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AGENT-BASED MODEL OF BROADBAND ADOPTION IN UNSERVED AND UNDERSERVED AREAS

by

ANKIT AGARWAL

A THESIS

Presented to the Graduate Faculty of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE IN ENGINEERING MANAGEMENT

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Approved by:

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ABSTRACT

In the last two decades, demand for broadband internet has far outpaced its availability. The Federal Communications Commission's (FCC) 2020 Broadband Deployment report suggests that at least 22 million Americans living in rural areas lack access to broadband internet. With the COVID-19 pandemic affecting normal life, there is an overwhelming need to enable unserved and underserved communities to adapt to the "new normal". To address this challenge, federal and state agencies are funding internet service providers (ISPs) to deploy infrastructure in rural communities. However, policymakers and ISPs need open-source tools to predict take-rates of broadband service and formulate effective strategies to increase the adoption of high-speed internet. We propose using an agent-based model grounded in "The Theory of Planned Behavior" – a long-established behavioral theory that explains the consumer's decision-making process. The model simulates residential broadband adoption by capturing the interaction of a broadband service's attributes with consumer preferences. We demonstrate the model's performance, present a case study of an unserved area, and perform a sensitivity analysis. The major findings support the appropriateness of using theoretically based agent-based models to predict take-rates of broadband service. We also find that the take-rates are highly influenced by presence of existing internet users in the area as well as affordable or subsidized prices. In the future, this model can be extended to study the impact of online education, telecommuting, telemedicine, and precision agriculture on a rural economy. This type of simulation can guide evidence-based decision-making for infrastructure investment based on demand as well as influence the design of market subsidies that aim to reduce the digital divide.

ACKNOWLEDGEMENT

I would like to express the deepest appreciation to my advisor, Dr. Casey Canfield, for her generosity with support and motivation to help me in my research. She has been a patient audience to my thoughts and ideas throughout this journey and has always been able to nudge them in the right direction. I also extend my heartfelt gratitude to Department of Engineering Management and Systems Engineering for funding my tuition expenses and giving exposure to the latest developments in the industries. I would also like to extend my sincere gratitude to Dr. Dagli and Dr. Cen for their agreeing to evaluate my work and providing their valuable feedback. I would like to thank Mrs. Melinda Stormes, Mr. Andrew Blanton, Mr. Mark Keeling and Mrs. Carmen Hartwell of Gascosage Electric Cooperative for lending me their precious time and advice about rural broadband adoption. I acknowledge the support shown by Mr. Lynn Hodges of Ralls Technologies for sharing information about their data which helped me do a demonstration of my model. I am indebted to my parents and brother for their unconditional love and support throughout my life. They have shown utmost enthusiasm in knowing the developments in my research. Last but not the least, I would like to thank my friends who had my back every time I hit a dead-end and celebrated every little success I achieved.

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1. INTRODUCTION

1.1. MOTIVATION

Inequity in high-speed internet access, better known as the “digital divide”, has been a matter of grave concern over the years. The 2020 Broadband Deployment report by the FCC states that as of December 2018, 22.3 % of the population living in rural areas and 27.3% in Tribal areas do not have access to a fixed high-speed broadband terrestrial service (FCC, 2020). Broadband enables economic growth as it has a positive impact on the sales and revenue of local businesses, household income, and number of operational businesses (Gallardo et al., 2018). Consequently, the digital divide in the USA is leaving out at least 22 million people from opportunities to enhance their lifestyles. Unfortunately, the access gap may be worse than what is reported by the FCC. Microsoft’s Airband Initiative anonymously tracked the bandwidth used by computers to install Microsoft updates and found that almost 160 million people are not using internet at broadband speed.

The Federal Communications Commission (FCC) defines broadband as high-speed transmission of Internet data that is faster than dial-up services and is always connected(FCC, 2014). There are several ways to access broadband internet – i) Satellite, ii) Wireless, iii) Digital Subscriber Line (DSL), iv) Cable, and v) Optical Fiber. Satellite internet is accessed via low-orbiting satellites that are linked directly to the end-consumer. Wireless service connects a household to the service provider via radio links. Wireless service may be fixed or mobile. DSL provides broadband through copper telephone lines to homes and businesses. The quality of service depends on the distance of the service station from the user. Cable internet is usually available in combination with television service at home where coaxial cables transmit data to computers as well as audio/video input to the TV set. The latest innovation in high-speed internet access is optical fiber, where data is transmitted in the form of light through thin glass fibers. Fiber can transmit data faster than any other wired or wireless medium.

The FCC acts as a regulatory body for defining the broadband internet speeds in response to the growing demand. Until 2015, broadband speeds were set at 4 Megabits per second download speeds and 1 Megabit per second upload speed (4/1 Mbps). Currently, broadband speeds are required to have at least 25 Megabits per second for downloading and 3 Mbps upload speed (25/3 Mbps).

Satellite, though available in every part of the country, is not a popular choice amongst rural consumers due to high cost, high latency, and dependency on weather conditions (BroadbandNow, 2021). Fixed wireless internet is a better alternative than satellite in terms of cost and reliability. However, a line-of-sight connection is needed with an access point located within a 10-mile radius, which limits availability. Considering these limitations, a wired medium may be a more suitable alternative for last-mile delivery of service in rural areas. However, this may not always be feasible for service providers as laying infrastructure for wired internet service could be costlier than wireless and satellite(Galloway, 2007).

There are two key challenges faced by government agencies and internet service providers to bridge this gap. Firstly, rural areas have a lower density of internet users compared to urban areas, which significantly drives up the cost of service per household (Canfield et al., 2019). This leaves unappealing revenue prospects for ISPs and therefore is a poor incentive to introduce service in these areas. Secondly, irrelevance of digital technology is another key issue for non-adopters

(Horrigan, 2009). As of 2019, only 63% of Rural households own personal computers compared to 80% urban households. Furthermore, more than 35% of adults who are 25 or older have attained up to high-school level education or lower in rural areas, leaving concerns about computer literacy(USDA, 2018).

In the context of the COVID-19 pandemic, the worst impacts of the digital divide became apparent because telecommuting to work and online courses became the new normal. This has brought a change in people's attitude towards high-speed internet. According to a survey by Pew Research, 53% of Americans believe that broadband internet is "essential" while another 35% agreed that it is important during the pandemic (Vogles et al., 2020). An earlier survey also revealed that school-age children in lower-income families are likely to face challenges in completing their schoolwork due to technology limitations (Vogles, 2020). The increased dependency on internet despite the wide gap in access has made it a priority to provide service to as many unserved and underserved areas as possible.

The FCC defines unserved areas as those where ISPs can only provide up to 10/1 Mbps speeds while underserved areas have less than 25/3 Mbps internet service. Under the Coronavirus, Aid, Relief, and Economic Security Act (CARES Act), the government-sanctioned $150 billion to states and local governments to fight the impact of the pandemic. States such as Missouri, Ohio and Tennessee set aside $10 million, $20 million and $50 million respectively, to fund digital learning initiatives (de Wit, 2020). Even before the pandemic, the FCC was funding ISPs to expand internet services in unserved and underserved areas through the Connect America Funds (CAF) in 2018 and 2019. The United States Department of Agriculture (USDA) too, is actively involved in providing 25/3 Mbps broadband internet in rural areas where currently less than 90% of establishments have access to 10/1 Mbps or lower speeds. The USDA Broadband ReConnect Program invested over \$663 million in high-speed broadband infrastructure in 2019 and another \$675 million in 2020 to improve connectivity in rural areas across 33 states(USDA, 2021).

However, the services deployed in unserved and underserved areas with federal financial assistance can be successful only if they are adopted by consumers. Access alone is not sufficient to solve the digital divide. Research at the University of Missouri highlights the advantage given to fixed wireless/cable internet providers over fiber-based services due to the weighing formulas used by FCC in the Connect America Funds (CAF-II) bidding process in 2018 (Eisberg et al., 2020). Due to the higher per mile installation cost of fiber internet, lower-tier speeds (25 – 100 Mbps) provided by ISPs using technologies such as fixed wireless, were given preference. As a result, the ISPs which received most of the funds provide lower speeds at high cost to the consumer. This creates uncertainty about rural households being able to afford the service to fulfill their needs and the likelihood of achieving the funding's purpose.

1.2. OBJECTIVE

While government agencies are actively funding ISPs to provide service in unserved and underserved areas, it is crucial to analyze the effectiveness of these policies in reducing the digital divide. A simulation tool to predict the take-rates for broadband expansion projects could not only help ISPs strategize the best subscription plans to provide but also help policymakers to strategically allocate funds. To date, there has been inadequate research on consumer decision-making dynamics in broadband adoption. This study addresses this gap by demonstrating the value of using simulation models to facilitate prediction of consumer behavior.

In this study, we propose and demonstrate an agent-based simulation model that considers consumers' ability to afford and use internet services, as well as their attitude towards different attributes of broadband service, to predict adoption of a newly introduced internet service. To demonstrate the value of using this platform to conduct policy experiments, we address "what is a minimum viable subscription plan which fits the requirements of a majority of the consumers while also being within their budget?" In addition, we perform a sensitivity analysis of the influence of each input parameter to the predicted take-rates.

Our findings suggest that theoretically grounded models are an appropriate choice for modeling the broadband adoption phenomena in rural markets. A minimum viable broadband service needs to be reasonably priced while also providing high-tier (100 – 1000 Mbps) speeds. Overall, this model is most sensitive to percentage of existing internet adopters in the area and the price of the new broadband service, suggesting a higher presence of internet users in an area and lower or subsidized monthly cost can drive up the take-rates.

