Summer 2017

Modeling dynamic community acceptance of mining using agent-based modeling

Mark Kofi Boateng

Department: Mining Engineering

MODELING DYNAMIC COMMUNITY ACCEPTANCE OF MINING USING AGENT-BASED MODELING

by

MARK KOFI BOATENG

A DISSERTATION

Presented to the Faculty of the Graduate School of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfilment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

in

MINING ENGINEERING

2017

Approved by:

Kwame Awuah-Offei, Advisor

Samuel Frimpong

Nassib Aouad

Hooman Askari-Nasab

Xuerong Wen

ABSTRACT

This research attempts to provide fundamental understanding into the relationship between perceived sustainability of mineral projects and community acceptance. The main objective is to apply agent-based modeling (ABM) and discrete choice modeling to understand changes in community acceptance over time due to changes in community demographics and perceptions. This objective focuses on: 1) formulating agent utility functions for ABM, based on discrete choice theory; 2) applying ABM to account for the effect of information diffusion on community acceptance; and 3) explaining the relationship between initial conditions, topology, and rate of interactions, on one hand, and community acceptance on the other hand.

To achieve this objective, the research relies on discrete choice theory, agent-based modeling, innovation and diffusion theory, and stochastic processes. Discrete choice models of individual preferences of mining projects were used to formulate utility functions for this research. To account for the effect of information diffusion on community acceptance, an agent-based model was developed to describe changes in community acceptance over time, as a function of changing demographics and perceived sustainability impacts. The model was validated with discrete choice experimental data on acceptance of mining in Salt Lake City, Utah. The validated model was used in simulation experiments to explain the model's sensitivity to initial conditions, topology, and rate of interactions. The research shows that the model, with the base case social network, is more sensitive to homophily and number of early adopters than average degree (number of friends). Also, the dynamics of information diffusion are sensitive to differences in clustering in the social networks. Though the research examined the effect of three networks that differ due to the type of homophily, it is their differences in clustering due to homophily that was correlated to information diffusion dynamics.

ACKNOWLEDGMENTS

First and foremost, I would like to thank the Almighty God for His grace and blessings, which have brought me this far in my life. I would like to express my profound gratitude to all those who helped and encouraged me throughout my PhD studies. Most importantly, my recognition to Dr. Kwame Awuah-Offei, my academic advisor, for his outstanding support and unflinching guidance which ensured the success of my PhD studies. I would also like to thank my PhD advisory committee members: Dr. Samuel Frimpong, Dr. Nassib Aouad, Dr. Hooman Askari-Nasab and Dr. Xuerong Wen for their support and input towards my work. I appreciate Dr. Kyle Bahr for his feedback in the early part of producing my dissertation.

Again, I would like to acknowledge the Department of Mining & Nuclear Engineering, Missouri S&T, and Ma'aden, Saudi Arabia partnership, which offered me the financial assistance for my PhD education. I am grateful to Ms. Tina Alobaidan, Ms. Barbara Robertson, Ms. Shirley Hall, Ms. Judy Russell, Ms. Justina Lewis, Ms. Amanda Kossuth, and Ms. Jade Sinnott for their administrative support during my PhD studies. I remain thankful to all my friends for their encouragement through my PhD studies. My special thanks go to my loved one, Ms. Danyelle Lockett for her constant encouragement while working on this dissertation.

Finally, I am forever indebted to my mother, Mrs. Christiana Sarkodee, my aunt, Ms. Diana Boadu, my daughter Olivia Boateng, my siblings and my entire family for their prayers and support throughout my education. I would like to acknowledge my late father, Mr. Ernest Sarkodee whose advice and guidance made me take an interest in science. Thank you Dad for what you did for me.

TABLE OF CONTENTS

Page

LIST OF ILLUSTRATIONS

Page

LIST OF TABLES

NOMENCLATURE

Symbol	**Description**
U_{ni}	Utility of alternative *i* to individual *n*
V_{ni}	Observed component measured for alternative *i* of individual *n*
ε_{ni}	Unobserved random component for alternative *i* of individual *n*
X_{n}	Vector of characteristics specific to the individual decision maker
β_{i}	A vector of coefficients specific to the *i* th alternative
X_{ni}	A vector of attributes specific to the *i* th alternative as perceived by the *n* th individual
U_{a}	Alternative *a*
β_{j}	Taste coefficient associated with attribute *j*
χ_{j}	Variable for attribute *j*
OR_{ab}	Odds of selecting alternative *a* over *b*
ψ	Probability of a connection
α	Close neighbor ratio, which measures homophily in the social network
P	Proximity value
ΔR	Difference in zip code
V	New perception’s value

N_T	Total number of agents
ρ	Fraction of the population that has adopted the new perception
θ	Characteristic value of the product adoption model
d	An exponent that determines the steepness of the function associated with the product adoption model
Z	Output (level of acceptance at a particular time instance)
Z^{F1}	Output when a particular factor *F* is set to level 1
Z^{F0}	Output when a particular factor *F* is set to level 0
nF_1	Number of experiments where the factor is set to 1
nF_0	Number of experiments where the factor is set to 0
A	Number of friends
B	Close neighbor ratio
C	Number of early adopters
$\hat{a}$	An initial user-provided estimate for the average degree
P_{ij}	Probability of a connection between agents *i* and *j*
μ_{ij}	A factor, which is a mapping of inverse of the degree of similarity between agents
$\bar{\mu}$	Average factor that normalizes uniform distribution associated with agents' connection
C_2	Average local clustering
$a_i - a_j$	Difference between social attributes of agents *i* and *j*

LIST OF ABBREVIATIONS

ABM	Agent-Based Model or Agent-Based Modeling
ICMM	International Council on Mining and Metals
GDP	Gross Domestic Product
SLO	Social License to Operate
COI	Community of Interest
FPIC	Free Prior and Informed Consent
DCE	Discrete Choice Experiment
TBL	Triple Bottom Line
ISEA	Institute of Social and Ethical Accountability
IFC	International Finance Corporation
MCMPR	Ministerial Council on Mineral and Petroleum Resources
USGS	United States Geological Survey
AMD	Acid Mine Drainage
EPA	Environmental Protection Agency
SIA	Social Impact Assessment
EIAs	Environmental Impact Assessments
MNL	Multinomial Logit
CL	Conditional Logit
NL	Nested Logit
GEV	Generalized Extreme Value
MNP	Multinomial Probit

ML	Mixed Logit
ABMS	Agent-Based Modeling and Simulation
UML	Unified Modeling Language
O-O	Object-Oriented
SIS	Susceptible Infected, Susceptible
SIR	Susceptible, Infected, Removed
RUM	Random utility Maximization
OAT	One-Factor-at-a Time

1. INTRODUCTION

1.1. BACKGROUND

Mining provides the raw materials for human development. It is worth noting that minerals and metals are crucial to all services and infrastructure that are used by society (ICMM, 2012a; Martens & Rattmann, 2001). World demand for minerals will be affected by three broad factors: uses for mineral commodities, the level of population consuming these mineral commodities, and the standard of living, which determines how much is consumed per a person (Kesler, 2007). For instance, population growth and the speed of urbanization in China and other Asian countries, together with current demand in the developed world have resulted in an unprecedented demand for minerals and metals.

Mining operations can result in several economic impacts including: job opportunities and income increase for individuals in the host region. Job opportunities and related economic impacts created by mining operations are well documented in the literature. Increases in income as a result of higher paying jobs and/or the jobless joining the mine's supply chain is another significant impact of mining (ICMM, 2012a; Petkova et al., 2009; Que, 2015). In the United States (U.S.), for instance, the economic contribution made by U.S. mining in 2015 through employment, labor income, contribution to gross domestic product (GDP) and taxes is presented in Table 1.1. In 2015, U.S. mining directly and indirectly created nearly 1.7 million full-time and part-time jobs. In addition, U.S. labor income associated with mining exceeded $100 billion, which includes wages and salaries, other employee benefits and owner-operator business income (National Mining Association, 2016). At both national and local levels, mining generates government revenues, foreign and domestic investment. National Mining

Association (2016) reports that U. S. mining activity generated about $18 billion in federal, state and local taxes in 2015, and that supported direct, indirect and induced taxes of $ 44 billion. U.S. mining contributed about $220 billion to the GDP in 2015 (National Mining Association, 2016).

Table 1.1. Economic Contribution of U.S. Mining, 2015

Item	Direct	Indirect and Induced	Total
Employment	565,548	1,122,816	1,688,364
Labor Income (billions of dollars)	$39.8	$63.9	$103.7
Contribution to GDP (billions of dollars)	$100.4	$120.0	$220.4
Taxes Paid (billions of dollars)	$18.0	$26.0	$44.0

Source: National Mining Association (2016)

Regardless of the fact that mining benefits the society, mining now and in the future has to take place in an economically, ecologically and socially acceptable manner. Besides, society expects that mining operations meet more exacting environmental, social and cultural standards of performance. Thus, mining and metals companies have a major role to play in a sustainable world. Project development cycles for mining and metals companies require a plan for how the operation will be carried out in a sustainable manner. Communities, civil society, investors or governments will not accept unsustainable mining, so a proactive response is extremely important (ICMM, 2012a; Martens & Rattmann, 2001; World Economic Forum, 2014). By and large, concerns regarding corporate sustainability have increased globally over the years (Freeman & Gilbert, 1998; Friedman & Miles, 2001; Gao & Zhang, 2006; Mathews, 1997; Rotheroe et al., 2003; Rowe& Enticott, 1998; Schaefer, 2004; Shrivastava, 1995). Poor sustainability performance affects the profitability of a business. Businesses should have an interest and a responsibility to incorporate sustainable development into their long-term business plans (Elkington, 1998; Gao & Zhang, 2006; Russo & Fouts, 1997).

Community acceptance of mineral projects is an important concern, if these projects are to be carried out in a sustainable manner. Regulatory bodies, engineers, related professionals and investors in the mineral extraction business need to gain more insight into the drivers of community acceptance. More importantly, professionals need a better understanding of approaches to designing more sustainable projects, which can influence community acceptance.

Communities around the world are increasingly requesting a greater portion of benefits from local mining projects, more involvement in decision making, and assurances that mineral development will be conducted safely and responsibly (Prno, 2013). At the same time, full legal compliance with state environmental regulations has become an increasingly insufficient means of satisfying society’s expectations of mining. There is now a recognized need for mineral developers to gain a social license to operate (SLO) to avoid potentially costly conflict and exposure to business risks (Bridge, 2004; Prno, 2013). Lack of social license to operate (SLO) for natural resource projects constitutes a major risk to the success of these projects. A SLO can be said to exist when a mining project is perceived to have the broad, ongoing approval and acceptance of society to conduct its activities (Joyce & Thomson, 2000; Thomson & Boutilier, 2011).

In other words, SLO refers to the level of acceptance that the local community and other stakeholders constantly give to an organization's operations or project (Black, 2013). The lack of community acceptance leads to political and social unrest, which increases security and public relations trepidations for mining companies. These concerns reduce the value of the project through increasing costs as a result of delays or temporal shutdowns and can even dent the corporate image to render the project unattractive to the capital markets.

As a result of the fact that there have been significant consequences because of lack of community acceptance, regulations in many regions clearly demand that the project is accepted by the affected community or community of interest (COI), during the permitting of resource projects (Joyce & Macfarlane, 2001). Some regulators encourage free prior and informed consent (FPIC) of the affected communities or indigenous populations. This aims to ensure that these communities express their right in the decision making regarding the project. For example, Canada has endorsed the FPIC approach by providing the affected communities and indigenous peoples the right to partake in decision making and the right to say "yes" or "no" to development decisions and activities affecting their lands and resources (Hart, 2012). Nevertheless, stakeholders including private companies, government agencies, regulators, and NGOs still have no a quantitative approach to incorporate community acceptance into designing and planning new mining projects, and even into expanding existing mining projects. Primarily, these stakeholders need to gain better insight into design choices and their impacts on community acceptance and eventual sustainability of the project. For example, designing a project to use over-head conveyor systems as opposed to overland conveyor systems might add to design complexities and extra cost to the project. However, the community may be more likely to accept the project because this option allows them space, and does not cause any undesirable traffic issues. Also, stakeholders need a means to understand how information transfer within these communities can cause changes in community acceptance. Research is required to explore the nature and dimensions of such information transfer. This dissertation seeks to address these questions and concerns.

1.2. STATEMENT OF PROBLEM

It is important to understand the relationship between sustainability and community acceptance in order to facilitate design and execution of sustainable resource projects that provide raw materials for industrial activity. "Community acceptance" in this context means individuals in the mining community prefer the proposed mining project over the status quo. This may be more than "acceptance" but less than "approval" in social license to operate (SLO) parlance (Thomson and Boutilier, 2011). Community acceptance is affected by factors such as the impacts of the mine on the environment and host community, the mine owner (corporate reputation, etc) and governance issues, and demographics of the community (Que, 2015; Wang et al., 2016).

Community acceptance has direct and major implications on sustainability. Mining projects impact social, environmental and economic characteristics of the host communities and as such affect the community's acceptance of the mining project. The capability of the project team to successfully execute a sustainable mining project is dependent on the community's acceptance of the project. Besides, project risks can be influenced by community acceptance. For example, several conflicts in mining regions are partially due to companies' inability to reliably predict community acceptance, and incorporate it early into the project planning and design. These conflicts can potentially be handled by a methodical and reproducible modeling framework, which defines the relationships between community acceptance and sustainability, on one hand, and engineering design and project execution decisions, on the other hand. Such a framework can be applied, in addition to current tools, to highlight issues related to emergent (grassroots) behavior that is difficult to understand with these other approaches.

The literature does not contain any such framework that can be used to evaluate the effect of information diffusion on the changing level of acceptance over time. This research is aimed at filling the gap by providing a framework that can be applied to understand community acceptance of mining over time given changes in community's demographics and perceptions. The framework would assist mine managers and stakeholders to make more informed decisions to promote sustainable mining.

