, L., & Fantini, A.-M. (2003). A system dynamics approach to monitoring and evaluation at the country level: An Application to the Evaluation of Malaria-Control Programs in Bolivia. Paper presented at the Fifth Biennial World Bank Conference on Evaluation and Development: Evaluating Development Effectiveness: Challenges and the Way Forward, Washington, D.C. <http://csdnet.dyson.cornell.edu/papers/newman.pdf>
- O'Grady, M. J., & Capretta, J. C. (2009). *Health-care cost projections for diabetes and other chronic diseases: The current context and potential enhancements: Partnership to Fight Chronic Disease*. Washington, DC: <https://www.fightchronicdisease.org/latest-news/national-coalition-hosts-event-examine-costs-projections-chronic-diseases>
- ODPHP. (2018). Clinical Preventive Services. Retrieved from <https://www.healthypeople.gov/2020/leading-health-indicators/2020-lhi-topics/Clinical-Preventive-Services>

- Pecora, P. J. (2017). *Evaluating family-based services*. New York, USA: Routledge.
- Rhodes, K. V., Bassey, S., Friedman, A. B., Kenney, G. M., Wissoker, D., & Polsky, D. (2017). Access to primary care appointments following 2014 insurance expansions. *The Annals of Family Medicine*, 15(2), 107–112.
- Rosero-Bixby, L. (2004). Spatial access to health care in Costa Rica and its equity: A GIS-based study. *Social Science & Medicine*, 58(7), 1271–1284.
- Sabounchi, N. S., Hovmand, P. S., Osgood, N. D., Dyck, R. F., & Jungheim, E. S. (2014). A novel system dynamics model of female obesity and fertility. *American Journal of Public Health*, 104(7), 1240–1246.
- Scheffran, J., BenDor, T., Wang, Y., & Hannon, B. (2007). A spatial-dynamic model of bioenergy crop introduction in Illinois. Paper presented at the 25th international conference of the system dynamics society, Boston, USA. <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.482.7472&rep=rep1&type=pdf>
- Sharareh, N., Sabounchi, N. S., Roome, A., Spathis, R., & Garruto, R. M. (2017). Model-based risk assessment and public health analysis to prevent Lyme disease. *Royal Society Open Science*, 4(11), 170841.
- Sharareh, N., Sabounchi, N. S., Sayama, H., & MacDonald, R. (2016). The ebola crisis and the corresponding public behavior: A system dynamics approach. *PLoS Currents*, 8.
- Shaw, N., & McGuire, S. (2017). Understanding the use of geographical information systems (gis) in health informatics research: A review. *Journal of Innovation in Health Informatics*, 24(2), 228–233.
- Singhasaneh, P., Lukens, J. E., Eiumnoh, A., & Demaine, H. (1991). *Integration of Raster-Based GIS and System Dynamics and Its Application*. Paper presented at the 9th international conference of the system dynamics society, Bangkok, Thailand. <https://www.systemdynamics.org/assets/conferences/1991/proceed/main-pdfs/singh563.pdf>
- Sommers, B. D., & Rosenbaum, S. (2011). Issues in health reform: How changes in eligibility may move millions back and forth between Medicaid and insurance exchanges. *Health Affairs*, 30(2), 228–236.
- Srijariya, W., Riewpaiboon, A., & Chaikledkaew, U. (2008). System dynamic modeling: An alternative method for budgeting. *Value in Health*, 11, S115–S23.
- Starfield, B., Shi, L., & Macinko, J. (2005). Contribution of primary care to health systems and health. *The Milbank Quarterly*, 83(3), 457–502.
- Sterman, J. D. (2000). *Business dynamics: Systems thinking and modeling for a complex world*. Boston, USA: Irwin/McGraw-Hill.
- USCB. (2015a). United States Census Bureau. Retrived from <http://quickfacts.census.gov/qfd/states/36/36007.html>
- USCB. (2015b). United States Census Bureau [United States Census Bureau]. Retrived from <http://quickfacts.census.gov/qfd/states/36/36007.html>
- USCB. (2016). U.S. Census Bureau, 2012–2016 American Community Survey 5-Year Estimates [United States Census Bureau]. Retrived from <https://factfinder.census.gov/bkmk/cf/1.0/en/place/Whitney.Point.village,NewYork/INCOME>
- USCB. (2017). QuickFacts - Vestal town, Broome County, New York [United States Census Bureau]. Retrived from <https://www.census.gov/quickfacts/fact/table/vestaltownbroomecountyny/PST045217>
- Ventana. (2015). Model Calibration [Vensim]. Retrieved from <http://vensim.com/optimization/#model-calibration>
- Wolstenholme, E. (1999). A patient flow perspective of UK health services: Exploring the case for new “intermediate care” initiatives. *System Dynamics Review*, 15(3), 253–271.
- Xu, Z., & Coors, V. (2012). Combining system dynamics model, GIS and 3D visualization in sustainability assessment of urban residential development. *Building and Environment*, 47, 272–287.
- Yasobant, S., Vora, K. S., & Upadhyay, A. (2016). Geographic information system applications in public health: Advancing health research. In P. Manolitzas, E. Grigoroudis, N. Matsatsinis & D. Yannacopoulos (Eds.), *Effective methods for modern healthcare service quality and evaluation* (pp. 137–166). Hershey, PA: IGI Global.