2. LITERATURE REVIEW

This section consists of a review of past literature on agent-based modelling and key theories including the theory of planned behavior and small-world networks. We also summarize findings from broadband related empirical studies and simulation experiments.

2.1. AGENT-BASED MODELING

Agent-based modeling (ABM) is a simulation tool where agents with distinct properties interact with other agents and their environment to yield emergent outcomes (Bonabeau, 2002). Agents' heterogeneity may be expressed in the form of motives, preferences, or attributes to give them complete autonomy in decision-making and allow for macro-level outcomes through micro-level behaviors. This bottom-up feature not only gives ABM an advantage over aggregate-level modeling (i.e., equation-based modeling) techniques but also makes it a sound choice for representing non-linear complex systems driven by human behavior. ABM differ from Equation-based modeling in terms of the primary focus, method of validation, heterogeneity, spatial representation and applicability (Füllsack, 2017). A comparison of agent-based modeling and equation-based modelling is elaborated in Table 2.1.

Emergent phenomena resulting from complex individual behavior can be simulated using ABM (e.g., panic-stricken people evacuating an enclosed area through a single exit). An evacuation simulation backed by real-world data revealed that introducing a pillar before the emergency exit can help streamline the outflow of the crowd and result in fewer stampede deaths (Bonabeau, 2002). This outcome is counter-intuitive in nature, and a demonstration of the capabilities of ABM. This modeling technique has been applied to study a wide variety of other social systems including the emergence of slums (c), the spread of infectious diseases(Luke & Stamatakis, 2012), dismantling terrorist social networks(Keller et al., 2010), and technology adoption. (Kiesling et al., 2012). The latter is the most relevant application of ABM for this research. Technology adoption models have been developed in areas such as rooftop photovoltaic cell adoption(Mittal & Krejci, 2017; Rai & Robinson, 2015), smart metering(Zhang & Nuttall, 2012), and organic farming practices(Kaufmann et al., 2009).

Table 2.1. Agent-based modelling vs Equation-based modelling

Characteristics	Agent-based modeling (ABM)	Equation-based modeling (EBM)
Focus	Micro-level behavior of individual entities	Overall behavior of the system
Validation	Individual agent's behavior as well as overall output can be compared with real-world systems	Only model output can be compared with real system behavior.
Heterogeneity	Allows agents to have diverse decisions, characteristics, and preferences	System is considered as a whole, no room to capture diversity
Spatial representation	Topological characteristics can be represented at high or low resolution along with spatial details of agent -agent interactions	Representation of physical space lacks granularity to capture interaction between entities
Application	Appropriate to model human social systems	Suitable for modeling physical systems driven by homogenous entities

In the field of organic practices, an empirically grounded model of diffusion of organic farm practices in two Eastern European countries was developed to explore the effects of peer influence, government subsidies, and expert advice. The major findings suggested that Estonian farmers were driven to adopt organic farming due to positive influence received through agent-agent interactions whereas Latvian farmers were driven by subsidies as well as influence from their peers(Kaufmann et al., 2009).

ABM has been a popular choice for modeling the adoption of renewable energy innovations such as smart-metering technology, heat pumps, and residential solar panels. While some of the works used conceptual models that are theoretically based for policy analysis (Mittal & Krejci, 2017; Zhang & Nuttall, 2012), others are empirically grounded to study the respective diffusion phenomena(Rai & Robinson, 2015). The empirically grounded model suggests that when an agent had a favorable opinion about solar energy and their ability to afford installation was greater than the payback, they are more likely to adopt the technology. The conceptual model on smart-metering technology suggests that promoting the technology in geographically dispersed areas and having competing products in the market leads to higher adoption.

A common feature in technology adoption models is the use of Theory of Planned Behavior to define the rules for individual agent's decision-making. Further, the agent-agent interactions are spatially defined using a small-world network as it optimizes the diffusion of information and the effect of social influence on the agent's decision-making. These aspects of agent-based modeling are discussed in greater detail in the subsequent sub-sections.

2.1.1. Theory of Planned Behavior. The Theory of Planned Behavior states that the intention to perform a behavior can be attributed to three belief constructs – attitude, subjective norms, and perceived behavioral control(Ajzen, 2012). Attitude is defined as an individual's opinion of the behavior in question. Subjective norms can be elaborated as the influence an individual receives from their surroundings (e.g., their social network, mass media). Perceived Behavioral Control expresses the ease with which an individual can perform the behavior. Therefore, if an individual has a favorable opinion of a behavior, sees their peers engaging in the behavior, and has the means to perform it, they are likely to have the intention to engage in the behavior themselves (see Figure 2.1).

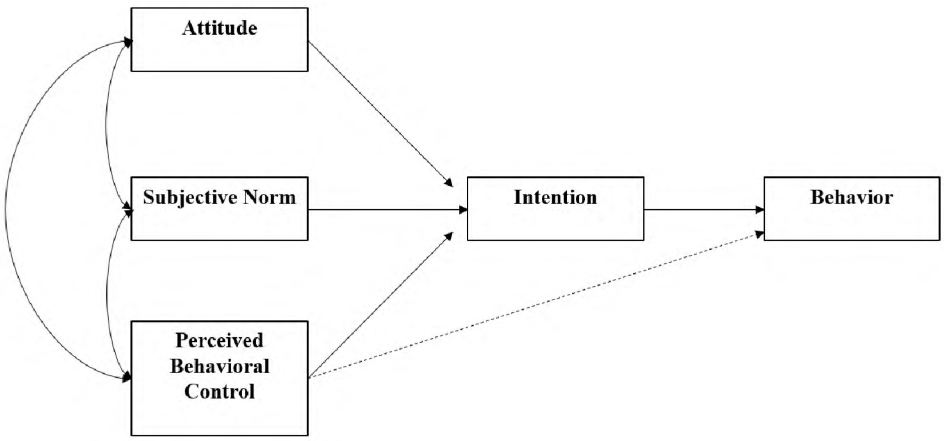

Figure 2.1. The theory of planned behavior model

The Theory of Planned Behavior (TPB) has been applied to numerous empirical studies such as predicting smoking cessation(Farnworth, 2008), dietary choices(Lien et al., 2002), preference towards B2C e-commerce (Pavlou, 2002), and adoption of Internet banking(Shih & Fang, 2004). In the smoking cessation study, 84 smokers were interviewed twice over a span of 6 months with questions designed to measure the strength of each belief construct. The responses were fit using hierarchal linear regression to predict the intention to quit, attempt to quit, and timespan of avoiding smoking. The model showed high correlation between perceived behavioral control, perceived susceptibility, and intention to quit. The findings show that behavioral intention and perceived susceptibility are strong predictors of cessation behavior (Farnworth, 2008).

In recent years, the theory of planned behavior has become a popular choice in the field of agent-based modeling to define behavioral rules for agents in technology adoption models (Kiesling et al., 2012). These are an improvement over the diffusion of innovation models where agents were assumed to be rational consumers with homogeneous preferences(Bass, 1969). A utilitarian approach allows agents to perceive the utility of the innovation as per their heterogeneous preferences which is equated to the attitude factor of TPB (see Figure 2.2) (Muelder & Filatova, 2018). The subjective norms are expressed as a social utility which is defined as the perceived utility of the agent's neighbors in the social network. The perceived behavioral control is often used as a constraint that addresses the agent's ability to afford and/or operate the innovation (Muelder & Filatova, 2018). The agents' intrinsic properties can be initialized using survey data with questions designed specifically to measure the three belief components in the adoption decision(Rai & Henry, 2016). These empirically backed individual properties and theoretically grounded behavioral rules influence the outcomes of agent-agent interactions.

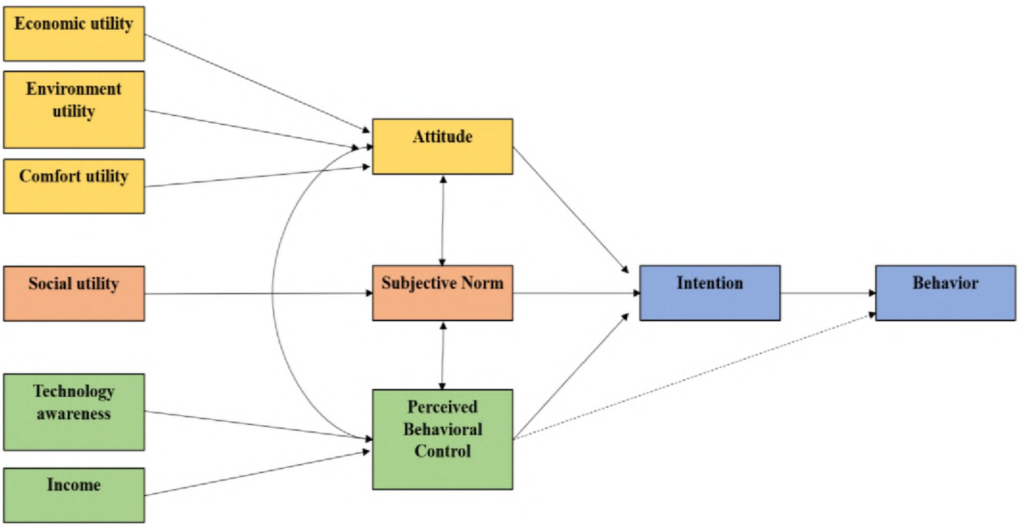

Figure 2.2. Renewable energy adoption model

2.1.2. Small-World Network. Defining topological characteristics of agent-agent interaction and information diffusion rules is also an advantage of agent-based models. Precisely conceptualizing presence, frequency, and strength of interaction can be enabled using popular graphs in network theory (Füllsack, 2017). Random-graphs generated with small-world characteristics have a high clustering coefficient and short average-path length (Watts & Strogatz, 1998). This model was inspired by the small-world phenomenon which states that any two individuals in geography are six degrees of separation away from each other (Kochen, 1989). The network could be any lattice with n nodes and k edges per node. Some edges are reconnected randomly with a rewiring probability p. This network is the middle-ground between a random and a regular lattice network as shown in Figure 2.3. This allows an optimized speed of information diffusion along with a high degree of clustering.