The system under consideration is complex, adaptive and dynamic (state variables change with time) (Figure 1.1). Therefore, there is the need to develop a dynamic community acceptance model with a complex-adaptive system framework. Over time, the mining project characteristics and impacts change. These impacts affect community demographics (people migrate and immigrate in search of jobs, quality of life changes, among others), which may in turn affect individual perceptions and decisions in relation to acceptance of the mine. Consequently, community acceptance is affected by demographics and project characteristics and impacts. As presented on the right side of Figure 1.1, the people in the community (agents) interact with one another which may influence their decisions to accept the project ("Yes") or not ("No"). Ultimately, the agent makes its own decision to accept or not based on its utility function. It is essential to integrate the dynamic interactions between the technical/manufacturing system (i.e. the mine) and the enviro-socio-economic impacts, demographics, and project characteristics (Halog & Manik, 2011). This task can be accomplished through complex-adaptive system modeling techniques like agent-based modeling (also referred to as multi-agent modeling). This dissertation is focused on developing such a framework to understand how perceived project sustainability affects community acceptance over time. Eventually, this framework will help mine managers and other stakeholders better understand and evaluate dynamic community acceptance.

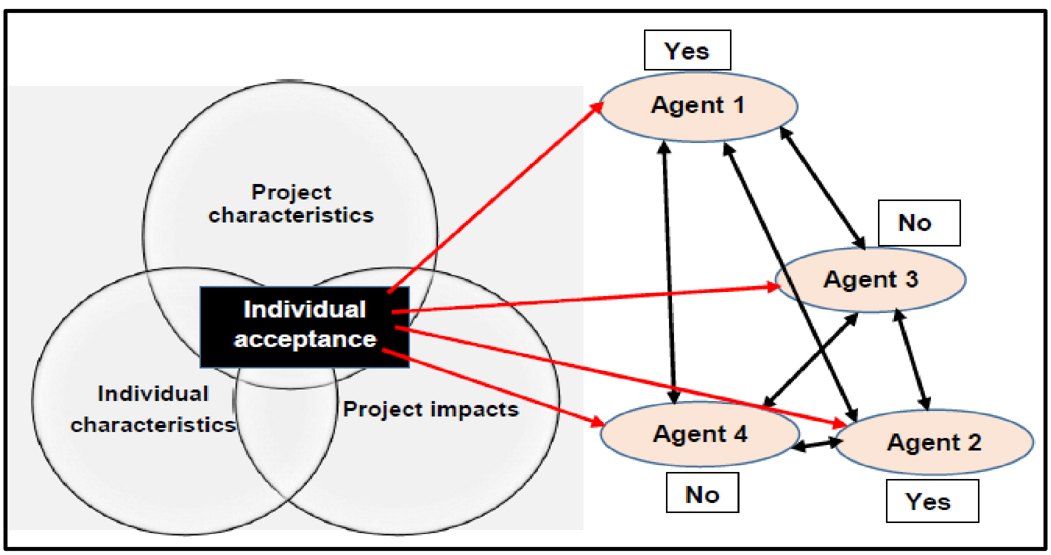

Figure 1.1. System Interactions for Community Acceptance Model

Literature review shows that there is no established framework for quantitatively understanding community acceptance of mining projects over time. A good framework would make mine design and permitting, and policy decisions by stakeholders less challenging than it is, presently. A reliable model, capable of quantitatively assessing changes in community acceptance over time will help stakeholders do a better job in evaluating options and, therefore, make better decisions.

The application of agent-based modeling has been extensive and successful in modeling economic and other social behavior (Aguirre & Nyerges, 2014; Bonabeau, 2002; North & Macal, 2007). ABM describes “agent” interaction in a way that captures dynamic and emergent behavior (Bonabeau, 2002; Macal & North, 2010). A complex adaptive system, such as the community acceptance of mineral projects can be modeled using ABM. The current ABM work in mining community/stakeholder modeling (Berman et al., 2004; Li & Liu, 2008; Nakagawa et al., 2013) does not offer a rigorous (i.e. routed in decision theory) theoretical basis for the agent utility function. The candidate believes that application of discrete choice theory will advance the science of ABM application to mining community/stakeholder modeling by incorporating sound decision theory to describe individual motivation to support or oppose a mining project. This study is, therefore, at the intersection of mining community/stakeholder analysis, discrete choice theory and complex-adaptive system modeling using ABM.

Discrete choice theory, based on the Nobel winning work by McFadden (McFadden, 1974), and others (Brock & Durlauf, 2001; Gramming et al., 2005), has been successfully applied in econometrics and other disciplines to understand consumer behavior. For instance, discrete choice theory has been applied to evaluate community acceptance of renewable energy projects (Dimitropoulos & Kontoleon, 2009). Some researchers have also used discrete choice theory to model individuals’ choice concerning whether or not to support mining (Ivanova & Rolfe, 2011; Que & Awuah-Offei, 2014).

Discrete choice theory can be applied to formulate rigorous utility functions for agent-based model (ABM) of community acceptance. For example, Hunt et al (2007) successfully used a discrete choice model and ABM to examine recreational behaviors so as to guide the choice and implementation of given scenarios. Similarly, Lee et al (2014) used ABM, which relied on decision-making algorithm using discrete choice experiment (DCE) to simulate energy reduction situations of owner-occupied homes in the United Kingdom (UK). In spite of the examples of the application of ABM and discrete choice experiments (DCEs), independently, to model consumer and individual preferences (Brock & Durlauf, 2001; Gramming et al., 2005; McFadden, 1974; Zhang et al., 2011), the combination of the two approaches to model community acceptance of mining project does not exist in the literature. Actually, ABM applications in resource exploitation wholly have not been supported by rigorous utility functions based on sound social science. Nevertheless, work done by researchers including (Hunt et al., 2007) attests to the possibility for these two approaches to be applied to model mining community acceptance over time.

Also, the structure of a community's social network can affect information diffusion within the community. For instance, the structure of a social network can favor or impede the diffusion of information in the network (Deroian, 2002; Kong & Bi, 2014). In order to use ABM to understand the effect of information diffusion on changes in community acceptance, social network and diffusion models have to be included in the agent-based models. However, there has been no work that used ABM and discrete choice theory in conjunction with diffusion models through social network to quantitatively understand dynamic community acceptance of mining.

Community acceptance is usually influenced by numerous factors, including effectiveness of local community engagement, individual preferences, and requirements for community acceptance, and perceptions of legitimate ownership of mineral rights (Ballard & Banks, 2003; Joyce & Macfarlane, 2001). In general, community acceptance is an essential element in the sustainability of a particular mining project. This presents several questions and concerns: How does new information change the community acceptance over time? Can an agent-based modeling framework that uses discrete choice theory be proposed to study this question? If so, what are the essential input parameters that the model is most sensitive to? What is the effect of social network on the dynamics of information diffusion and community acceptance? Based on the aforementioned complexities related to achieving perceived sustainability, further research is needed to explore these issues. Though combining ABM with rigorous decision science and incorporating social network structure is a promising method to investigate these issues, there are many challenges such as: (1) how to define valid agent utility functions using discrete choice theory; and (2) how to describe the interaction between perceptions of sustainability and community acceptance using an ABM diffusion model through social network. The main contribution of this dissertation is to overcome the above-mentioned challenges, and provide more understanding into changes in community acceptance over time due to changes in community demographics and perceptions.

In this dissertation, the candidate uses the odds ratio as the utility function. The application of odds ratio has been wide in decision applications, especially in the field of medicine for selecting options and making decision. For example, it helps patients decide to accept or waive painful or expensive treatments, and thus, enables health care providers to make treatment decisions (Mchugh, 2009). However, to the best of the candidate's knowledge, it has never been used in ABM. This research is mainly aimed at providing better understanding of the relationship between perceived mine sustainability attributes and community acceptance. In other words, this study will provide engineers, stakeholders and regulatory bodies' additional tools to assess the impact of various design options that affect community perception of sustainability on community acceptance. Ultimately, this will contribute to improving sustainability impacts of mining, and enhancing mining engineering practice and research.

1.3. RESEARCH OBJECTIVES AND SCOPE

The goal of this PhD research is to provide rudimentary understanding of the relationship between perceived sustainability of mineral projects and community acceptance. Particularly, the main objective of this research is to apply agent-based modeling (ABM) and discrete choice modeling to understand changes in community acceptance over time due to changes in community demographics and perceptions. This objective focuses on:

1. Formulating agent utility functions for ABM, based on discrete choice theory;
2. Applying ABM to account for the effect of information diffusion on community acceptance; and
3. Explaining the relationship between initial conditions, topology, and rate of interactions, on one hand, and community acceptance on the other hand.

To achieve this objective, this research relies on discrete choice theory, agent-based modeling, innovation and diffusion theory, and stochastic processes. Discrete choice models of individual acceptance of mining projects was used to formulate utility functions for this research. To account for the effect of information diffusion on community acceptance through social network, an agent-based model was developed to study changes in community acceptance over time, as a function of changing demographics and perceived sustainability impacts. The model's utility function was validated with data from Salt Lake City, Utah, USA.

This research has the following limitations that require clarification. Firstly, social network used in this research is only assumed to be representative of the mining community and has not been observed in the community. There is no information on the type of social network in a particular mining community in the literature even though some researchers have qualitatively discussed social networks in the mining communities. However, the general framework and the sensitivity analysis can be useful in providing stakeholders with a better understanding of how social networks of mining communities influence the rate of change in project acceptance because of information diffusion. Secondly, the ABM model in this study does not account for the possibility of different roles (e.g. active or passive, resistant or receptive, and innovators or followers) of individuals during information diffusion. Thirdly, the ABM model has not been fully validated with empirical data from a mining community or communities. Besides, the model assumes that the "local community" can be defined and isolated. This suggests that the system is thus bounded to a particular community and there is no significant interaction between individuals in the community under study and in other communities that can impact perceptions. Nevertheless, this research will offer better knowledge of the factors that influence community acceptance. The model will advance the application of agent-based models to manage sustainable mineral projects and can be used for future research in sustainability.

1.4. RESEARCH METHODOLOGY

Table1.2 presents the research methodology adopted in this study. To begin with, a critical literature review was conducted to clearly understand current issues regarding sustainability and community engagement, various community engagement processes, factors affecting community, and existing tools to quantitatively understand community acceptance of mining over time. Although the literature review, by itself, does not accomplish any of the objectives, it is the basis of all the solutions proposed in this research. The literature review provided the required information and knowledge that guided the candidate to clearly understand the current challenges facing mining sustainability and the approaches (agent-based modeling, discrete choice theory, and social networks) to address these challenges.

With the first two objectives, the candidate developed an agent-based modeling framework for modeling the effect of information diffusion on community acceptance of mining. The candidate developed the information diffusion model by assuming that the probability of a person adopting the new perceptions of the mine's sustainability depends on the number of friends that person has and a random process that is a function of the fraction of friends who have adopted the new perception. This research used the Bass model to describe word-of-mouth information transfer because it is consistent with this assumption (Jackson, 2008).

Table 1.2. Research Approach and Organization of this Dissertation

Section	Task
Section 2	**Literature Review:** 1. Sustainability and community engagement 2. Mining community engagement 3. Mining community and social license to operate 4. Factors that affect community acceptance 5. Discrete choice theory and models 6. Agent-based model (ABM) 7. Social network 8. Applications of ABM, social network and discrete choice theory to model community behavior
Section 3 (Objectives #1 and #2	**Agent-Based Modeling (ABM):** 1. Modeling framework 2. Utility function validation 3. Case study
Section 4 (Objective #3)	**Experiment and Sensitivity Analysis of the ABM:** 1. Sensitivity analysis of the ABM
Section 5 (Objective # 3)	**Effect of Social Networks on Information Diffusion and Community Acceptance of Mining** 1. Investigating social networks and their effects on information diffusion and community acceptance of mining

Many researchers have modeled word-of-mouth information transfer as a diffusion process. For instance, the model developed by Bass describes the diffusion of an innovation as a contagious process that is propelled by word-of-mouth (Kiesling et al., 2012). Using data from the literature, a case study was used to illustrate the framework. The model, constructed in MatLab, defines individuals in the community as independent agents that interact with other agents via their social network for information. The agents' utility function was derived from discrete choice models.

An individual's utility (payoff) for an alternative and the odds of selecting an alternative over another can be estimated using discrete choice theory. This work uses the odds ratio, which is the ratio of the probability of an individual selecting one alternative over another, as the decision criteria to determine whether agents have accepted the proposed mining project or not. An agent accepts a proposed alternative over the status quo if its odds ratio is greater than one. The odds ratio is estimated for all agents participating in the decision at each time step in the simulation. The model then tabulates all agents' state (accepted or not accepted) to determine the level of acceptance as a percentage of agents who have accepted. This approach is implemented in the framework presented in section 3.

Third objective is achieved by conducting sensitivity analysis of the agent-based model (ABM). This is done in two parts, the first of which examines all sensitivity factors but the social network. This activity investigated how the ABM is sensitive to key input parameters of the model. Specifically, this task examined the sensitivity of the ABM to average degree (total number of friends) of the social network, close neighbor ratio (a measure of homophily in the social network) and number of early adopters ("innovators"). A two-level full factorial experiment was used to investigate the sensitivity of the model to these parameters. The primary (main), secondary and tertiary effects of each parameter was estimated to evaluate the model's sensitivity to these key input parameters.

The second part of the third objective was to investigate the effect of social networks (topology) on information diffusion and its resultant effect on community acceptance of mining. The ABM built from the second objective, which incorporates social network to model community acceptance of mining projects, was employed to evaluate the effect of social network by simulating three different social networks: network with homophily based on social distance, network with homophily based on physical distance (propinquity) and network without homophily. This work further discusses the relationship between the simulated social networks and documented mining communities.

1.5. STRUCTURE OF THE DISSERTATION

This dissertation contains six sections, including this section. Section 2 presents relevant literature review. Section 3 presents an agent-based modeling framework for modeling the effect of information diffusion on community acceptance of mining. Section 4 discusses the sensitivity analysis of the agent-based models. The effect of social network on information diffusion and community acceptance is discussed in Section 5. Section 6 provides the conclusions of this dissertation and recommendations for future work.

2. LITERATURE REVIEW

2.1. SUSTAINABILITY AND COMMUNITY ENGAGEMENT

Sustainable development has been defined in various ways. However, the most frequently cited definition defines sustainable development as the ability of current generations to meet their needs without compromising the ability of future generations to meet their own needs (Brundtland, 1987). Sustainability as a business idea was introduced by John Elkington, who coined the phrase “triple bottom line” (TBL). TBL refers to a new approach of doing business accounting that considers social, economic, and environmental impacts and risks when making business decisions. Elkington advised the business world to adopt the TBL approach as a way to include social and environmental impacts in making business decisions. This has resulted in defining the “three pillars” of sustainability as the society, the economy and the environment (Elkington, 1998). In essence, sustainable development comprises social, economic and environmental impacts (Munashinge & Shearer, 1995). Other definitions of sustainability have been proposed in recent times. These include sustainable development defined with regards to social, natural, human, physical, and financial capital (the five capitals) (Goodwin, 2003) and the concept of shared value (Porter & Kramer, 2011).

Concerns regarding corporate sustainability have increased globally over the years (Freeman & Gilbert, 1998; Friedman & Miles, 2001; Gao & Zhang, 2006; Mathews, 1997; Rotheroe et al., 2003; Rowe& Enticott, 1998; Schaefer, 2004; Shrivastava, 1995). Poor sustainability performance impacts the triple-bottom profitability of a business. That is businesses should have an interest and a responsibility to integrate sustainable development into their long-term business plan (Elkington, 1998; Gao & Zhang, 2006; Russo & Fouts, 1997).

The real meaning of sustainable development can be captured by analyzing stakeholder opinions through a multi-stakeholder approach (Rotheroe et al., 2003). A stakeholder represents any group or individual who can affect or is affected by the achievement of the organization's objectives (Freeman, 1984). The Institute of Social and Ethical Accountability (ISEA) defines stakeholder engagement as "the process of seeking stakeholder views on their relationship with an organization in a way that may realistically be expected to elicit them" (Cumming, 2001). The term "stakeholder engagement" is emerging as a means of describing a broader, more inclusive, and continuous process between a company and those potentially impacted its operations that comprises a range of activities and approaches, and spans the whole life of the project (IFC, 2007). A mining project and its stakeholders are interdependent. Rotheroe et al (2003) suggest that industry has to engage stakeholders in the decision-making process and throughout the entire project to achieve sustainable development (Cheney & Christensen, 2001).

Notably, the relationships between mining companies, local communities and other stakeholders begin long before mine construction begins, and companies should prudently invest in establishing good local relationships at the earliest stages possible (ICMM, 2012). From a mining perspective, ICMM (2012) defines stakeholders as a comprehensive list of people and groups who may be affected by, can affect, or have an interest in a project. The list of stakeholders for a project may include individuals, interested groups, government agencies, corporate organizations, politicians, labor unions, media, public sector agencies and other groups. It is important to note that project's stakeholders may change over time as the project goes through its life cycle, and thus, stakeholder identification should be a dynamic process (ICMM, 2012b). Local mining communities are the first stakeholder on the checklist of possible stakeholders proposed by International Council on Mining and Metals (ICMM) (ICMM, 2012b). The Ministerial Council on Mineral and Petroleum Resources (MCMPR) defines a community as a group of people living in a particular area or region. In mining industry terms, community is applied to the inhabitants of the immediate and surrounding areas who are affected by a company's activities (MCMPR, 2005). The term local or host community usually refers to those living in the immediate vicinity of an operation, whether indigenous or nonindigenous people, who may have cultural affinity, claim, or direct ownership of an area in which a company has an interest. The term affected community applies to the members of the community affected by company's activities (Evans & Kemp, 2011).

Studies have indicated that mining community engagement is important for the success of mining operations and other industrial activities and inadequate engagement can result in disrupted projects (Browne et al., 2011; Davis & Franks, 2011; Moffat & Zhang, 2014; Prno & Slocombe, 2012; Thomson & Boutilier, 2011). Communities must be acknowledged as legitimate participants in the decision-making about when mining is desirable and under what conditions. Only then can mineral development contribute to sustainable development (Keenan et al., 2003).

Community engagement is necessary for acquiring permits before beginning mining project. Regulations in many regions clearly request that the project is "accepted" by the affected or community of interest (COI), during the permitting of resource projects (Joyce & Macfarlane, 2001). Other regulators encourage free prior informed consent (FPIC) of the affected communities or indigenous populations. This is focused on allowing these communities to express their right in the decision making concerning the project. For instance, Canada has endorsed the FPIC approach, which provides the affected communities and indigenous peoples the right to participate in decision making and the right to say 'yes' or 'no' to development decisions and activities affecting their lands and resources (Hart, 2012). In the USA, the local community's acceptance is not necessarily a requirement for issuing a permit. Nonetheless, public participation is required during environmental impact assessment (EPA, 1998).

In the past decade, the concept of community approval of mining operations and its relationship to socio-political risk has been defined as the social license to operate (Thomson & Boutilier, 2011). Social license to operate (SLO) refers to a community's perceptions of the acceptability of a company and its local operations (Thomson & Boutilier, 2011). However, other researchers have claimed that SLO is vague and question whether it is useful, as a practical matter (Owen & Kemp, 2013; Wang et al., 2016). For instance, Owen and Kemp (2013) argue that corporate goals to "obtain" or "retain" SLO assume that it can certainly be granted by communities in a manner similar to legally-mandated permits, which have particular permit conditions and result in particular consequences if the conditions are violated by the company. Notwithstanding, this work uses SLO to describe the host or affected community's level of approval. This is because SLO, conceptually, is a measure of community-related socio-political risk (Owen & Kemp, 2013; Wang et al., 2016) and is applied in that context in this study.

Davis & Franks (2011) showed that one of the major non-technical risks responsible for project delays is community-associated risk. The cost of these delays can be substantial. For example, Davis and Franks (2011) estimate that the delay of a new mine at the exploration stage costs approximately US$ 10,000 per day. Good community engagement is the best way to mitigate these community-related risks (Que, 2015). Mines and mining companies still struggle to avoid community conflict despite increased effort. Actually, there seems to be an increase in conflicts in the presence of increased community engagement from mines (Hodge, 2014). This increase in conflicts could be the result of the dynamic nature of community issues and other factors affecting community acceptance, which reduce the efficacy of conventional engagement processes.

2.2. MINING COMMUNITY ENGAGEMENT

Characteristics of stakeholders, whether individuals, groups or organizations greatly impact the decision making-process. Stakeholder analysis is the tool to analyze this impact and has gained increasing popularity in the past decade (Que, 2015). Stakeholder analysis is a process that seeks to identify and describe the interests and relationships of all the stakeholders in a given project. It is a necessary precondition to participatory planning and project management (ICMM, 2012b). Other researchers also consider stakeholder analysis as a process for understanding the behavior and interests of a group of targeted stakeholders, who have the potential to influence an organization, project, or policy direction, through surveys and data analysis (Mason & Mitroff, 1981; Walt, 1994). The results of stakeholder analysis are employed to manage stakeholders by knowing and satisfying their preferences and facilitating the decision making processes for management and policy-makers (Que, 2015).

Bryson (1995) describes a basic analysis technique that provides a quick and useful method of: identifying stakeholders and their interests, clarifying stakeholders' views of a local organization, identifying some key strategic issues and beginning the process of identifying coalitions of support and opposition. This technique involved nine steps, starting with brainstorming to find the list of potential stakeholders and ending with identifying and recording longer-term issues with individual stakeholders and with stakeholders as a group (Bryson, 1995).The most recently accepted stakeholder analysis method was proposed by Reed et al. (2009) and has three main steps: (i) identifying stakeholders; (ii) differentiating between and categorizing stakeholders; and (iii) investigating relationships between stakeholders (Que, 2015).

From mining standpoint, organizations such as the International Council on Mining & Metals (ICMM) and the International Finance Corporation (IFC) have discussed stakeholder engagement (ICMM, 2008, 2009, 2010, 2012b; IFC, 1998, 2007, 2009). The academic literature also contains several works that discuss stakeholder engagement from mining perspective (Azapagic, 2004; Davis & Franks, 2011; Jenkins & Yakovleva, 2006; Kempe, 1983; Moffat & Zhang, 2014; O'Faircheallaigh, 2012; Thomson & Boutilier, 2011). By and large, the stakeholder engagement method in the mining industry comprises the three key parts suggested by Reed et al. (2009): stakeholder identification, stakeholder analysis and iterative consultation (ICMM, 2012b; IFC, 2007).

The local communities, as prominent stakeholders, do not attract special attention in the stakeholder analysis procedure as they should (Que, 2015). Compared to other stakeholders (such as government, internal company stakeholders like employees and unions, and regulators), the local community is the most unrepresented group but, frequently, has the most varied views and diversity in demands. This is intensified in situations where mines operate on land belonging to indigenous people (Native Americans), and poor and disadvantaged communities. As a result, community engagement in mining becomes difficult, needing special attention and unique methods for stakeholder analysis (IFC, 2007; Que, 2015).

Existing stakeholder analysis processes for engaging local communities (ICMM, 2012b; IFC, 2014; Ivanova & Rolfe, 2011; Moffat & Zhang, 2014; Nakagawa et al., 2013; Prno, 2013; Que, 2015; Que & Awuah-Offei, 2014; Thomson & Boutilier, 2011) are mainly qualitative, using public forums, surveys, analysis of comments to public announcements of permit application and others. Current qualitative community analysis approaches alone lack the capacity to provide enough understanding into the community's trepidations, expectations, and particularly level of acceptance to achieve the project's sustainability. Generally, community acceptance is influenced by several factors, such as effectiveness of local community engagement, individual preferences, and requirements for community acceptance, and perceptions of legitimate ownership of mineral rights (Ballard & Banks, 2003; Joyce & Macfarlane, 2001).

Additionally, current approaches (qualitative or quantitative) do not easily predict the level of community acceptance over time. For example, these approaches require repeated surveys administered frequently and over time to capture changes in the level of community acceptance over time. Other approaches that can be useful in providing understanding into the level of community acceptance over time, and the correlation between community acceptance and sustainability of mineral project are not currently available. Developing such approaches could transform mining engineering practice by providing tools for considering social acceptance of mining during the design and planning phase, which has the potential to contribute to successful permitting and management. This is because it will provide policymakers, engineers, and regulators quantitative tools to incorporate sustainability and social requirements into design choices.

Decision theory and complex adaptive system modeling can be employed to understand the correlation between community acceptance and sustainability of mineral project. A complex adaptive system, such as the community acceptance of mineral resources can be modeled using ABM (Aguirre & Nyerges, 2014; Bonabeau, 2002; North & Macal, 2007). The current ABM work in mining community and stakeholder modeling (Berman et al., 2004; Li & Liu, 2008; Nakagawa et al., 2013) does not offer a rigorous (i.e. routed in decision theory) theoretical basis for the agent utility function nor account for the connection between the mine’s sustainability impacts and community acceptance over time. The application of discrete choice theory in this work advances the frontier by incorporating sound decision theory to describe individual preferences for a mining project. This research is the first attempt to apply discrete choice theory and agent based modeling (ABM) to understand the dynamic relationship between perceived project sustainability attributes and community acceptance. The only other study the candidate is aware of that applies discrete choice to generate ABM utility functions (Hunt et al., 2007) addresses preferences for recreational activities. This study is, therefore, at the intersection of mining community and stakeholder analysis, discrete choice theory and complex-adaptive system modeling using ABM.

2.3. MINING COMMUNITY AND SOCIAL LICENSE TO OPERATE

In the 1990s, the global mining industry experienced unprecedented expansion, establishing a presence in nations with no prior history of commercial mining particularly in the global south. Also, West Africa and Southeast Asia experienced rapid growth in mining activity. The expansion, which was motivated by increasing mineral prices in response to growing demand and promoted by the policies of the international financial institutions, imposed significant environmental and social costs on communities (Keenan et al., 2003). In some situations, mining threatens the very existence of local subsistence economies. As a result, conflict between mining companies and communities has grown in parallel with the industry. Communities seek to impede the development of mining projects in their regions, judging them to be irreconcilable with local development. In some cases, communities have accepted the existence of mining activity and have tried to form a new, more equitable relationship with industry that integrates mining with local strategies for sustainable development (Keenan et al., 2003).

Communities around the world are increasingly requesting a greater share of benefits from local mining projects, more involvement in decision making, and assurances that mineral development will be conducted safely and responsibly (Prno, 2013). At the same time, full legal compliance with state environmental regulations has become an increasingly insufficient means of satisfying society’s expectations of mining.

There is now a recognized need for mineral developers to gain a social license to operate (SLO) to avoid potentially costly conflict and exposure to business risks (Bridge, 2004; Prno, 2013).

The concept of social license to operate (SLO) was initially used by mining industry practitioners in the late 1990s after it was coined by a Canadian mining Executive, Jim Cooney. Its use and operationalization in the mining industry have only recently attracted meaningful attention from researchers (Prno, 2013). A SLO can be said to exist when a mining project is perceived to have the broad, ongoing approval and acceptance of society to conduct its activities (Joyce & Thomson, 2000; Thomson & Boutilier, 2011). Social license to operate refers to an intangible and unwritten, tacit, contract with a society, or a social group, allowing a mining operation to enter a community, start, and continue operations (Franks et al., 2010). Some researchers have shown that SLO is linked to a mine's effectiveness in addressing social and other sustainability-oriented considerations in mineral development planning (Que et al., 2015). Irrespective of the fact that SLO can be "granted" by different elements and scales of society such as communities, regions, and the general public, local communities are often a main arbiter in the process by virtue of their proximity to projects, sensitivity to effects, and ability to affect project outcomes (Prno, 2013).