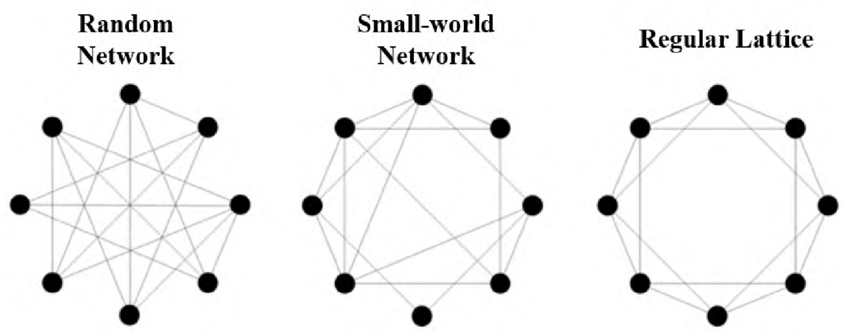

Figure 2.3. Networks in decreasing order of randomness

Small-world networks have been used in technology adoption ABMs owing to their similarities with real-world social networks in terms of topological characteristics (Kiesling et al., 2012). The clustering of agents is done by measuring similarity and proximity in renewable energy adoption models (Mittal & Krejci, 2017;

Rai & Robinson, 2015). A small-world graph model was used to study the diffusion of telecommunications technology in an agent-based opinion dynamics model by varying the rewiring probability and faction of initial innovators(Kocsis & Kun, 2008). In this model, agents interacted with each other to upgrade their communications technology with the objective of minimizing their cost.

2.2. PAST LITERATURE ON BROADBAND

Earlier studies about broadband diffusion in the United States are mostly empirical in nature. In 2005, a nationwide survey in 44 states focusing on service attributes such as price, speed, installation complexity, reliability and always-on service to consumers was conducted (Scott, 2005). The survey was designed to measure people's willingness to pay for each of the attributes. The estimates were highest for speed, reliability, and always-on feature in the service. A more recent empirical study aimed at determining willingness to pay was done by surveying households who presently do not subscribe to a residential broadband service (Carare et al., 2015). The authors collected 15,000 data samples and analyzed the factors of households which are most willing to pay for broadband service. They concluded that households with a computer, located remotely, or in minority communities are likely to adopt if service is priced reasonably. They predicted a 10% increase in demand if price fell by 15%. Both studies are helpful in highlighting the factors that are favorable to consumers and internet service demand. However, their findings determined from consumers living in urban as well as rural areas. It is unclear whether the respondents chose not to adopt broadband despite having access or is it because they are living in unserved/underserved areas. Surveying people who are disadvantaged in terms of connectivity, could get better willingness to pay estimates for policymakers.

The barriers for telecommunication companies to provide in high-cost and low-density markets have been studied using a probit regression model (Glass & Stefanova, 2010). The article concluded that the rural market needs DSL internet, which was the most widely used technology at the time. DSL would be able to provide access to multimedia features on the internet, such as video streaming, which could promote diffusion. This helps understand the trends in rural broadband market demands when 70% of ISPs provided DSL internet at 1-3 Mbps download speed. The minimum requirement for an internet service to qualify as a broadband is currently 25 Mbps. While these studies do give a general sense of the factors that drive adoption, they could be inadequate for policymakers as technology has evolved and the applications of internet in our lives has broadened.

Empirical studies in other countries have been done in the context of customer loyalty to the ISP (Akroush & Mahadin, 2019) and household valuation of service (Thomas & Finn, 2018). A confirmatory factor analysis of 1,297 responses from internet users in Jordan, shows that the customers feel more satisfied with service performance and price if the service provider has competent employees and is prompt in delivering effective solutions. In Canada, three studies using survey data from 2002 to 2014 shows how federal investments have made a difference in actual usage of internet services at the household level. A major finding was that having internet access influences the subscription rate in an area. However, access alone cannot ensure usage as consumers demand valuable services that can make their lives easier. These articles show that reliability of service and higher perceived utility levels is significant to customers.

In the past, broadband diffusion across nations was simulated using a hybrid model with characteristics of Agent-based and System Dynamics modeling (Swinerd & McNaught, 2014). The authors simulated the diffusion of mobile phone, fixed internet and fixed broadband using the theory of planned behavior and diffusion of innovation to define agent's interaction rules and validate the outcome with publicly available data. The primary focus of the paper was demonstrating the integration of two different modeling techniques rather than providing policy-level insights to promote broadband adoption. Further, this article also captures broadband diffusion phenomena at a wider geographic scale than the scope of this thesis. A digital divide inspired simulation was built by integrating ABM with a network simulator to measure economic impact as a result of increased throughput of wireless LTE services to agents (Legaspi et al., 2020). The ABM scattered consumers with heterogenous requirements in a region and sprouted base stations at random locations. The consumer and base station locations were fed in the network simulator which calculated the throughput to each consumer based on distance. Agents positively benefited if the throughput received is at par with their usage requirements. The economic impact of each base station is measured by the number of agents it can serve and how high well did the throughput matches their requirements. This study laid a foundation for broadband allocation policy experiments using both human and technical factors.

In the context of broadband adoption, empirical studies conducted in the United Kingdom, India, and South Korea integrate behavioral theories such as the technology acceptance model, diffusion of innovations, and theory of planned behavior to determine the factors that influencing residential broadband adoption (Choudrie & Dwivedi, 2006; Irani et al., 2009; Manzoor, 2014; Oh et al., 2003). In

Korea, broadband adoption was found to be influenced by compatibility with needs, trialability of the technology and visible popularity in use (Oh et al., 2003). The empirical study in India revealed social outcomes, service quality, availability of facilitating resources, and ability to use Internet applications as major factors influencing broadband adoption at household level (Manzoor, 2014). A similar study in the UK showed that utilitarian outcomes, social influence, perceived resources and self-efficacy, and behavioral intention were statistically significant to the adoption decision (Irani et al., 2009) (shown in Figure 2.4). We observe that belief constructs defined by the theory of planned behavior are common across these studies. The differences in results could be explained by cultural differences across the countries.

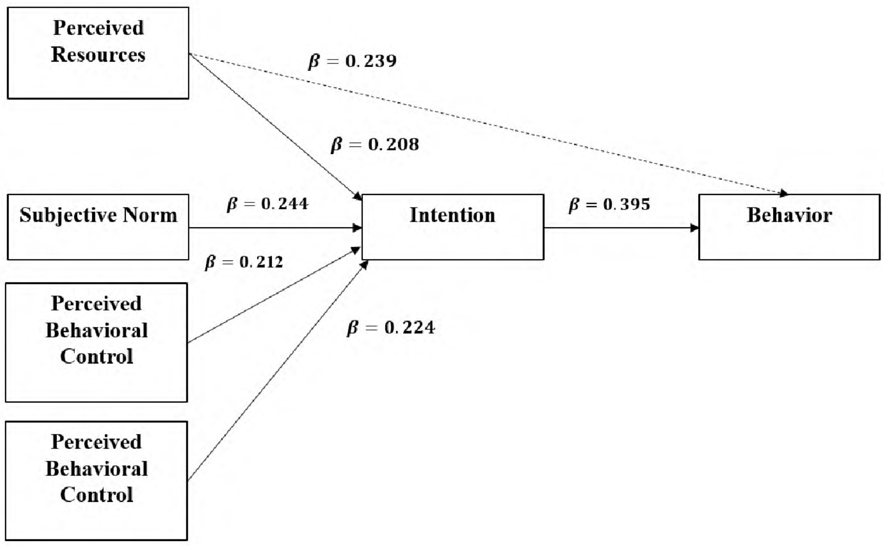

Figure 2.4. Empirically validated broadband adoption model

Theory of planned behavior is conceptually parsimonious and widely cited in the agent-based model literature. Therefore, we propose using an agent-based model grounded in the theory of planned behavior to predict the take-rates of broadband service. The agent-agent interaction is modeled using small-world network. Product attributes such as the price, download speeds, data-cap and reliability are used to allow agents to form their individual opinion and determine whether to adopt a service.

3. MODEL OVERVIEW

The agent-based simulation is summarized in Figure 3.1. This simulation (1) defines the environment, (2) generates agents, (3) defines the interactions between agents, (4) defines the interactions between agents and the environment, and (5) calculates outcome metrics. The model is instantiated as a simulation on the Netlogo platform (Version 6.1.1). Netlogo is an open-source programming software, designed exclusively to facilitate agent-based modeling approaches (Wilensky, 1999).