The conditions of a social license are different from the explicit, regulatory requirements set by governments, such as environmental approvals, because they are tacit, intangible and context specific (Franks et al., 2010; Owen & Kemp, 2013; Thomson & Boutilier, 2011). A social license cannot be issued, but it has to be earned (Lacey et al., 2012). Social license to operate can only be sought from project stakeholders (Franks et al., 2010). The conditions of a social license change over time, based on people's ongoing experiences of an operation and changes in their perceptions and opinions (Thomson & Boutilier, 2011). The procedure by which social license is expressed is contextually specific, dynamic and non-linear. Community perceptions of mining activities and how they affect them depend on the community and current operation, and can change over time (Franks et al., 2010) . The level of support 'granted' depends on society's expectations of the operation and the extent to which those expectations are met. Such expectations can be about social, economic and environmental impacts of a company's operations, and benefits that flow to the local communities and the region (Gunningham et al., 2004; Nelsen & Scoble, 2006). Additionally, the local communities usually have expectations about how the company interacts and engages with local inhabitants. At the community level, a social license suggests a type of perceived acceptance of a company's activities (Thomson & Boutilier, 2011).

Nonetheless, others argue that SLO is unclear and question whether it is useful to accomplishing real sustainability outcomes because it cannot be really granted like a permit and other approvals (Owen & Kemp, 2013; Wang et al., 2016). Regardless of these objections, many others agree that as a business goal and a framework, SLO helps mining companies and other companies engage their stakeholders and operate in a more sustainable manner (Que et al., 2015; Thomson & Boutilier, 2011).

Levels of SLO have been widely discussed based on the "pyramid" model introduced by Thomson and Boutilier (2011). The model considers four potential levels of support: withheld, acceptance, approval and identification as shown in Figure 2.1 (Williams & Walton, 2013). The host community will say an operation that is considered by interest groups to have a minimum level of social license has *legitimacy*. This reflects a perception that there is some probability that their concerns may be addressed and that they may experience some benefits from the operation. If an operation is perceived to have *credibility* (i.e. company demonstrates behaviors such as listening, keeping promises, reciprocity and dealing fairly), then the level of social license is *approval*. If relationships between interest groups and the company develop to the stage where there are high levels of trust, it is suggested that people may come to identify with the company and realize their future is connected to the future of the operation. Trust is fundamental to moving through the levels (Williams & Walton, 2013).

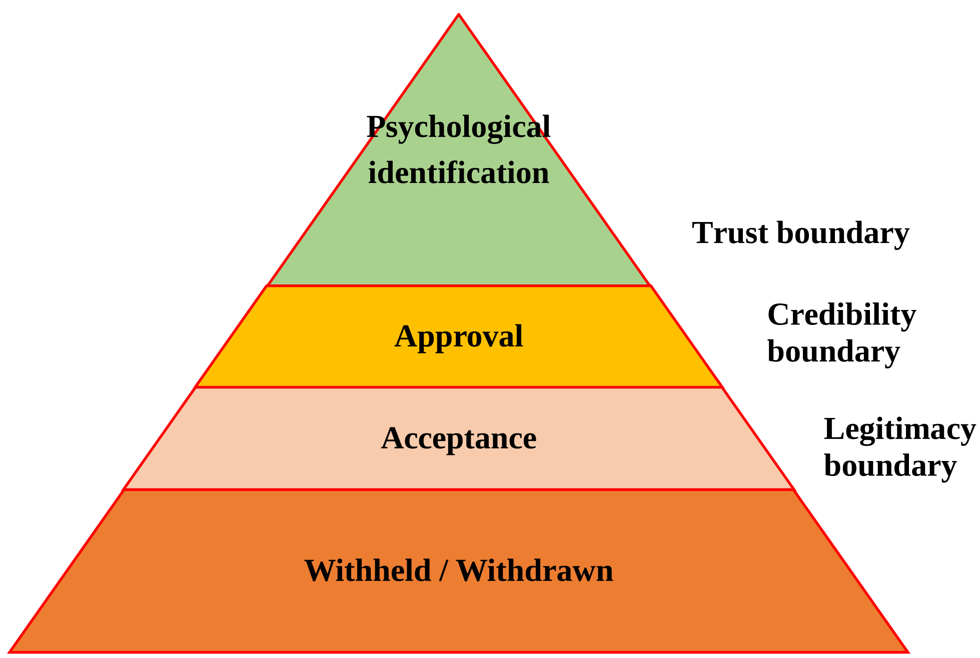

Figure 2.1. The 'Pyramid' Model of the SLO (after Thomson & Boutilier (2011))

A range of factors influence a company’s capacity to earn a social license. These factors are a combination of external and internal factors, and are affected by the company’s management style and performance (Gunningham et al., 2003).

Regardless the current work in the area of SLO, key conceptual questions remain. For instance, what does it actually mean to have a SLO? What level of community support is required to say it has been issued? What indications and methods are most appropriate for the analysis and measurement of SLO? (Prno, 2013). Admittedly, knowing and understanding the factors affecting community acceptance of mining project can be useful in addressing these key questions.

2.4. FACTORS THAT AFFECT COMMUNITY ACCEPTANCE

Several factors can affect an individual's perception of a mining project and, subsequently, affects whether such an individual accepts the mine or not. It is important to understand these factors because they motivate the community's perception, which is a summation of the individual's perceptions. The community's perception of the project directly affects the mine's social license to operate (Wang et al., 2016). The factors that affect community acceptance include the impacts of the mine on the environment and host community, the mine owner (corporate reputation etc.) and governance issues, and demographics of the community (Que, 2015; Wang et al., 2016).

2.4.1. Environmental Impacts. Environmental impacts are a leading cause of anti-mining campaign and a leading reason for communities to reject mining projects. Environmental impacts of mining include water use and pollution, and air, land, and noise pollution (Que, 2015). Regarding water use, for instance, the United States Geological Survey (USGS) estimates that the water table around areas surrounding open-pit mines in Nevada has dropped 300 meters due to water demand from mining (Rockwell, 2000). According to Solley et al. (1999), the Betze-Post mine alone pumps out 380,000 cubic meters (100 million gallons) of groundwater daily.

There are numerous sources of contaminants at a mine site that can pollute nearby water bodies. These include sediments from exposed soil, diesel fuel and process chemicals. Acid mine drainage (AMD) is recognized as one of the more serious environmental problems in the mining industry due to the number of watersheds affected and the costs incurred for remediation (Akcil & Koldas, 2006; Wang et al., 2016). For example, acid mine drainage from the Summitville gold mine in Colorado destroyed all the biological life within seventeen miles of the Alamosa River. The place was designated a Federal Superfund site and the Environmental Protection Agency (EPA) spent $30,000 daily in handling the drainage (Earthworks and Oxfam America, 2004). In 2000, a truck transporting mercury from the Yanacocha mine in Peru spilled its load. The spill resulted in poisoning at least a thousand people in the small village of Choropampa (Keenan et al., 2003). Challengers of mining are concerned about potential environmental impacts, especially, possible water contamination (ICMM, 2010).

Contamination also often results from inadequate containment of mine tailings. Tailings disposal has been a historical problem for the mining industry. For example, in 1995, the Omai gold mine in Guyana recorded a failure of a dam wall on its tailings holding pond. This led to discharging over three billion liters of cyanide and heavy metal-laced effluent into the Essequibo River, the country's main waterway and a source of livelihood (Keenan et al., 2003). Mining activity can possibly affect terrestrial ecosystems. For instance, contaminated water can affect terrestrial ecosystems, including accumulation of toxic elements in soil, soil acidification, and damage to soil biota, loss of soil fertility, plant contamination, plant toxicity and food chain contamination (Dudka & Adriano, 1997; Wang et al., 2016). Solid waste is another big concern, since mining products are, mostly, a small fraction of total mined mass. As it pertains to surface gold mining, for example, one ton of ore is likely to yield less than one gram of gold, with the remaining ending up as tailings. Also, several tons of barren rock may be excavated to expose the ore (Wang et al., 2016).

Air pollution, resulting from mining activities is another significant impact. The main concern is dust, from excavation and transportation, causing air quality degradation (Que, 2015; Wang et al., 2016). Besides, processing activities such as refining and smelting of material generate pollutants that pollute the air. Globally, smelters add about 142 million tons of sulfur dioxide to the atmosphere every year, 13 percent of global emissions (Earthworks and Oxfam America, 2004).

Noise pollution results from traffic, blasting and operating heavy machinery (Que, 2015; Wang et al., 2016). Noise pollution has been reported to be the sole largest type of community complaint (ICMM, 2009). For instance, BHP Billiton reports that their sites received 536 complaints in 2008, and the most common type of community complaint was noise-related (BHP Billiton, 2008). Also, Ivanova & Rolfe (2011) described noise impact, as well as vibration and dust, to be a significant factor at 90% confidence in elucidating community members' preferences for mining developments.

The aforementioned environmental issues impact how community members perceive a specific mining project. If members of the community perceive that a particular mine (e.g., due to its reputation for environmental violations) has a reputation for poor environmental performance, they are less likely to accept the mine and, thus, grant SLO (Moffat & Zhang, 2014; Wang et al., 2016).

2.4.2. Economic Impacts. Mining operations can result in significant economic impacts, including job opportunities, income increases, increases in housing cost and shortage of labor. Job opportunities and related economic impacts created by mining operations are well documented in the literature. Job opportunities is described as the first issue and most frequent question from members of the local community, when they learn that a mine may be developed in their community, is “how many jobs will go to their community members?” (ICMM, 2012a). Increases in income as a result of higher paying jobs and/or the jobless joining the mine’s supply chain is another significant impact of mining (ICMM, 2012a; Petkova et al., 2009; Que, 2015).

In the United States (U.S.), for instance, the economic contribution made by U.S. mining in 2015 through employment, labor income, contribution to gross domestic product (GDP) and taxes is presented in Table 2.1. In 2015, U.S. mining directly and indirectly created almost 1.7 million full-time and part time jobs. Besides, U.S. labor income associated with mining exceeded $100 billion, which includes wages and salaries, other employee benefits and owner-operated business income (National Mining Association, 2016). At both national and local levels, mining generates government revenues, and foreign and domestic investment. National Mining Association (2016) report indicates that U. S. mining activity generated about $18 billion in federal, state and local taxes in 2015 that supported direct, indirect and induced taxes of $ 44 billion. U.S. mining contributed about $220 billion to the GDP in 2015 (National Mining Association, 2016).

Table 2.1. Economic Contribution of U.S. Mining, 2015

Item	Direct	Indirect and Induced	Total
Employment	565,548	1,122,816	1,688,364
Labor Income (billions of dollars)	$39.8	$63.9	$103.7
Contribution to GDP (billions of dollars)	$100.4	$120.0	$220.4
Taxes Paid (billions of dollars)	$18.0	$26.0	$44.0

Source: National Mining Association (2016)

Additionally, mining can also result in increase in housing costs and labor shortages, particularly for those businesses in the local community that cannot compete with large mines for skilled labor (Ivanova & Rolfe, 2011; Petkova et al., 2009). Petkova et al (2009) reported that in five out of six communities they studied in Australia, labor shortage for other businesses was recognized as a concern.

2.4.3. Social Impacts. Social impacts of mining have had a long history. Thus, mines sometimes required to conduct social impact assessment (SIA) studies prior to the approval of large projects in order to predict and mitigate major social issues (Dale et al., 1997; Petkova et al., 2009) . Social impacts associated with mining activity include mining-induced displacement issues, crime increase and traffic increase.

Mining displacement and the associated threat to human rights presently occurs in several countries globally (Aboagye, 2014). In some circumstances, communities are forcibly relocated to allow mine development (Keenan et al., 2003). For example, in Ghana, many mining projects have induced displacement. Between 1990 and 1998 in the Tarkwa district of Ghana, more than 30,000 people were displaced due to gold mining operations (Aboagye, 2014). Mining-induced displacement issues affect acceptance of mining projects by community members. Also, international law and best practices frown on it. For instance, free prior and informed consent (FPIC) is mandatory in relation to resettlement or relocation and consequently, involuntary relocation of indigenous peoples is forbidden by international law. Resettlement should be avoided if possible and should not occur without FPIC of affected individuals (Miranda et al., 2005).

Traffic and crime increase in host communities with the arrival of large-scale mining has been discussed in the literature. According to Lockie et al (2009), for instance, two social impact assessment (SIA) analysis of Central Queensland's Coppabella coal mine indicates that residents observed an increasing trend in crime risk, general anti-social behavior and crimes against property in the community. Such an observation was confirmed by the police, and stating that they perceived that the criminal activity increase was proportional to population growth from 2003 to 2006. This connection between criminal activity and mining is supported by other research (Wang et al., 2016). Crime and domestic violence reflects serious social problems in mining communities (Hajkowicz et al., 2011).

The SIA studies by Lockie et al (2009) also report traffic increase. Their studies show that inhabitants near the Coppabella coal mine in Australia believed that traffic congestion and accidents have increased, including the large trailers and mining equipment. An increase in traffic volumes was confirmed by road use data. Similar studies (environmental impact assessments (EIAs)) in Bowen Basin, Australia, also show an increase in road traffic and traffic incidents. The increased road traffic and incidence of drivers travelling home while exhausted because of end of shift were documented in mining communities (Ivanova et al., 2007; Lockie et al., 2009).

2.5. DISCRETE CHOICE THEORY AND MODELS

Discrete choice analysis can be used to describe the influence of the attributes of alternatives and characteristics of decision makers (demographics) on choices they are presented with. The basic theory of discrete choice modeling is random utility maximization (Marschak, 1959). That is, the individual decision maker's overall preference for a choice alternative is a function of the utility, which the alternative holds for the individual. Such individual's utility (U_{ni}) for an alternative is divisible into two components, as presented in Equation (2-1): (i) the component which can be explained by the observed (by a researcher) variables; and (ii) the component, which can be explained by unobserved variables – often, considered random (Que, 2015).

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{2-1}$$

U_{ni}: Utility of alternative i to individual n

V_{ni}: observed component measured for alternative i of individual n

ε_{ni}: unobserved random component for alternative i of individual n

The theory suggests that an individual will prefer the choice alternative perceived to have the greatest utility to him/her. The probability that individual n prefers the mining project or plan i of choice set *J*, is described by Equation (2-2).

$$P_{ni} = \Pr ob\left(U_{ni} \geq U_{nj}, \forall_i \neq j,\ \ i \ \ and \ \ \ j \in J\right)$$

$$= \Pr ob\left(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj},\ \ \forall_i \neq j,\ \ i \ \ and \ \ \ j \in J\right) \qquad (2\text{-}2)$$

$$= \Pr ob\left(\varepsilon_{ni} - \varepsilon_{nj} \geq V_{nj} - V_{ni},\ \ \forall_i \neq j,\ \ i \ \ and \ \ \ j \in J\right)$$

j : alternatives (other than i)

J : the total number of alternatives

U_{nj} : utility of alternative j to individual n

V_{nj} : observed component measured for alternative j of individuals n

ε_{nj} : unobserved random component for alternative j of individual n

Discrete choice theory has been successfully applied in econometrics and other disciplines to understand consumer behavior. For example, discrete choice theory has been employed to evaluate community acceptance of renewable energy projects (Dimitropoulos & Kontoleon, 2009). Other researchers have also used discrete choice theory to model individuals' preferences for mining projects (Ivanova & Rolfe, 2011; Que & Awuah-Offei, 2014). Undoubtedly, discrete choice theory can be used to formulate rigorous utility functions for ABM of community acceptance. For instance, Hunt et al (2007) successfully applied a discrete choice model and agent-based model to investigate recreational behaviors so as to guide the choice and implementation of given scenarios.

Discrete choice models are of several forms, such as: binary logit, binary probit, multinomial logit (MNL), conditional logit (CL), nested logit (NL), generalized extreme value(GEV), multinomial probit (MNP), and mixed logit (ML) models (Que, 2015;

Train, 2002). The formulation, development, description and application of various discrete choice models are well discussed in the literature (Daganzo, 1979; Hausman & Wise, 1978; Ivanova & Rolfe, 2011; Ivanova et al., 2007; Mcfadden & Train, 2000; McFadden, 1974; Que, 2015; Thurstone, 1927). This study discusses the two most popular discrete choice models namely: the multinomial logit and conditional logit models. The interested reader can refer to the literature for information on the other models.

2.5.1 Multinomial Logit Model. The multinomial logit (MNL) model, which is also known as multinomial logistic regression, describes the observed utility of each choice alternative, V_{ni}, as a linear function of X_n, the vector of characteristics specific to the individual decision maker, and the random component (ε_{ni}). The utility of alternative *i* to individual *n* and probability that individual *n* will choose alternative *i* are presented in Equations (2-3) and (2-4). In the MNL model, the utility for each alternative is dependent on the same variables, X_n but different alternatives have different coefficients. β_i is the vector of coefficients particular to the $i-th$ alternative. Therefore, this model comprises choice-specific coefficients and only individual specific repressors. The error terms, ε_{ni} , are considered to have independent and identical distribution (iid) with a type 1 extreme value distribution.

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \beta_i X_n + \varepsilon_{ni} \tag{2-3}$$

X_n: Characteristics specific to the *nth* individual

ε_{ni} : iid Type 1 extreme value distribution

The probability that individual *n* will choose choice i :

$$P_{ni} = \frac{\exp\left(\beta_i X_n\right)}{\sum_{j=1}^{j} \exp\left(\beta_j X_n\right)} \tag{2-4}$$

2.5.2. Conditional Logit Model. The conditional logit model (CL), sometimes also known as the multinomial logit model, was originally formulated by McFadden in the 1970s (McFadden, 1974). For this model, the observed utility of each alternative, V_{ni} is a linear function of X_{ni} and the random component $\left(\varepsilon_{ni}\right)$. The error terms, ε_{ni} are assumed to be independently and identically distributed (iid) with type 1 extreme value distribution. X_{ni} is a vector of attributes specific to the ith alternative as observed by the nth individual. Equations (2-5) and (2-6) show the associated utility and probability.

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \beta X_{ni} + \varepsilon_{ni} \tag{2-5}$$

β: a coefficient vector for X_{ni}

X_{ni}: a vector of attributes specific to the ith alternative as perceived by the *nth* individual.

The probability of choice i to individual *n* is:

$$P_{ni} = \frac{\exp\left(\beta X_{ni}\right)}{\sum_{j=1}^{j} \exp\left(\beta X_{nj}\right)} \tag{2-6}$$

The Equation (2-5) is quite similar to Equation (2-3) for the MNL model. However, in the CL model, the explanatory variables X_{ni} include characteristics specific to the *n*th individual, and describe the relationship between the selector (*nth* individual) and the alternative (i th alternative). It is an important attribute that differentiates the conditional logit model from the MNL model. Besides, the MNL model presents distinct coefficient vectors, β_i for each of the probable outcomes. However, with the MNL model, there is only one coefficient vector but different X vectors, for each outcome in the conditional logit model. Given these two characteristics, the conditional logit model provides a key advantage over the MNL model. The model has considerably fewer parameters than the MNL model. In the case of CL model, each factor has one coefficient, while MNL model has the number of coefficients equal to the number of its levels minus one.

2.6. AGENT BASED MODEL (ABM)

In any type of modeling, the objective is to understand some aspect of the whole system by examining the underlying phenomena and not to perfectly reproduce a “real” object. Models are useful tools that allow individuals to contextualize phenomena and behavior that are not well understood into something familiar, or at least tractable. Every type of model has its usefulness and limitations, and the type of model to use for a particular application is largely dependent on the system or phenomena under study (Bahr, 2015).This study applies agent-based model (ABM).

An agent based model is a computational model that employs qualitative and quantitative information at a microscopic level to produce information about a system at a macroscopic or aggregate level. It is useful for modeling systems that have no analytical solutions, multiple scales of manifested behavior, and heterogeneous constitutive parts (Bahr, 2015). Agent based-modeling focuses on modeling and simulating the behavior of a complex system. It emphasizes the detailed description of agents in the complex system (Fujiono, 2011). Some of the general characteristics of agent-based model and simulation include: (i) it describes heterogeneous and autonomous agents; (ii) it explicitly represents the environment; (iii) it describes local interaction between agents; and (iv) it involves bounded rationality (Epstein, 1999; Fujiono, 2011; Goldstone & Janssen, 2005). ABM allows modeling of systems that consist of agents with unique attributes (e.g., preferences, options, strategy, and size) (Fujiono, 2011). It is usually a stochastic modeling approach and generally applies stochastic elements to model the range of outcomes for agent behaviors and interactions which are not known with certainty (Macal & North, 2006).

The benefits and applications of ABM are well explained in the literature (Bonabeau, 2002; Macal & North, 2006). ABM allows modelers to represent, in a natural way, multiple scales of analysis, the emergence of structures at the macro level from individual action, and various kinds of adaptation and learning, none of which is easy to do with other modeling approaches (Gilbert, 2008).

Agent based model has had a number of applications in the last few years, including applications to real-world business problems (Bonabeau, 2002). ABM applications include application to fields of study where the main agents are individual humans or organizations, such as politics, economics, business management (Caldart & Ricart, 2007), public policy, military, operations research, traffic simulation, geographic systems (Torrens, 2010) and anthropology (Premo, 2006). Table 2.2 presents ABM applications in different research fields as summarized by Fujiono (2011).

Table 2.2. ABM Applications in Different Research Fields

Research Fields	Examples of ABMS Applications
Biology	Basic Immune Simulator (BIS), an agent-based model created to study the interactions between the cells of the innate and adaptive immune system (Folcik et al., 2007)
Geographical System	Constructing and implementing an agent-based model of residential segregation through vector GIS (Crooks, 2010)
Business & Management	Evaluation of corporate strategy (Caldart & Ricart, 2007) and impact of market interventions on the strategic evolution of electricity markets (Bunn & Oliveira, 2008)
Operations Research	Optimization of supply chain configurations (Akanle & Zhang, 2008) and scheduling problems with two competing agents (Agnetis et al., 2004)
Politics	Modeling adaptive parties in spatial elections (Kollman et al.,1992)
Anthropology	Study of the evolution of Plio-Pleistocene hominid food sharing in East Africa (Premo, 2006)
Economics	Agent-based computational economics (Tesfatsion, 2002) and multi-agent social and organizational modeling of electric power and natural gas markets (M. J. North, 2001)
Public Policy	Evaluation of government policy on promoting smart metering in retail electricity markets (Zhang & Nuttall, 2011)
Military	Evaluation of the U.S. Army's network-based Future Force to perform with degraded communications, observing how unmanned surface vehicles can be used in force protection missions, evaluation of standard Army squad size (Cioppa et al., 2004)
Traffic Simulation	Air traffic management system, the effect of advanced driver assistance systems on road traffic accidents (Yuhara & Tajima, 2006)

Beside, ABM affords opportunities for multi-disciplinary collaboration. ABM also allows implementation of various modeling techniques from different research fields, such as agents' decision making process, agents' learning and adaptation mechanism, and agents' interaction (Fujiono, 2011).

In mining, ABM has had some applications, which include an agent-based model of fluctuations in social license to operate through the use of opinion diffusion and stakeholder network creation (Bahr, 2015); and agent-based model framework to show ways innovations can be adopted in the mining industry (Fujiono, 2011).

ABM structural design, characteristics, and its relationship to information diffusion are discussed in the subsequent sections.

2.6.1. Structural Design of ABM. Generally, an agent-based model can be built in much the same way as any other type of model. Firstly, identify the purpose of the model, the questions the model is intended to answer and engage the potential users in the process. Secondly, systematically analyze the system under study, identifying components and component interactions, relevant data sources, and so on. Then, apply the model and conduct a series of "what-if" experiments by systematically changing parameters and assumptions. Finally, use sensitivity analysis and other techniques to understand the robustness of the model and its results. These general steps of model building apply to agent-based modeling as well (Macal & North, 2006). Law & Kelton (2000) provide an excellent description of good simulation model building practices.

Agent-based modeling possesses a few unique aspects due to the fact that agent-based modeling and simulation (ABMS) mostly considers the agent's perspective as opposed to the process-based perspective that is the traditional hallmark of simulation modeling. Besides the standard model building tasks, practical ABMS requires modeler to: (i) identify the agents and get a theory of agent behavior, (ii) identify the agent relationships and get a theory of agent interaction, (ii) get the requisite agent-related data, (iv) validate the agent behavior models in addition to the model as a whole, and (v) run the model and analyze the output from the standpoint of linking the micro-scale behaviors of the agents to the macro scale behaviors of the system (Macal & North, 2006).

According to Macal and North (2006), agent-based modeling does not currently have a mature set of standard formalisms or procedures for model development and agent representation such as those that are part of systems dynamics modeling (system dynamics are a problem evaluation approach based on the premise that the structure of a system, that is the manner important system components are linked, generates its behavior (Stave, 2003)). Except the implemented software code, there is no scheme for explicitly representing an agent-based model. However, Grimm et al (2006) proposed agent modeling documentation schemes intended to promote agent model transferability and reproducibility. Agent-based modeling can benefit from the use of the Unified Modeling Language (UML) for representing models. UML is a visual modeling language for representing object-oriented (O-O) systems (Booch et al., 1998) that is commonly adopted to support agent-based models in both the design and communication phases. UML comprises a number of high-structured types of diagrams and graphical elements that are assembled in various ways to represent a model. The UML representation is at a high level of abstraction, independent of the model’s implementation in the particular O-O programming language used (Macal & North, 2006).

The general steps in building an agent model as presented by Macal and North (2006) are as follows: (i) *Agents:* Identify the agent types and other objects (classes) along with their attributes; (ii) *Environment:* Define the environment the agents will live in and interact with; (iii) *Agent Methods:* Specify the methods by which agent attributes are updated in response to either agent-to-agent interactions or agent interactions with the environment; (iv) *Agent Interactions:* Add the methods that control which agents interact, when they interact, and how they interact during the simulation; (v) *Implementation:* Implement the agent model in computational software.

2.6.2. ABM Characteristics. There are numerous references for modelers using ABM, which explain the concept and characteristics of ABM. For instance, North and Macal proposed a guide that particularly allows the use of ABM to optimize production streams for better understanding of markets (North & Macal, 2007). Chen (2012) has discussed the historical evolution of agents in terms of computational economics. Modelers applying ABM in social science can refer to work on ABM done by Gilbert (2008) and others. Figure 2.2 presents a typical agent structure as described by Macal & North (2010).

2.6.2.1. Agents and their attributes. Agents have been defined in several terms by researchers. In ABM, a system is modeled as a collection of autonomous decision-making entities referred to as agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. Agents may execute various behaviors appropriate for the system they represent, for example, producing, consuming, or selling (Bonabeau, 2002). Agents possess behaviors, frequently described by simple rules, and interactions with other agents, which in turn influence their behaviors. By modeling agents individually, the full effects of the variety existing among agents in their attributes and behaviors can be observed as it leads to the behavior of the system as a whole (Macal &

North, 2010). Agents have limited computational capability and do not have global information (bounded rationality), and they create perceptions about their environment and choose to perform specific actions based on this limited information (Fujiono, 2011).