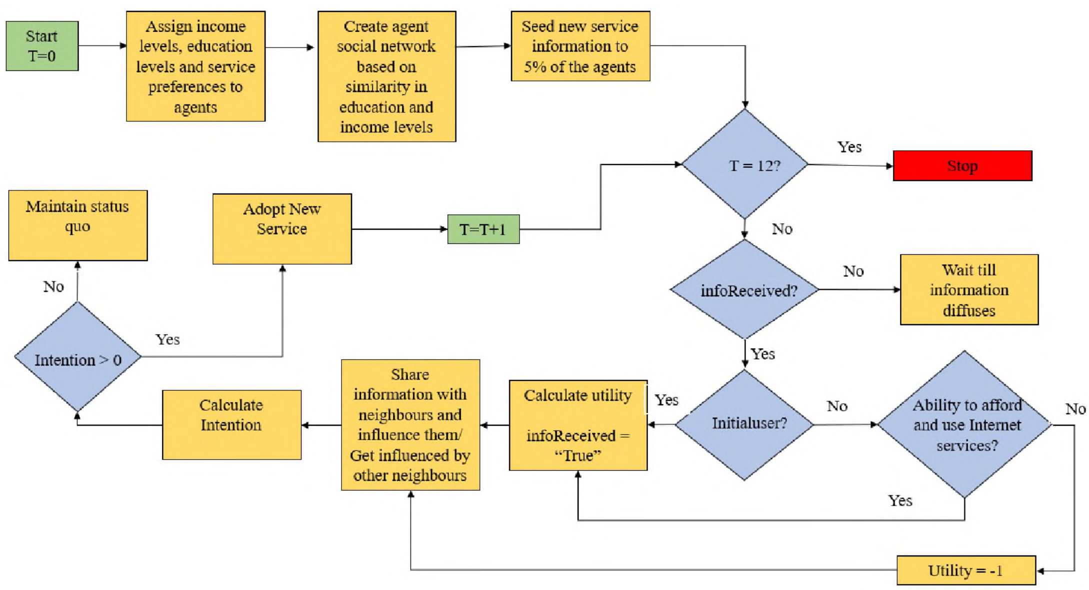

Figure 3.1. Flowchart of the agent-based model

The model represents a scenario where a new ISP deploys a service accessible to all households within a zip-code. A fixed percentage of households are currently using a residential internet connection provided by an existing ISP and the rest of the households are considered non-adopters. The information of the new subscription plan diffuses throughout the area. The households decide whether to adopt the new service by forming individual opinions and receiving influence from their peers.

Based on their decision, the existing internet adopters switch to the new service and the previously non-adopting households become residential internet service adopters. The households which decide against adopting the new service maintain status quo. Figure 3.1 explains how this scenario is simulated by the agent-based model.

3.1. ENVIRONMENT

The NetLogo environment shown in Figure 3.2 includes input variables, simulation space, and outcome plots. The NetLogo world is square shaped representing an unserved or underserved zip-code. The 1,089-cell lattice represents a 90 square mile area, which is the average area of a zip-code in the United States. Each cell is populated by residential consumers. Model inputs include the number of households per zip-code and percentage of users who have adopted internet at home. Agents are classified as an existing internet adopter using a Boolean parameter and color coded “blue” in the NetLogo environment. At initialization, the agents do not have information on new broadband services that are available in their area (see Figure 3.3). To model an unserved scenario, the current speed parameter is < 10 Mbps and < 25 Mbps for an underserved scenario. This is consistent with the FCC definitions of unserved and underserved areas (FCC, 2020). In the simulation, a new service is made available to all agents in both unserved and underserved scenarios. Additional input parameters include the current and new (1) price, (2) data-cap, and (3) reliability parameters. The price is the monthly amount charged by the service inclusive of taxes and equipment costs. The data-cap is the monthly limit of data that can be downloaded or uploaded in a month, and reliability captures the ISPs customer ratings (scale 0 -5) based on outage frequency and response

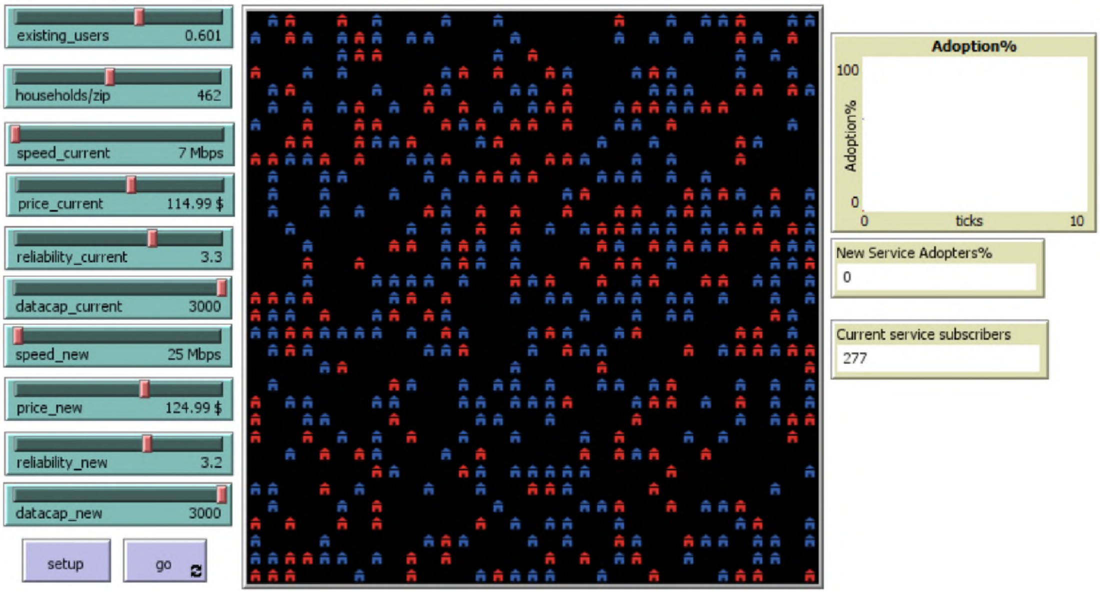

Figure 3.2. The NetLogo environment. Includes users (blue) and non-users (red). The sliders on the left represent model inputs and the displays on the right represent model outputs.

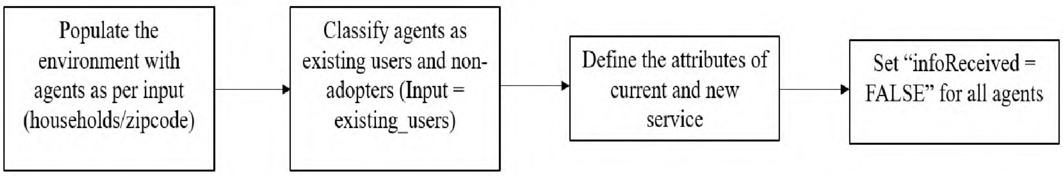

Figure 3.3. Environment setup at t=0

3.2. AGENTS

Each agent represents a household in a rural community. Agent's characteristics include demographic information such as annual income, education attained, and preference towards advertised internet speed, monthly cost, data-cap and service reliability (see Figure 3.4).

For modeling take-rates for any given zip-code, the agent's demographic levels may be assigned as per U.S. Census data. There are 14 income levels and 7 education levels to ensure representation is consistent with U.S. Census Bureau. As reported by(Horrigan, 2009), the primary reasons cited for non-adoption of internet are high monthly costs and the inability to operate a computer. The high monthly cost barrier is accounted for by assigning each agent with an affordability factor, calculated by multiplying the income level (normalized to 0-1 scale) with a random number between 0 to 1 (to eliminate a perfect correlation). Agent's computer skills are expressed as a digital literacy factor, which is calculated using the product of a random number between 0 to 1 with the normalized education level (consistent with Krejci et al, 2017). We assume that wealthy and educated households are more likely to adopt broadband internet.

The agents have heterogeneous preferences for internet speed (w_s), monthly costs (w_p), data caps (w_{dc}), and reliability (w_r). The aim is to represent all possible combinations of preferences in internet service (e.g., consumers who do not mind the price if they get their desired bandwidth and those who can accept data-caps if costs are low. Each agent has a different weight on the utility of the broadband service (w_u) and social influence (w_{soc}) they receive from their peers, randomly assigned from a uniform distribution. We assume that agents have diverse needs that may or may not require much bandwidth. In addition, we assume agents respond differently to social influence, ranging from resistive to responsive.

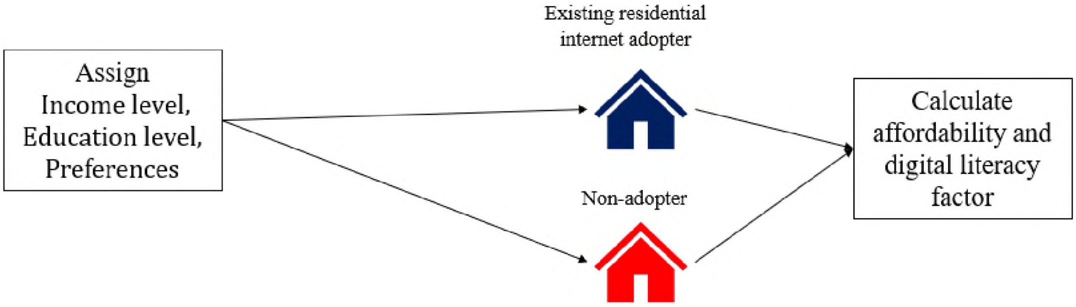

Figure 3.4. Assigning heterogenous properties to agents

3.3. INTERACTIONS BETWEEN AGENTS

The social network between agents is a small-world network. The agents choose their immediate social circle based on similarities in income and education of the agents within a radius of 5 units. The radius allows for clustering in the small-world network, which is a significant topological characteristic of real-world social networks (see Figure 3.5). These local connections represent the household's immediate neighbors. Similarity between agents is calculated by normalizing the differences in the incomes (Inc_i and Inc_j) and education levels Edu_i and Edu_j) of two agents. The similarity value varies between 0 and 1. The similarity index is calculated as shown in (1).

$$\mathrm{Similarity(i,j)} = \left[0.5 - \left|\frac{(\mathrm{Inc_i} - \mathrm{Inc_j})}{14}\right|\right] + \left[0.5 - \left|\frac{(\mathrm{Edu_i} - \mathrm{Edu_j})}{7}\right|\right] \qquad (1)$$

An agent forms links with another agent only if their similarity value is greater than 0.8. In addition, 50% of agents form links with one other randomly selected agent. The random connection represents other acquaintances that the members of the household have in the area. Random acquaintances include colleagues, classmates, relatives (consistent with Mittal & Krejci, 2017; Muelder & Filatova, 2018).