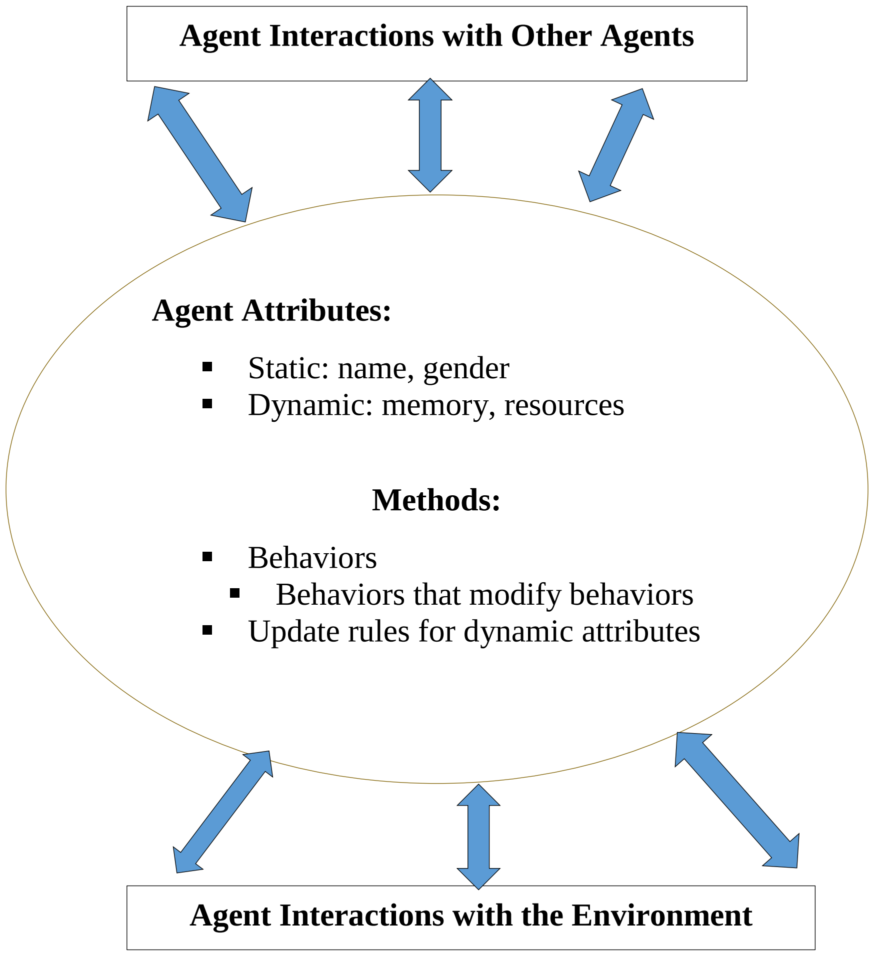

Figure 2.2. A Typical Agent Structure (Macal & North, 2010)

From a practical modelling perspective, depending on how and why agent-models are actually built and described in applications, modelers consider agents to have certain essential characteristics (Macal & North, 2010), which include:

i. An agent is *self-contained*. This implies that an agent has a boundary, and identifiable attributes that enable it to be distinguished from and recognized by other agents.

ii. An agent is *autonomous* and self-directed. An agent can function independently in its environment and in its interactions with other agents. An agent has behaviors that relate information sensed by the agent to its decisions and actions.

iii. An agent has a *state* that changes over time. An agent's state comprises a set or subset of its attributes. An agent's behaviors are conditioned on its state. In an agent-based simulation, the state at any time is all the information needed to make a decision.

iv. An agent is *social* having dynamic interactions with other agents that influence its behavior. Agents have rules for interaction with other agents for communication, movement and contention for space, the capability to respond to the environment, and others. Agents are capable of recognizing and distinguishing the traits of other agents.

Other attributes of agents, which may be useful include the fact that an agent may be adaptive, goal-directed and heterogeneous (Macal & North, 2010).

2.6.2.2. Agent environment and topology. As discussed by Macal and North (2010), agents interact with their environment and with other agents. The environment may simply be used to give information about the spatial location of an agent in relation to other agents or it may provide a set of geographic information. Complex environmental models can be used to model the agents' environment. For instance, hydrology or atmospheric dispersion models can provide point location-specific data on groundwater levels or atmospheric pollutants, respectively, which are accessible by agents. Thus, agent actions can be constrained by the environment. An example is the environment in an agent-based transportation model that would include the infrastructure and capacities of the nodes and connections of the road network. These capacities would result in congestion effects (reduced travel speeds) and limit the number of agents moving through the transportation network at any given time (Macal & North, 2010) .

The term topology is used to describe how agents are connected to each other in agent-based modeling. Classic topologies comprise a spatial grid or network of nodes (agents) and links (relationships). The topology in ABM describes who transfers information to whom. In some cases, agents interact based on multiple topologies. For instance, an agent-based pandemic model has agents interacting over a spatial grid to model physical contact as agents perform daily activities and possibly give infections. Agents also are members of social networks that model the likelihood of contact with relatives and friends (Macal & North, 2010).

2.6.3. ABM and Information Diffusion. Researchers have applied agent based model in the study of information diffusion and related diffusion of innovation. Some researchers have conducted literature reviews of the application of agent-based modeling in the study of innovation diffusion (Dawid, 2006; Garcia, 2005; Kiesling et al., 2012). The main characteristics of ABM that make it a popular method for studying diffusion of innovation is its capability to model population heterogeneity, including interactions between agents in the population. Research on diffusion of innovation mostly focuses on agents' internal and external adoption factors (e.g., risk preference, adoption strategy, policies, network structures, and effect of opinion leaders) and their influence on the rate of innovation adoption (Fujiono, 2011).

Agent-based models have been used for modeling agents' decisions to innovate or to imitate innovation (Bullnheimer et al., 1998; Debenham & Wilkinson, 2006) as well as their strategies for collaboration (Fujiono, 2011). Ahrweiler et al (2011) used ABM to study innovation networks, which shows how knowledge becomes an important aspect of agents' tactics in choosing their research partners. As highlighted by Fujiono (2011), different types of agents have different roles in the diffusion of innovation (e.g. producers of innovation and potential adopters). Each agent has its own distinct attributes that influence its decision to create or adopt an innovation, such as knowledge, innovation strategy, capital resources, and risk preference. Table 2.3 presents some examples of various types of agents included in ABM to study diffusion of innovation as listed by Fujiono (2011).

Agents' rules of behavior, in the framework of agent-based modeling of innovation diffusion, dictate agents' activities in searching for an innovation (e.g. agents acting as consumers that always seek for a better product, a better idea, and a better practice) and in making decisions to adopt a specific innovation (Fujiono, 2011).

Some researchers have studied the interaction between agents and agents' diversity in understanding the dynamics of the innovation diffusion process in the mining industry (Barczak, 1992; Fujiono, 2011; Souder & Palowitch, 1981; Tilton & Landsberg, 1999). Mines obtain information about other mines through interaction in the form of informal discussion, observing their competitors (Ala-Härkönen, 1993), and visiting other mines (Souder & Palowitch, 1981). For example, Fujiono (2011) provided and implemented a framework for an agent based model to show ways innovations can be adopted in the mining industry with emphasis on modeling the diffusion of the longwall mining method in the United States (U.S.).

Table 2.3. Various Types of Agents in ABMs and Innovation Diffusion Applications

Agent-Based Model	Agents	Agents' Attributes
New product diffusion of novel biomass fuel (Günther et al., 2011).	Consumers	Consumer type, capacity of fuel tanks, travel behavior, refueling behavior
The diffusion of agricultural technology (Berger, 2001)	Farm households	Farms with biophysical and economic attributes such as soil, quality, land use, water supply, etc.)
The diffusion of medical innovation (Ratna et al., 2008)	Doctors	Adoption thresholds, locations of practice, level of innovation

None of these studies used ABM to model individuals in a mining community and the unique challenges (e.g. defining valid agent utility functions using decision science, diffusion models and social networks) related to this have not been addressed yet. It will be beneficial to extend ABM to other aspects of the mining business (e.g. assessing social risks associated with mineral projects). This will benefit the mining industry in diverse areas including effective mining community engagement, which can lead to gaining and maintaining social license to operate and more sustainable mining. This dissertation makes a contribution in this direction by introducing a framework for modeling the effect of information diffusion on community acceptance of mining.

2.7. SOCIAL NETWORK

Social networks have received great attention in recent years due to their relevance to many processes, such as information processing, distributed search, and diffusion of social influence. Social scientists have also been interested in social networks as dynamic processes (Kossinets & Watts, 2006).

A social network is defined as a set of actors and the set of ties signifying some relationship or lack of relationship between the actors (Brass et al., 1998). Potts et al (2008) also defined social network from a market perspective as a connected group of individual agents who make production and consumption decisions based on the actions or signals of other agents on the social network. This definition places emphasis on communicative actions rather than to connectivity alone. *Social,* in this context, means the capability of one agent to connect to and interpret information generated by other agents, and to communicate in turn; and *network,* in this case, implies that these are specific connections, and not an abstract aggregate group such as a nation or a people (Potts et al., 2008). Social networks may influence an individual's behavior. However, they also reflect the individual's own activities, interests, and opinions (Bakshy et al., 2012). The definition of social network by Potts et al (2008) is more appropriate for this research because it relates to how social networks can affect information diffusion in a given community.

Social network formation is a complex process by which several individuals concurrently attempt to satisfy their goals under multiple, possibly conflicting constraints. For instance, individuals frequently interact with others similar to themselves, a tendency known as homophily and endeavor to shun conflicting relationships while exploiting cross-cutting circles of acquaintances. (Kossinets & Watts, 2006). Social networks have some important properties as outlined by Potts et al (2008): Firstly, a social network is not necessarily only the group of people an agent or individual knows personally and communicates or interacts with frequently (e.g. family, friends, and colleagues), but there are many other processes that are also important such as in information networks. For instance, social network response from reviews of movies by expert opinion or just observation of box-office totals, and reviews of restaurants whether a restaurant is crowded, give social network information that agents or individuals use in making choices. Secondly, a social network is not always regular, but may comprise hubs, weak and strong connections, and close and distant connections. Besides, agents may show significant heterogeneity regarding their connections in social networks. Thirdly, a social network implies social origination, adoption and retention processes. This partially makes social networks usually more complex than physical networks, because the switching mechanisms (human agents) are far more complex than neurons or genes in cognitive or genetic regulatory networks.

2.7.1. Structure of Social Networks. Researchers have studied the structure of social networks and its effects on spreading awareness, information, and opinions about innovation. For instance, the influence of the structure of connections in consumers' social network, through which awareness, information, and opinions about an innovation are spread, is one of the most intensively researched topics in the agent-based innovation diffusion literature (Kiesling et al., 2012). Jackson (2008) outlined some of the characteristics of social networks structure, which include diameter and small worlds, clustering, degree and degree distributions, correlations and assortativity, patterns of clustering, homophily, the strength of weak ties, structural holes, social capital and diffusion. This dissertation briefly discusses the structures of social network that are relevant to this study. The interested reader is referred to Jackson (2008) for a more comprehensive review.

- *Diameter and small worlds*

The *diameter of a network* is the largest distance between any two nodes in the network. The diameter of a network tells about how "big" the network is (that is, how many steps are necessary to get from one side of it to the other). The diameter is a useful quantity since it can be used to set an upper bound on the lengths of connections (Hanneman & Riddle, 2005). Social network exhibiting features of small worlds is one of the earliest, best-known, and most widely studied aspects of social networks. The term small worlds represents the idea that large networks tend to have small diameters and small average path lengths. To understand why several social networks exhibit small diameters, it is useful to think about neighborhood sizes.

- *Clustering*

Level of clustering in a network is measured by the clustering coefficient (Newman, 2003b). Clustering is an interesting observation about social networks because social networks tend to have high clustering coefficients relative to what would emerge if the links were simply determined by an independent random process. Concepts about clustering have been important in sociology and in triads (triples of mutually connected nodes). A range of large socially generated networks exhibit clustering measures much greater than would arise if the network were generated at random.

In the case of directed networks, which is used in this dissertation, clustering can be measured by ignoring the direction of a link and considering two nodes to be linked. Another approach is to keep track of the percentage of *transitive triples* (the condition where a link between agents i and k, and j and k, means that there is higher probability of a link between i and j). This approach takes into account situations in which node i has a directed link to j, and j has a directed link to k, and then questions whether i has a directed link to k. The fraction of times in a network that the response is "yes" is the *fraction of transitive triples* given in Equation 2-7:

$$Cl^{TT}(g) = \frac{\sum_{i:\, j \neq i; k \neq j} g_{ij} g_{jk} g_{ik}}{\sum_{i:\, j \neq i; k \neq j} g_{ij} g_{jk}} \tag{2-7}$$

- *Degree distributions*

The degree of a particular node in a network is the number of links. Networks differ in their average numbers of links. Even though the average degree of a network offers a rough understanding for connectivity, there is much more information that could be of interest. For instance, how variable is the degree across the nodes of the network? Individuals can gain a much better understanding for the structure of a social network by examining the full distribution of node degrees rather than just looking at the average.

Degree distribution of a network is a description of the relative frequencies of nodes that have different degrees. There are various types of degree distributions including *regular* degree distribution (where all nodes have the same degree), *scale-free* degree distribution, which follows power law. This research relies on *directed random graph* where degree distribution is more directional and link is formed by a given probability and the formation is independent across links.

- *Correlations and Assortativity*

Apart from the degree distribution of a network, knowledge about the correlation patterns in the degrees of connected nodes is also important. For example, do relatively high-degree nodes have a higher tendency to be connected to other high-degree nodes? This tendency is called positive assortativity. While there is little systematic study of assortativity, there is a hypothesis that positive assortativity is a property of many socially generated networks.

In relation to assortativity, studies of some social networks have also suggested "core-periphery" patterns, where there is a core of highly connected and interconnected nodes and a periphery of less-connected nodes. Additionally, theories of structural similarity postulate that people tend to use other people who are similar to themselves as a reference group (Festinger, 1957). It is hypothesized that people with similar structural positions tend to have similar issues, which lead them to communicate with one another. Since the patterns of connections in a network can have a great impact on processes like the diffusion of behavior, information, or disease, it is important to have a better understanding of assortativity and other characteristics that describe who tends to be connected to whom in a network.

- *Homophily*

Homophily refers to the fact that people are more likely to maintain relationships with people who are similar to themselves. Several social networks show *homophily* due to age, race, gender, religion, or profession. McPherson et al (2001) present an overview of research on homophily. Homophily was first noted by (Burton, 1927), who coined the phrase "birds of a feather." Homophily is an important aspect of social networks, since it means that some social networks may be largely segregated. For example, homophily has profound implications for access to job information (Calvó-Armengol & Jackson, 2004). It can also have intense implications for the spread of other kinds of information, behaviors, and many more.

- *The strength of Weak Ties*

The strength of the social relationships is measured by frequency of interaction. There are various ways to measure the strength of a tie. Granovetter (1973) proposed a rudimentary notion that strength is linked to the "amount of time, the emotional intensity, the intimacy, and the reciprocal services which characterize the tie". He measured the strength of a tie through the number of times individuals had an interaction in the past year; categorizing it as *strong*, at least twice a week; *medium*, less than twice a week but more than once a year; and *weak*, once a year or less. Granovetter's idea was that individuals involved in a weak tie were less likely to have overlap in their neighborhoods than individuals involved in a strong tie. These ties then are more likely to form bridges across groups that have fewer connections to one another, and can consequently play critical roles in the diffusion of information.

- *Diffusion*

One key role of social networks is as channels of information. As indicated by Jackson (2008), individuals frequently learn from one another, which has important implications not only for how they find employment, but also about what movies they watch, which products they purchase, which technologies they adopt, whether they participate in government programs, whether they protest, and so forth. There have been various studies on the diffusion of innovation, comprising some typical early ones, such as the diffusion of hybrid corn seed among Iowa farmers by Ryan & Gross (1943) and examination of diffusion and the telephone by Hagerstrand (1967). These studies on diffusion of innovation have indicated how important social connections are in determining behavior.

2.7.2 Social Network and Information Diffusion. Social networks are very dynamic and complex networks. All kinds of information flow on social networks. Such information can be classified as positive or negative (Ma et al, 2008). Research on how information flows in a social network began from a work on “Diffusion of Innovations” by Rogers (2003). Rogers proposed that adopters of any new innovation could be categorized as innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%) and laggards (16%) (Ma et al., 2008). Other researches have also worked on developing theories of innovation adoption (Coleman et al., 1966; Valente, 1995).

Social networks influence the degree of an innovation's diffusion by determining which potential adopters can become aware of information about this innovation and adopt it. Social networks channel information about innovations to some potential adopters who might adopt these innovations and also prevent information from reaching others, who then have no opportunity to adopt them (Abrahamson et al., 1997). It is well acknowledged that the structure of a social network can favor or impede the diffusion of innovations in the network (Deroian, 2002; Kong & Bi, 2014). Bass model, one of the most applied diffusion models, describes the process of how new products are adopted in a social network (Bass, 2004; Meade & Islam, 2006).

Social network research suggests that access to useful information might be greatest in a network with diverse members such as persons from different units within an organization, since this diversity permits tapping multiple pockets of information (Morrison, 2002). Such diversity has been termed as network *range* (Campbell et al., 1986). Social network research has also underscored the value of network *status,* defined as the extent to which one's network contacts hold high positions in the relevant status hierarchy (Morrison, 2002). For example, research has emphasized the political advantages of a high-status network (Ibarra, 1995; Morrison, 2002). Also, people at higher levels in an organization may be better sources of certain categories of information than those at lower levels (Morrison, 2002; Ostroff & Kozlowski, 1992).

Besides, individuals with weak ties are said to have access to more diverse information because they usually have fewer mutual contacts; each individual has access to information that the other does not. For information that is virtually only embedded within few people, such as job openings or future strategic plans, weak ties play an essential role in facilitating information flow. Weak ties, which are defined directly in terms of interaction propensities, diffuse novel information that would not have otherwise spread (Bakshy et al., 2012).

There are some information diffusion paradigms which are captured in ABM research (e.g. (Abdollahian et al., 2013)). For instance, Berlo et al (1969) proposed a model that describes how a receiver's likelihood of receiving/accepting a message depends on whether they are exposed to it or not, their attentiveness, and their disposition to the sentiment of the message. Also, social judgment theory postulates that the likelihood of an agent or an individual accepting a piece of information depends on the "distance" between the positions of the two agents (individuals) involved in the communication (Siero & Doosje, 1993). Other researchers have noted that the likelihood of an agent accepting a message also increases with repetition and the use of various channels of communication (Corman et al., 2007).

The origins and application of diffusion models have been vastly described in the literature and cuts across several disciplinary boundaries (Boyle, 2010). Jackson (2008) has comprehensively described the various diffusion models. According to Jackson (2008), the Bass model is one of the earliest models of diffusions that is still in application today. The model is tractable, and it incorporates social aspects into its structure. Even though it does not have any explicit social network structure, it still incorporates rates of imitation. The model is developed on two key parameters: one captures the rate at which agents (individuals) innovate or spontaneously adopt, and the other captures the rate at which they imitate other agents or adopt because others have. The innovation can be interpreted as a response to outside stimuli, including media or advertising, while the imitation aspect captures social and peer effects. Other diffusion models described in the literature by Jackson (2008) are the *SIS* ("susceptible, infected, susceptible") and SIR ("susceptible, infected, removed") models. The idea of the SIS model is that a node can be in one of two states: (1) it is infected, or (2) it is not infected and thus is susceptible to becoming infected. This model is a variation on the seminal SIR model. For more details on these diffusion models, readers can refer to Jackson (2008).

The candidate applies the Bass model to model changing perceptions, which are modeled as a diffusion process over a social network (e.g. word of mouth information transfer) in this dissertation. This is because the Bass model is consistent with the objective of the modeling framework in this research presented in section 3.

2.8 APPLICATION OF AGENT-BASED MODEL, SOCIAL NETWORKS AND DISCRETE CHOICE THEORY TO MODEL COMMUNITY BEHAVIOR

As discussed in section 2.6, agent-based modeling (ABM) has been applied in several disciplines in the past few years (Bonabeau, 2002). Applications of ABM include application to fields of study where main agents are individual humans or organizations, such as politics, economics, business management (Caldart & Ricart, 2007), public policy, military, operations research, traffic simulation, geographic systems (Torrens, 2010), and anthropology (Premo, 2006). ABM also offers an opportunity to implement various modeling techniques from different research fields including agents' decision making processes, learning and adaptation mechanisms and interaction (Fujiono, 2011). This dissertation focuses on agent-based models of communities and addresses the associated utility functions and other technical challenges for mining applications.

2.8.1. Agent-Based Models of Communities. Agent-based models are able to represent the behavior of human actors more realistically, accounting for bounded rationality, heterogeneity, interactions, evolutionary learning and out of equilibrium dynamics. They are also able to combine this representation with a dynamic heterogeneous representation of the spatial environment (Filatova et al., 2013).

ABM has received attention from researchers modeling communities. For instance, ABM has been applied in the land-use modelling community (Matthews et al., 2007). Also, Brown et al (2004) used an agent-based model to evaluate the effectiveness of using a greenbelt adjacent to a developing area to delay development outside of the greenbelt. In their model, agents chose where to locate based on preferences for minimizing distance to services and maximizing aesthetic quality of the chosen location. Similarly, Valbuena et al (2010) developed a framework for ABM, which they used to simulate regional land-use change. They combined agent diversity, an agent typology and a probabilistic decision-making approach to simplify and incorporate the inherent variability of the population and decision-making in rural regions. In another application, Berger & Troost (2012) adopted the agent-based simulation approach to understand how heterogeneous populations of farm households and their agro-ecological resources are affected by agricultural technology, market dynamics, environmental change, and policy intervention. Additionally, ABM has been used to simulate energy reduction strategies of owner-occupied homes in the UK. The agents in this model were home-owners who had to choose whether or not they wanted to carry out any energy efficiency development in their house (Lee et al., 2014). Gao & Hailu (2012) employed agent-based simulation to assess the effect of management strategies, related to managing recreational fishing resources, on stakeholders.

From the foregoing, we can conclude that there is enough evidence in the literature to motivate the hypothesis that ABM can be used to study the impact of management’s decisions and other events on community perceptions of mining. Many researchers have studied similar phenomena in other industries. The challenge then is how to build valid agent utility functions and overcome other technical challenges necessary to extend ABM application to the evaluation of the effect of management decisions and other events (e.g. new information becoming available in the community) on mining community acceptance.

2.8.2. Utility Function. In an agent-based model, the utility function relates the various relevant variables to the utility of particular alternatives to the agent. The agent utility function guides the agents (individuals) to make a decision regarding whether to choose an alternative or not. Since ABM relies on a model of utility maximization (which assumes among other things that the agent is rational and has clear preferences), the agent chooses the option that maximizes its utility (as per the utility function). Utility functions can vary from model to model based on the modeling objectives. For example, in the work by Brown et al (2004), which evaluates the effectiveness of greenbelt, the utility function dictating the residents' (agents') preferences was based on the tradeoffs between aesthetic quality and distance to services, and weighted near locations much higher using an inverse squared distance. In their model, the utility function had a random component based on heuristics such that to choose a location, a new resident looks at some number of randomly selected cells and moves into the cell that has the highest utility. Also, Valbuena et al (2010) used a discrete stochastic process to describe agent's utility function relative to farm expansion. In their work, they divided the choices into three mutually exclusive options: buy, keep and sell land. They assigned a probability to each option based on the type of agent to represent the diversity in decision making of agents.

Conversely, Gao and Hailu (2012) used an empirically formulated random utility model to characterize the behavior of angler agents in their recreational fishing simulation. Angler agents select angling locations depending on individual characteristics and attributes of the alternative locations. Lee et al (2014) developed their model by relying on a decision-making algorithm, which used discrete choice experiment (DCE) data from two different surveys.

Regardless of the type and nature of the utility function, most ABM models rely on the concept of random utility maximization (RUM). The assumption is that choice behavior is governed by an objective to maximize utility within the constraints of available resources (i.e., time and monetary budgets) and cognition (i.e., limited information and mental effort) (Arentze et al., 2013). In the literature, several ABMs are described that use some type of discrete choice model in the agents' utility function. The information for the discrete choice models stem from a wide range of sources (Holm et al., 2016). Discrete choice models based on discrete choice theory are better sources of agent utility functions than other approaches because discrete choice theory is based on decision science and is based on random utility maximization. Most other researchers who do not use discrete choice theories use empirically generated utility functions or heuristics. For instance, Dia (2002) developed a model to guide route choice decision, which was a discrete choice problem and recommended that the two approaches to addressing this problem are discrete choice and artificial neural network techniques. Also, an iterative system was used together with a set of specific parameters for agent's utility function (Evans & Kelley, 2004). These utility functions are limited because the models cannot be used to reliably evaluate scenarios beyond the conditions under which empirical functions were formulated. Hence, this work relies on utility functions formulated from discrete choice models.

Discrete choice theory has been applied to evaluate community acceptance of renewable energy projects (Dimitropoulos & Kontoleon, 2009). Other researchers have also used discrete choice theory to model individuals' choice regarding whether or not to support mining (Ivanova & Rolfe, 2011; Que & Awuah-Offei, 2014). Discrete choice theory can be employed to formulate rigorous utility functions for ABM of community acceptance (Hunt et al., 2007; Lee et al, 2014).

In spite of the extensive application of ABM and discrete choice experiments (DCEs), separately and together, to model consumer and individual preferences (Brock & Durlauf, 2001; Gramming et al., 2005; McFadden, 1974; Zhang et al., 2011), there is no work in the published literature that combines the two approaches to model community acceptance of mining projects. ABM applications in resource exploitation have not been supported by rigorous utility functions based on sound social science. For example, Fujiono (2011) used agent-based model framework to show ways innovations can be adopted in the mining industry but did not apply rigorous utility functions based on sound social science to determine agents' adoption. Instead, each individual mining company representing an agent, was set to constantly aim for lesser mining cost and higher productivity compared to its competitors and to avoid failures at their mines. When any of these objectives was not met, a mining company (an agent) was set to find information about a better technology to improve its performance. Such an approach was more heuristic. Nonetheless, work done by other researchers (Hunt et al., 2007) proves that it should be possible for these two approaches to be applied to model mining community acceptance over time.

The main technical challenge of ABM is how to formulate rigorous utility functions that describe the agent's motivation for decision making. Even though discrete choice models are valid for estimating the utility of the various alternatives presented in the discrete choice experiment, they do not, by themselves, provide a means to make an accept/reject decision. This binary (accept/reject) decision is what is required to estimate the level of acceptance of a particular mine. This dissertation overcomes such a challenge by using odds ratio as the utility function in the ABM. Odds ratio has been widely applied in making decisions, especially in the field of medicine for choosing options and making decision. For example, it helps patients decide to accept or waive painful or expensive treatments, and thus, enables health care workers to make treatment decisions (Mchugh, 2009).

2.8.3. Other Technical Challenges and Issues for Mining Applications.

Besides formulating rigorous utility functions, there are other challenges to be overcome in order to apply ABM to study the effect of mine management and other external events on community acceptance. One of these is the nature of the social network that describes the connections between individuals in the community. Various studies have indicated that the structure of social network can affect information diffusion (Deroian, 2002; Kong & Bi, 2014). However, there has been no work that used ABM and discrete choice theory in conjunction with diffusion model through social network to understand dynamic community acceptance of mining. For example, Bahr (2015) uses ABM and social networks to explore the effect of different scenarios on the social network of a stakeholders and the resulting changes in community perception. However, Bahr (2015) used heuristics to formulate the utility functions and was more interested in how stakeholders (not individuals) form stable connections (strategic social network formation) than information diffusion and its effect on community perceptions.

Generally, community acceptance is affected by several factors, including effectiveness of local community engagement, individual's preferences, and requirements for community acceptance, and perceptions of legitimate ownership of mineral rights (Ballard & Banks, 2003; Joyce & Macfarlane, 2001). On the whole, community acceptance is an important element in the sustainability of a particular mining project. This presents several questions: Can technical considerations (design for sustainability) be sufficient to influence community acceptance? How do other competing factors, such as economic considerations, influence community acceptance? Under what conditions are these competing factors dominating the decision of the local community to accept sustainable projects? How do all these change over the life of the mining project? Given the abovementioned complexities associated with achieving perceived sustainability, further research is required to investigate these issues. Combining ABM with rigorous decision science and incorporating social network structure is a promising approach to examine these issues. Nevertheless, combining ABM and DCE together with social network structure to model community acceptance has many challenges such as: (1) how to define valid agent utility functions using discrete choice theory; and (2) how to describe the interaction between perceptions of sustainability and community acceptance using an ABM diffusion model through social network. The main contribution of this dissertation is to overcome these challenges.