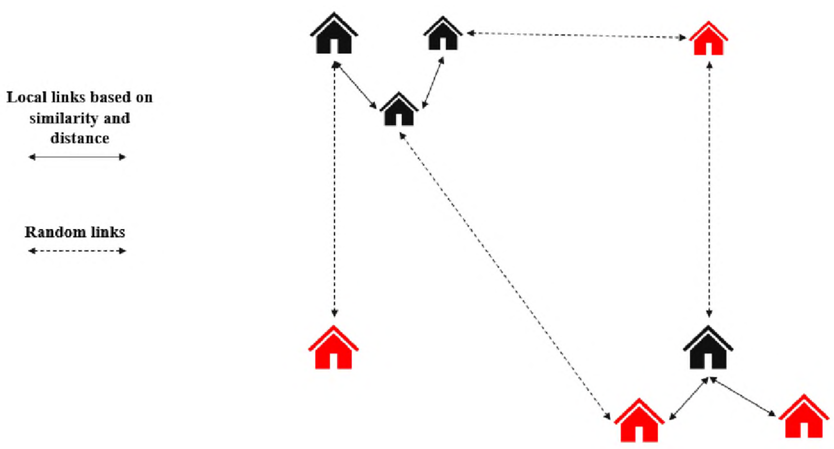

Figure 3.5. Small-world network of agents

As the agents are forming their individual opinion about the new service, they are also influenced by their peers. The influence (I) received by an agent is a function of the perceived utility of broadband by their peers and the number of peers as given in equation (2) where U_i is the utility of an agent's link-neighbor and N being the total number of link-neighbors (consistent with Snape et al., 2015). Agents with more neighbors who have a positive perceived utility of broadband are more likely to be positively influenced in their perception of the new broadband service.

$$I = \frac{\sum_{i=1}^{N} U_i}{N} \tag{2}$$

3.4. INTERACTIONS BETWEEN AGENTS AND THE ENVIRONMENT

Based on the initial users' parameters, agents are classified as fixed residential internet adopters and non-adopters. Information about the new broadband service is randomly seeded to 5% of the agents. This represents the households which received information on the newly introduced residential internet service through an advertisement and decided to propagate the information to their peers. The following sub-sections describe how the product information diffuses through the model, calculations performed by agents to form opinion, and finally the decision-making process to adopt or reject the new internet service.

3.4.1. Check Utility. The agents pass on the product information to their respective linked neighbors. On receiving the information, the infoReceived? variable becomes "TRUE". The initaluser? parameter is used to check if an agent is an existing internet user. If "TRUE" the agents calculate their utility U by comparing the service with the current plan. The comparison is done in terms of the speed provided, monthly cost, data-cap, and reliability rating. In this equation, ns and cs are the normalized values of the speed provided by both services. The monthly costs of both services are expressed as cp and np which are also scaled to 0 and 1. These attributes of the current service and new service are normalized and used in equation (3):

$$U = w_s \times (ns - cs) - w_p \times (np - cp) + w_{dc} \times (ndc - cdc) + w_r \times (nr - cr) \quad (3)$$

If an agent is not an existing internet adopter, the sum of affordability factor and digital literacy factor must exceed 0.5 for them to consider the broadband plan (Alonso-Betanzos et al., 2017). If the condition is not satisfied, the U is set to -1 which indicates that the agent does not have the means to purchase or digital literacy to use the internet. As a result, these users will negatively influence other agents. This condition acts as the threshold for the Perceived Behavioral Control (PBC) of the agent. This threshold is waived for existing internet users as past studies reveal that PBC is not a significant predictor of behavior if a person already owns a similar product (Taylor & Todd, 1995). The agents that meet the PBC threshold calculate utility using equation (4). The value of utility is used as a measure of the attitude that an agent has towards the subscription plan (consistent with Muelder & Filatova, 2018). A higher U value indicates that the agent has a favorable opinion of the broadband service.

$$U = w_s \times ns - w_p \times np + w_{dc} \times ndc + w_r \times nr \quad (4)$$

3.4.2. Intention to Adopt. The decision to subscribe to the new broadband service depends upon the values of the utility and influence, and an individual agent's weight for these beliefs. w_u captures agent's preference towards utility of the subscription plan and w_{soc} is the weight given to social utility. Intention to adopt is given by equation (5)The decision to subscribe to the new broadband service depends upon the values of the utility and influence, and an individual agent's weight for these beliefs (Muelder & Filatova, 2018; Zhang & Nuttall, 2012). The variable w_u captures agent's preference towards utility of the subscription plan and w_{soc} is the weight given to social utility. Intention to adopt is given by equation (5):

$$\mathrm{Int} = w_u \times U + w_{soc} \times I \tag{5}$$

If an agent has a favorable opinion of the broadband service (U>0) and has been positively influenced (I>0), the agent is more likely to adopt the service. If the agent's calculated Int > 0, the agent adopts the new service and if Int <= 0, the agent rejects the new service. Existing internet users are assumed to have switched to the new service.

3.5. OUTCOME METRICS

The outcome of the simulation is evaluated in terms of (a) absolute number of new service subscribers and (b) percent of new service adopters. Since the number of households in a zip-code can be any value within 0 and 1000, the percentage of agents adopting the new subscription plan is a better metric for analysis. The percent of adopters can be used interchangeable with "penetration rate" or "take-rate" used by ISPs as a performance metric for their services. The new service adoption percent is calculated by counting the total number of agents with Intention (Int > 0) divided by the total number of agents in the model.

4. METHODS

4.1. DATA

For the model demonstration and unserved area case study, the agents population, income, and education levels were assigned using census data (Census Reporter, 2019). The existing percentage of residential internet adopters was sourced from broadbandnow.com (BroadbandNow, 2021). The current service characteristics for both studies was sourced from the official website of the respective ISPs in question. For the model demonstration, the new service characteristics and the actual take-rate data were provided by Ralls Technologies from their November 2020 dashboard report. The new service characteristics for the FCC funded fixed wireless service were sourced from the ISP's website. The fiber service attributes were sourced from the CAF-II data discussed in the DEEDP report (Eisberg et al., 2020). The reliability ratings for all services were sourced from Google reviews, Facebook reviews and broadbandnow.com.

For the sensitivity analysis, the agent demographics were assigned randomly from a uniform distribution. The number of households were defined as per USDA data and the existing user percentage were set using U.S. Census Bureau data(ACS, 2018b; USDA, 2019). The current and new service baseline, minimum and maximum values were sourced from broadbandnow.com (BroadbandNow, 2021c). All input data, outputs, plots, and code can be found in this GitHub repository, https://bit.ly/3ln8nVv.

4.2. MODEL VALIDATION

For validation, we initialize the model to represent the broadband market in Perry (zip-code 63462) in Ralls County of Northeast Missouri. In 2019, a rural electric coop (Ralls Technology Fiber Solutions) started a new fiber service in the area where 70% of the households also had access to a DSL internet service provided by CenturyLink (BroadbandNow, 2021). As per census data, the environment is populated with 274 uniformly scattered agents (ACS, 2018). Each agent is assigned an income and education level to represent the distribution from the U.S. Census (Census Reporter, 2019). All service attributes (listed in Table 4.1) except reliability have been sourced from the ISPs website (CenturyLink, 2021; Ralls Technologies, 2020). The average reliability rating for the new ISP was 3.7 out of 5 on the company's Facebook page (http://bit.ly/2P2EMF6) whereas for the current ISP was 3.2 out of 5 on broadbandnow.com (http://bit.ly/2OYPQTm).

The agents' preferences w_s, w_p, w_{dc}, w_r, w_u, and w_{soc} are assigned randomly from a uniform distribution. To demonstrate the predictive capability of the model, we ran the ABM 1,000 times at these settings and the mean output was compared with the actual penetration rate provided by Ralls Technologies.

Table 4.1. Current and new service attributes

Current or New?	Technology	Speed (Mbps)	Price ($)	Reliability	Data-cap (GB)
Current	DSL	40	64	3.2	1024
New	Fiber	50	55	3.7	Unlimited

Figure 4.1. Internet availability map for Perry. Red represents unserved areas, amber represents one ISP available, yellow represents availability of two ISPs

4.3. MODEL DEMONSTRATION

This experiment forecasts the take-rate in an unserved area, zip-code 63662 in Bollinger County, MO, which lacks reliable broadband connectivity. Bollinger County was highlighted as an area with acute connectivity problems and was reported to be in immediate need for high-speed internet (Facilitators et al., 2020). This section focuses on predicting the outcome of FCC's policies during the CAF-II auction which gave the majority of the funds to lower speed ISPs. The ISP which won the most funds in CAF-II (Wisper Internet) also won the bid to provide broadband connectivity in Bollinger County, MO.

This area currently has Big Rivers Communication as the only fixed wireless provider with a maximum advertised speed up-to 7Mbps. Satellite Internet is an unfavorable choice as most residences do not have clear line of sight. Therefore, this zip-code can be classified as an unserved area. The take-rates were measured by allowing agents to compare the existing internet plans available in the area with the new service (fixed wireless) provided through the FCC funding (shown in Table 4.2).

Table 4.2. Comparing attributes of current service and FCC funded service. The new service provides speeds at 25Mbps, 50Mbps and 100Mbps while charging more than current service

Sl no.	Current or New?	Technology	Speed (Mbps)	Price ($)	Data-cap (GB)	Reliability
1.	Current	Fixed Wireless	7	114.99	Unlimited	3.3
	New	Fixed Wireless	25	125.00	Unlimited	3.2
2.	Current	Fixed Wireless	7	114.99	Unlimited	3.3
	New	Fixed Wireless	50	129.99	Unlimited	3.2
3.	Current	Fixed Wireless	7	114.99	Unlimited	3.3
	New	Fixed Wireless	100	149.99	Unlimited	3.2

The service attributes were sourced from websites of the respective ISPs (Big River Communication, 2021; Wisper Internet, 2021). The reliability ratings were sourced from broadbandnow.com (http://bit.ly/3cFXsCm, http://bit.ly/3rUvF7I). Further, the comparisons were also done with a high-speed fiber internet connection provided by a rural co-op to observe how policies favoring fiber infrastructure could potentially influence take-rates (see Table 4.3). The data for this service is sourced from the DEEDP report (Eisberg et al., 2020).

A total of 462 agents were initialized representing each household in the area. The agents' income and education levels were assigned as per publicly available Census data (Census Reporter, 2019). The initial-users parameter is set to 60.1% as per FCC's Form 477 data which shows what percentage of people could potentially access internet through a fixed wireless/cable provider (BroadbandNow, 2021). Each comparison was performed 1,000 times for a given set of inputs and the mean output and standard deviation are reported.

Table 4.3. Comparing the current fixed wireless service with new fiber service. The new service charges $35 to 65$ less for 1000Mbps and 100 Mbps speeds

Sl no.	Current or New?	Technology	Speed (Mbps)	Price ($)	Data-cap (GB)	Reliability
1.	Current	Fixed Wireless	7	114.99	Unlimited	3.2
	New	Fiber	100	50.00	Unlimited	4.9
2.	Current	Fixed Wireless	7	114.99	Unlimited	3.2
	New	Fiber	1000	80.00	Unlimited	4.9

4.4. SENSITIVITY ANALYSIS

The sensitivity of all input variables is tested to determine which factors are most influential to the take-rate according to this agent-based model. The One-At-A-Time (OAT) method was used for sensitivity measuring the adoption percentage at the minimum and maximum possible input value while keeping the rest of the parameters at their baseline values. For sensitivity analysis, we allow agents' demographics to be assigned arbitrarily from a uniform distribution.

The baseline, minimum and maximum values are reported in Table 5. Given that maximum population in rural area can be up to 2,500 and the number of individuals per household is approximately equal to 2.5, we set the maximum value number of households per zip-code as 1,000 (USDA, 2019). The baseline value for number of households is the assumed median number of households in a rural area.

The minimum value for this parameter is the least number of agents needed to initialize the small-world network (Watts & Strogatz, 1998). The baseline, minimum and maximum values existing users are set at 65%, 24.9% and 90.5% respectively. These values were sourced from American Community Survey which reported the trends of internet subscription rate across United States (ACS, 2018).

Table 4.4. Baseline, minimum and maximum input values. The best-case scenarios facilitate higher adoption of the new service and vice-versa

Parameter	Baseline	Worst Case	Best Case	Source
No. of Households/zip-code	500	10	1000	USDA
Existing Users	65%	24.9%	90.5%	ACS, 2018
		Current service characteristics		
Current Speed (Mbps)	12	1000	5	Broadbandnow.com
Current Price ($)	60	150	35	allconnect.com
Current Datacap (GB)	100	3000	30	Broadbandnow.com
Current reliability (out of 5)	3.2	4.9	2.8	Broadbandnow.com
		New service characteristics		
New Speed (Mbps)	100	25	1000	Broadbandnow.com
New Price ($)	60	150	35	allconnect.com
New Datacap (GB)	100	30	3000	Broadbandnow.com
New Reliability (out of 5)	3.2	2.8	4.9	Broadbandnow.com
Baseline Mean Adoption%	45.9%			

The baseline value of current speed is the mean satellite internet speed, the minimum is mean 4G LTE internet speed, and the maximum value is highest speed for fiber internet reported by broadbandnow.com. Current and new price values were derived from the average (baseline), lowest (minimum) and highest subscription (maximum) cost reported by allconnect.com. The new speed baseline value is set to be equal to the highest speed provided by lower-tier ISPs as reported in the DEEDP report. The minimum speed is the baseline requirement by FCC while the maximum speed is equal to the highest speed provided by fiber internet service. The baseline current and new reliability are the ratings given to DSL service in demonstrative study. The minimum and maximum values of reliability are equal to average reviews of satellite service and fiber service respectively. The data-cap baseline, minimum, and maximum values are sourced from broadbandnow.com. To account for the stochasticity in the model, each input setting was simulated 1,000 times. The mean output (new adoption percentage) for every setting is used to calculate sensitivity. Sensitivity is calculated as the percent change in new service adoption from the baseline.

5. RESULTS AND DISCUSSION

This section describes the results and implications obtained in the demonstrative study and the unserved area case study. The results of the sensitivity analysis show the influence of every input parameter on the model outcomes.

5.1. MODEL VALIDATION

The mean output reported for the 274 households in Perry, MO was 69% with a standard deviation equal to 5% (see Table 5.1). The minimum value yielded by the model in 1,000 simulation runs was 57% while the maximum was 80%. The first quartile value was reported to be 70% and the third quartile 72%. The model overpredicted the mean take-rate for this scenario. However, the actual take-rate in the region falls within the confidence interval of the prediction (see Figure 5.1). This suggests that a theoretically driven, rather than an empirical model, may be a reasonable approximation for consumer decision-making in the context of broadband adoption.

Table 5.1. Model validation results

Technology	Mean New Adoption%	Standard Deviation	Actual Penetration
Fiber	69%	5%	62%

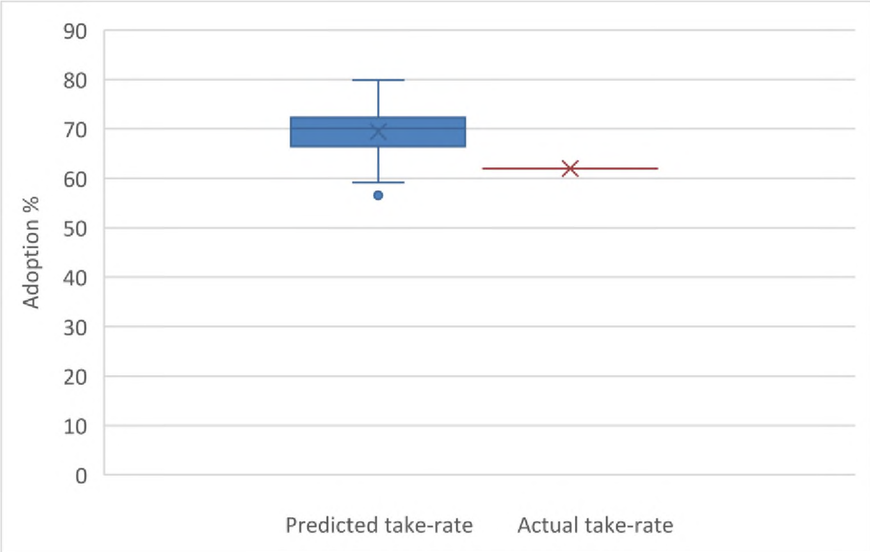

Figure 5.1. Box-whisker plot for adoption% of new fiber internet

5.2. MODEL DEMONSTRATION

To demonstrate the value of using this model to conduct policy experiments, the ABM was also used to simulate the unserved area of Patton, MO in Bollinger County. The FCC-funded cable service was first compared with an existing major service provider in the zip-code. The fixed wireless service has only one subscription plan with unlimited data and this was compared to the three plans proposed by the new fixed wireless service (Wisper Internet). The comparison in Table 5.2 shows that the 50 Mbps plan reported the highest take-rate in 1,000 simulation runs. All three subscription plans achieved a take-rate of 22% to 25%. As seen in the box-whisker plot, even the maximum value is far less than the mean take-rates of the fiber internet (see Figure 5.2).

Both the 100 Mbps and the 1,000 Mbps perform far better against the current service with mean take-rates reported as 72% (standard deviation = 3%) and 78% (standard deviation = 2%) respectively (see Table 5.3). The cheaper costs for better service compared to the cable service could be the main reasons why agents adopted the service in greater numbers.

Table 5.2. Take-rates for FCC funded service

Sl no.	Technology	Mean take-rate	Standard deviation
1.	Fixed Wireless	24%	3%
2.	Fixed Wireless	25%	3%
3.	Fixed Wireless	22%	3%

Table 5.3. Take-rates for fiber service

Sl no.	Technology	Mean take-rate	Standard Deviation
1.	Fiber	71%	3%
2.	Fiber	78%	2%

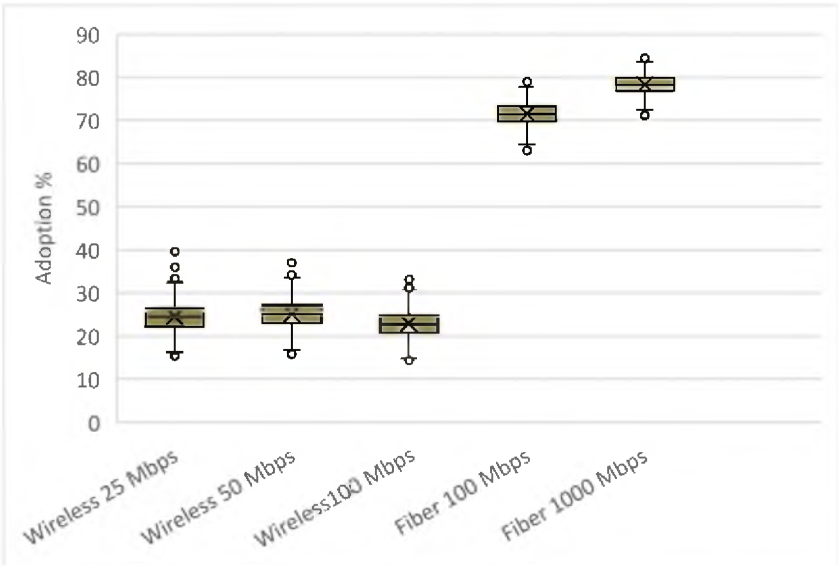

Figure 5.2. Comparisons of adoption% for every tier of service

5.3. SENSITIVITY ANALYSIS

We performed sensitivity analysis to determine which model parameters have the most influence on the percent of new service adoption. The sensitivity for best-case and worst-case scenarios was measured by calculating the ratio of change in mean output (from baseline) and baseline output. The sensitivity measurements for all input parameters of variables are visualized in Figure 5.3.

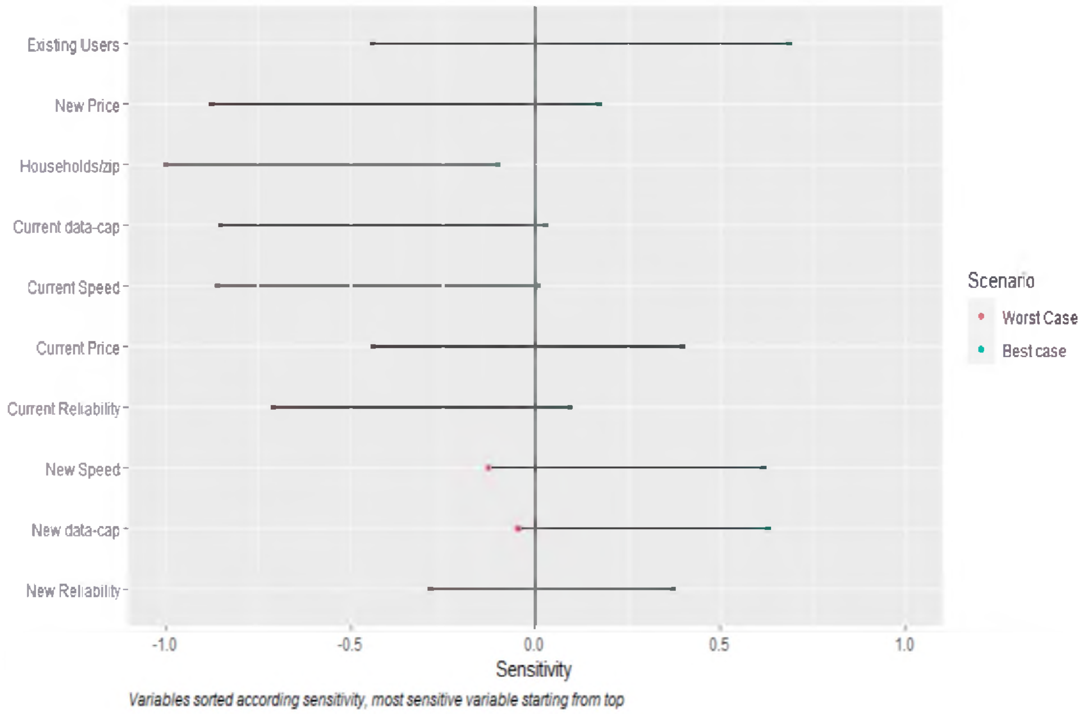

Figure 5.3. Sensitivity variation from worst case to best case

The first row shows the variation in the existing number of internet adopters in the region (see Table 5.4). The worst-case scenario (24.9%) meant fewer agents already had the capability to buy and use internet and most agents had to break the Perceived Behavioral Control barrier to have positive utility values (U).

Table 5.4. Sensitivity measurement with baseline output as 46%

	Worst Case		**Best Case**	
Variable	Mean Adoption	Percent Change	Mean Adoption	Percent Change
Existing Users	26%	-44%	77%	69%
New Price	6%	-88%	53.87%	17%
Households/zip	0%	-100%	41.28%	-10%
Current data-cap	7%	-85%	47.20%	3%
Current Speed	6%	-86%	46.21%	1%
Current Price	26%	-44%	64.16%	40%
Current Reliability	13%	-71%	50.19%	9%
New Speed	40%	-13%	74.16%	62%
New data-cap	43%	-5%	75.04%	63%
New Reliability	32%	-28%	63.06%	37%

For the households per zip-code parameter, at the best-case scenario (90.5%), most agents were not subjected to the PBC threshold condition and therefore adopted the service if they had a higher preference towards any of the attributes of the service. These adopters positively influenced non-users and therefore yielded a higher adoption percentage. This parameter showed the highest variation in output (Worst-Case = -44%, Best-Case = 69%). The adoption percentage sees a non-linear increase with increasing existing users (see Figure 5.5).

The second most sensitive input parameter was “new price” (Worst-Case = 88%, Best-Case = 17%). If the new service is costlier than the current service, fewer existing users preferred switching to the new service. These users may negatively influence other agents and thus lead to fewer adoptions overall.

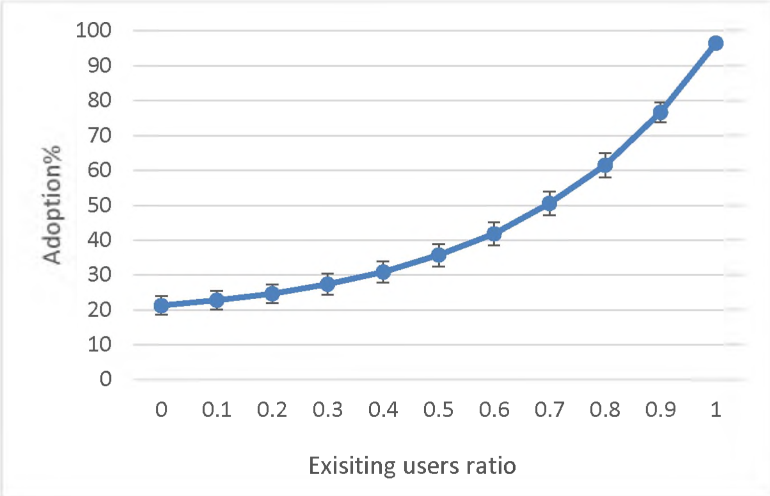

Figure 5.4. Sensitivity analysis of existing users

However, in the best-case, the adoption % does not spike much due to smaller difference from current service's price. The adoption percentage declines sharply once the new service becomes more expensive than the current service. The slope of adoption is constant until $60 and then reduces more sharply with increasing cost (see Figure 5.6). This could mean that the new price has a threshold beyond which the adopters cannot positively influence non-adopters as they themselves reject the new service.

At the worst-case value of households/zip-code, the agents are scattered far from each other which leads to fewer local links, and most of the agent-agent interactions are through the random links established. Low population led to fewer interactions and most agents do not receive much positive influence from their social network. At the best-case value, high adoption percentage could have been observed due to high number of agents who had the income and education to consider buying the new service and therefore influence more agents positively.

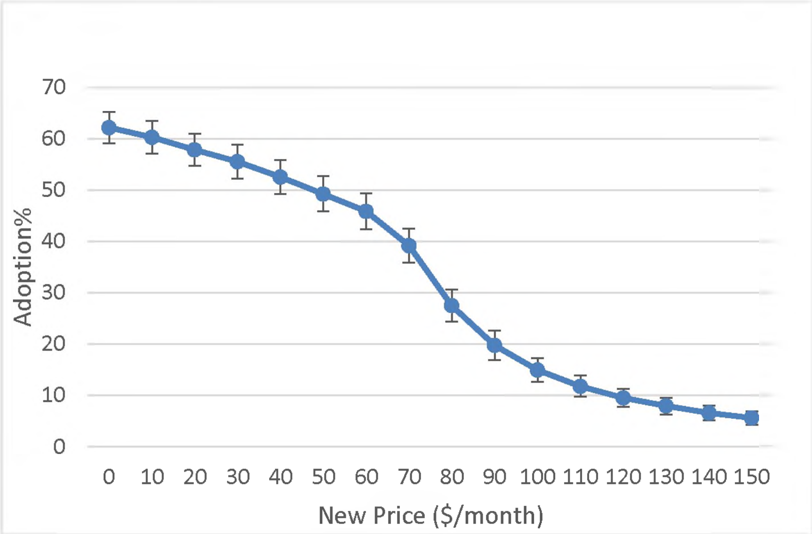

Figure 5.5. Sensitivity analysis of new price

The percent change in output was the second highest for this parameter (see Table 5.4) at the worst -case and best-case value (Worst-case = -100%, Best-case = -10%). We further observed the trends in adoption% as a function of households/zip-code (see Figure 5.7). At the worst-case scenario, none of the agents adopt the new service. The adoption increases rapidly with population density until 30% and then we see a gentle decline. It is counter-intuitive that a higher number of agents yields a lower adoption. This may be caused due to higher negative influence from a majority presence of non-adopters in the environment. At lower population density, there are larger standard deviations. This shows that the model is more stable when simulating densely populated areas.

The next four rows vary the current service attributes to measure the variation in adoption%. Data-cap shows the highest variation among all current service attributes. Agents favor unlimited usage even if the new speed offered is lower than the current service.

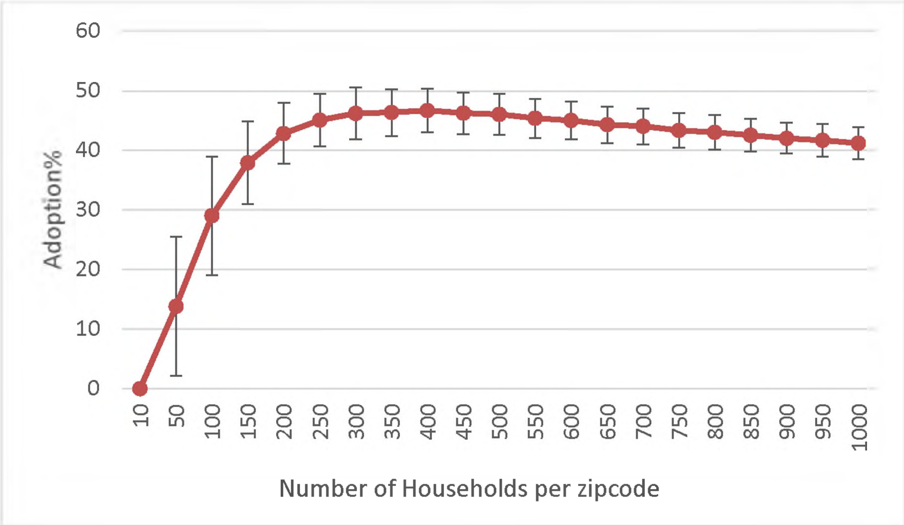

Figure 5.6. Sensitivity analysis of households/zip-code

Current speed yielded a variation similar to current data-cap. This could be because higher speed provided by the current service makes agents less likely to consider new service. The same could be used to explain the variation in adoption percentage for current price. At the worst-case value ($35), since current service became the cheaper choice, agents therefore rejected the new service. The best-case value ($150) being higher than the baseline new price, more agents adopt the new service. The new service adoption is moderately sensitive to reliability (Worst-Case = -71%, Best-Case = 9%). Agents were far more likely to stick with their current providers if they find their service more reliable. This suggests that agents perceive higher utility from the attributes which are directly related to usage experience of the current service.

In the last three rows of Table 5.4, the sensitivity of the remaining attributes of the new service are reported. The new speed provided had worst-case and best-case values set at 25 Mbps and 1000 Mbps, respectively. The agents end up with a high utility value for a larger difference in the current and new speed. The sensitivity reported for this parameter is second highest amongst all other new service attributes. New data-cap shows lower sensitivity than new speed for its worst-case (30 GB) and best-case values (3000 GB). The adoption percentage goes significantly higher at the best-case scenario, but there is moderate drop for the worst-case. New Reliability (Worst-Case =28%, Best-Case = 37%) showed the least sensitivity of all input parameters. This also suggests that agents preferred a new service if it provided better speeds at affordable prices.

6. CONCLUSION

The primary objective of this research is to develop a simulation tool to predict high speed broadband service adoption rate in a rural area. The agent-based model creates an environment consisting of rural households that decide whether to adopt a new internet service introduced in the area based on the service attributes and influence received from their neighbors and peers. We demonstrate the model's prediction capabilities followed by a case-study of an unserved area and explore the dynamics of the model through a sensitivity analysis.

The model demonstration slightly over-estimated broadband adoption in Perry, MO, but the true value was captured in the confidence interval. This gives us confidence about the output yielded by the agent-based model. This implies that the behavioral theory used to define agent rules and small-world network for spatial representation are appropriate to model the broadband adoption phenomena. This makes our agent-based model consistent with other conceptual models.

This set the foundation for the unserved area case study where a future market phenomenon was predicted due to current policies. The broadband service planned for the area is expected to be expensive for end-consumers but cheaper to deploy for the ISP. The low adoption rates yielded by the model suggest that this option may not prove to be a viable alternative to higher speed access. This is likely due to the combination of higher monthly costs and low reliability of the fixed wireless service. However, when a high-speed internet service was introduced to the agents for cheaper monthly costs, the adoption rates yielded were approximately three times higher. The fiber service provided 10 times higher speeds while charging 40-50% less monthly. This suggests that low-cost alternatives for consumers are critical for achieving high adoption rates for sustainable business models. Rather than assuming that access will translate into adoption, this model suggests that consumer subsidies may play an important role in driving adoption.

The sensitivity analysis suggests that rural areas with a high percentage of existing internet users would see higher take-rates for a new service. This outcome is consistent with the previous ABM literature, where the higher percentage of existing adopters yielded higher percentage of overall adoption of better communication technology (Kocsis & Kun, 2008). Lower costs provided by the new service were also observed as a key driver of broadband adoption. This is similar to the observations in earlier empirical studies where price was found to inversely influence demand (Carare et al., 2015; Glass & Stefanova, 2010). We also observe that best-case scenario values for attributes of current and new-service drive adoption. These outcomes are consistent with the findings of empirically studies which integrated behavioral theories. Higher utility positively influences the adoption behavior.

The model shows erratic outcomes when simulating the adoption phenomena for a sparsely populated area. The sensitivity analysis shows that lower households/zip-code yielded wider variations in adoption percentage. This suggests that in low density areas, a few individuals with extreme views may swing the opinion of the entire community to adopt or not adopt. This phenomenon needs to be verifies using empirical data. At the current stage, this model is not reliable for modeling low-population zip-codes. Another, major limitation in this simulation is input values of existing user parameter are taken from FCC Form 477 data. The Form 477 data considers a census block to be served even if an ISP can provide service only to a single user. For the sake of simplification, we assume that all households to which current service is available have adopted it. Further, our modeling strategy considers residential internet subscription owners as existing internet adopters and does not consider the presence of mobile internet users in the area. Our model also assumes that new service is deployed in the entire area simultaneously and not phase-by-phase as done in real world. Service providers may have a contractual agreement with consumers which might limit consumer's wish to immediately switch if a better service is available. This aspect is not accounted for in this model presently, but it can be included with the availability of empirical data. We also note that online reliability ratings fluctuate with time and so the predicted take-rates may also vary. This can be solved by using customer feedback recorded by ISPs for more stable prediction.

There is tremendous scope to increase the predictive capability of the agent-based model presented in this research. The two main steps towards validating and extending the model are elaborated below.

(i) Model Validation**:** The agent-based model is aimed at demonstrating the consumer adoption phenomena in the context of high-speed internet in rural areas. Empirical data could improve the predictive ability of the model and help answer more specific questions about policy effectiveness(Rai & Henry, 2016). The 3 key areas where empirical data could enhance this model are a) consumers' preferences, b) spatial representation of service availability, and c) service usage data provided by ISPs.

A popular way to capture the heterogenous interactions between product attributes and consumer-decision making is by collecting demographic and stated preference data from consumers to initialize the agent-based model. Discrete choice experiments have been used to determine the product attributes significant to the consumer in studies related to adoption of e-groceries in urban areas (Gatta et al., 2020), diffusion of solar PV in New Zealand (Araghi et al., 2014), and increase availability of wood in Swiss markets (Holm et al., 2016). In the context of rural broadband, a survey can be deployed to collect consumers' demographics, their individual applications of internet, the utility associated with each attribute of subscription plans, and their response to peer influence. The data can be fitted using a random utility model and the estimates can be used to assign preference variables such as w_s, w_p, w_{dc}, w_r, w_u, and w_{soc}. The discrete-choice experiment can also capture the reasons furnished by consumers to remain with their current service providers or without a broadband subscription. This can be very helpful in modelling agents who reject the service.

The internet service availability needs high resolution spatial representation especially for wired services. The FCC data has severe limitations in terms of accuracy. It would be valuable if ISP could provide data to researchers on their infrastructure layout in the geographical region they are providing or plan to provide service. The data could indicate residential and business establishments where connection is or could be provided. For wireless service, it would be valuable if we are provided data on the points where antennas are setup and the area that each antenna can service. There are existing models of wireless transmission that could be integrated to appropriately model signal strength.

Lastly, it would be helpful if ISPs could provide revealed preference data for take-rates of various subscription plans available. Along with the list of services, it would also be valuable to know the percentage of users subscribed to each of their plans. Since agent-based models can simulate adoption phenomena over a set timeframe, ISPs could provide historical trends of consumer adoption for each of their services. Additionally, more attributes of the service such as contractual terms, one-time costs, quality of service (QoS), and latency could also improve the model's predictive capability.

(ii) Model Extension: The current model's utility is restricted to predicting the take-rate of residential internet service in a region. This could be a stepping-stone for more elaborate models which can distinguish between the needs of commercial and residential establishments.

The environment can be extended to simulate more than two internet services competing at the same time, such as fiber, satellite, LTE, and fixed wireless available simultaneously. The take-rate could be used to predict the revenue inflow for the ISP in an area. The revenue inflow can further be determined by varying the resolution of the geographic region for, such as a census block, multiple zip-codes, or multiple counties. This approach can help to develop an expansion strategy for a service provider.

Broadband's impact on the sales and revenue of local businesses, household income, and number of operational businesses in an area can also be determined using this type of model. There is interest in studying the impact of specific applications of broadband such as telehealth and telemedicine, precision agriculture and online education on the lives of rural Americans. Policymakers could also use this type of model to study the fluctuations in rural populations because of local socio-economic development.

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