2.9. SUMMARY OF THE SECTION

The following key points summarize the discussions in this section.

1. Community engagement is important for ensuring sustainable mining
2. Current qualitative community analysis approaches do not fully provide enough understanding into the community's trepidations, expectations, and, particularly, level of acceptance to achieve the project's sustainability
3. The level of social license to operate changes over time based on people's ongoing experiences of an operation and changes in their perceptions and opinions, and the procedure by which social license is expressed, which is contextually specific, dynamic and non-linear
4. There are many factors that affect community acceptance, which include the impacts of the mine on the environment and host community, the mine owner (the corporate reputation etc.) and governance issues, and demographics of the community
5. Researchers have used discrete choice theory to model individuals' choice regarding whether or not to support mining. Such work indicates that discrete choice theory can be used to formulate rigorous utility functions for agent based model (ABM) of community acceptance
6. Agent based models are a potential tool for modeling agents' decisions to innovate or to imitate innovation as well as their strategies for collaboration.
7. Social networks channel information about innovations to some potential adopters who might adopt these innovations and prevent others from getting such

information who are, therefore, not in a position to adopt them. Thus, the structure of a social network can favor or inhibit the diffusion of innovations in the network

8. Literature review shows that several agent-based models use some type of discrete choice model in the agents' decision process
9. This dissertation aims to combine ABM, DCE and social networks structure to model community acceptance while addressing the following challenges: (1) how to define valid agent utility functions using discrete choice theory; and (2) how to describe the interaction between perceptions of sustainability and community acceptance using an ABM diffusion model through social network

3. AGENT-BASED MODELING FRAMEWORK FOR MODELING THE EFFECT OF INFORMATION DIFFUSION ON COMMUNITY ACCEPTANCE OF MINING

3.1. INTRODUCTION TO MODELING COMMUNITY ACCEPTANCE OF MINING

Changes in the community's perception of mine characteristics and impacts, which affect social license to operate (SLO), can be described as diffusion of information (perceptions) over a social network. This is particularly so if the changes in perceptions (or opinions) are basically because of interactions with others. In such circumstances, new perceptions or opinions can diffuse over a network of people in the mining communities. Ultimately, these new perceptions can result in changing acceptance levels of the mining project. Continual surveying and engagement can help monitor such changes. Nevertheless, such practices are expensive and time-consuming. Therefore, mine managers need approaches (including computational models) to predict such changes without (or in addition to) repeated surveys. Such approaches do not currently exist and researchers have not given the problem the required attention.

This dissertation is intended to fill this gap by proposing a framework for understanding how levels of community acceptance change over time given changes in social and environmental attributes of a mine, and community's demographics . The specific objectives of this section are to: (i) propose a framework for modeling the effect of information diffusion on community acceptance[1] of mining using ABM; and (ii) illustrate the framework using a case study. The case study, which uses data from Que

[1] As used in this paper, "community acceptance" means the individuals (agents) prefer the project over the status quo. This may be more than "acceptance" but less than "approval," in SLO parlance (Thomson & Boutilier, 2011).

(2015), examines the effect of agents' changing perceptions of the levels of air pollution on the level of acceptance of a mine. The work in this section accounts for the effect of new information about the mine's relevant sustainability impacts on changing perceptions. The purpose is to understand how in a given mining community, interactions and communications among the people in the presence of changing perceptions of mine impacts can affect community acceptance of the mining project.

Modeling the effect of information diffusion on community acceptance of mining needs a complex adaptive system framework such as agent-based modeling (ABM) (Miller & Page, 2009). ABM is predominantly appropriate for this case because it is much easier to characterize the interactions between individuals, how such interactions might influence an individual's perceptions and preferences, and the uncertainties surrounding such processes for individuals than for the entire population. ABM provides the opportunity to explicitly model the social interactions between individuals of different characteristics and takes into account the structure of social network (Kiesling et al, 2012). ABM models can capture dynamic and emergent behavior in ways that cannot be achieved by other approaches (Bonabeau, 2002; Macal & North, 2010).

This study contributes to improving mining sustainability practice and research and can inform broader discussions about the interactions between large engineering and manufacturing projects and their host communities. It will help facilitate better inclusion of community opinions in evaluating design options during project design and planning (Howard, 2015; Soste et al., 2015). This helps project managers obtain informed consent and social license to operate, which are sustainable outcomes (Szablowski, 2010; Yates & Horvath, 2013). Additionally, this work contributes to current research at the boundaries of social science, complex adaptive systems and sustainability (Fiksel, 2003; Schluter et al., 2012). Mines, which are often relatively large enterprises in small rural communities, are typical examples of the interaction between social, environmental and economic impacts of the mine and demographics of the community that hosts them.

3.2. MODELING FRAMEWORK

The major determinants of the level of community acceptance of a mining project can be classified into characteristics and impacts of the mine, and demographic factors (Que et al., 2015). Mines have social, environmental and economic impacts. For instance, Que et al found that the relevant characteristics of a mining project include the life of the project (the project duration), buffer between the mine and residents (how far is the community or communities are from the mine), decision making mechanism for permit approval, and availability of independent and transparent information on potential impacts of the mine. These impacts and characteristics depend on the type of mine and technology (equipment, engineering design, and mitigation techniques) employed in mining.

To model the level of community acceptance of mining, the model has to account for these determinants. In ABM, the model state "emerges" from the state of individual agents in the model. The level of community acceptance could be modeled from deducing the percentage of individual agents that prefer a proposed mining project over the status quo. To accomplish this, the determinants of individual preferences for mining projects have to be incorporated into the agent's utility function, which determines the agent's state (prefer or not). For this proposed framework, these determinants are incorporated into the model as agent attributes, which can change with time. The general framework is presented in Figure 3.1.

The main assumptions of the modeling framework are that it assumes:

1. The influence of other agents (individuals) who live outside the mining community under consideration on the preferences of agents in the community is negligible (i.e. boundary condition)
2. The effect of other variables, besides those captured in the utility function (the so-called unobserved variables in discrete choice theory), on individual preferences are negligible
3. Information diffusion is primarily through word of mouth and the effect of other forms of information transfer are negligible
4. All agents have similar roles in the information diffusion process (i.e. all agents are open to new information and can influence others).

The framework in this research (Figure 3.1), implemented in MATLAB 7.7 2014, predominantly relies on two input data sets: (1) demographic data (e.g. age, gender, education, number of children, length of residence, location, etc.); and (2) non-demographic data (e.g. job opportunities, income increase, noise pollution, traffic increase, crime rate, mine life, mine buffer etc.), which define the mine impacts and characteristics (section 3.2.1 describes how this is incorporated into the agent’s utility function). These two data sets, which are modeled as agents’ attributes, are used to describe agents' motivations (utility function). The examples of these data sets in this study are not exhaustive. The factors that influence an individual's preference for a mine differ from one situation to the other. Therefore, the number and type of factors in the model depend on the number and type of factors that are deemed important for describing an individual's preference. For instance, (Que, 2015) found the individual's level of education to be statistically significant but not the number of children. Ivanova & Rolfe (2011), on the other hand, found the number of children to be significant but did not consider level of education (Table 3.1). Likewise, whereas Que (2015) found 20 (4 demographic and 16 non-demographic) factors to be relevant, Ivanova & Rolfe (2011) found 13 (8 demographic and 5 non-demographic) factors to be relevant. Que’s significant factors were used to model agents’ attributes and define utility function variables in this research.

The algorithm initializes agents at the beginning of each iteration. In this step, agents are created with various attributes depending on the input. The important state variables for this framework are the “decision” and “preference” variables. The decision variable is used to describe whether the agent is participating in the decision (above 18 years old and alive) or not (below 18 years or dead). Agent preference state describes whether the agent prefers the proposed mining project over the status quo or not, and is determined using the decision criteria based on the utility function. Some agent attributes are dynamic as they change over time. These attributes are updated at each time step. These include age and agent's decision state (i.e. alive or dead, or attained 18 years). In order to use the model to understand the effect of information diffusion on community acceptance, at least one non-demographic attribute has to be dynamic. Also, such attribute should be affected by information diffusion over a social network. The model is run for a number of iterations to adequately estimate the output from Monte Carlo simulation, which is used to model stochasticity in the model.

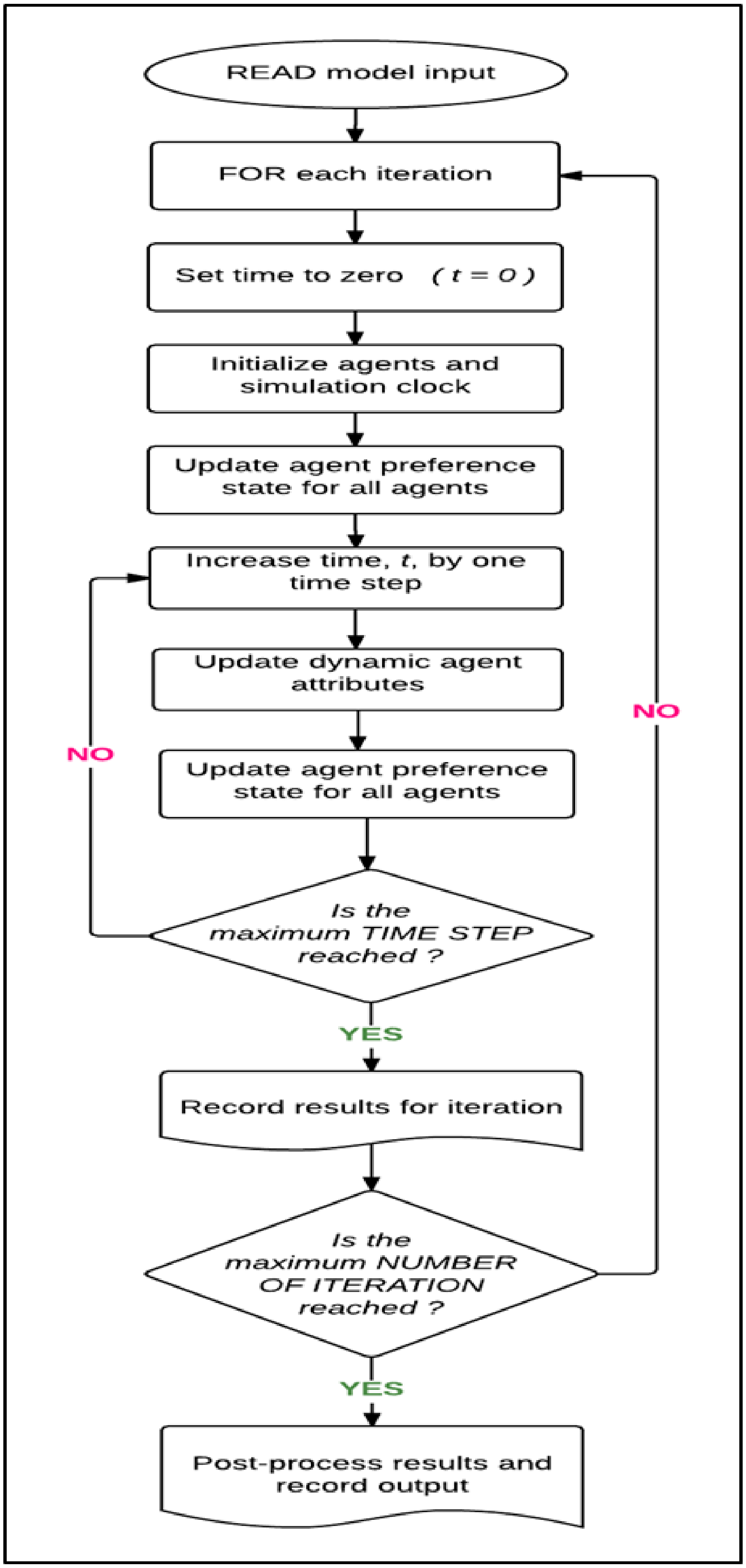

Figure 3.1. Framework for Modeling Community Acceptance

Table 3.1. Comparing Ivanova and Rolfe's, and Que's Significant Factors (Ivanova & Rolfe, 2011; Que, 2015)

Ivanova and Rolfe's significant factors	Que's significant factors
• Cost • Housing and rental prices • Water restrictions • Buffer for mine impacts • Population in work camps • Gender • Number of children • Age • Length of residence • Enjoy living in Moranbah • Spending in Moranbah • Improved Services will reduce travel	• Age • Gender • Annual income • Education • Job opportunities • Income increase • Increase in housing costs • Labor shortage for other business • Noise pollution • Water pollution and shortage • Air pollution • Land pollution and subsidence • Population increase • Infrastructure Improvement • Traffic increase • Crime increase • Permit approval decision making mechanism • Availability of information • Mine buffer • Mine life

The three major aspects of this framework are the approach to modeling agents, agents' topology, and changing perceptions. These are discussed in detail in the following sub-sections.

3.2.1. Modeling Agents. An agent is a discrete, autonomous entity with its own goals and behaviors, which it can adapt and modify (Macal & North, 2006). Agents have attributes (variables) that are used to describe them. In this modeling framework, individuals are modeled as agents, with attributes that depend on the study objective and variables in the utility function. As explained earlier, the factors that affect an individual's preference for a mine differ from one context to the other. Hence, the number and type of attributes in the model depend on the number and type of factors that are important for predicting an individual's preference. Physical location can be an agent's attribute, if it is deemed important for the diffusion process. Agents are more likely to interact based on their locations (e.g. individuals in the same neighborhood are more likely to be friends).

The modeling framework is based on utility functions derived from discrete choice theory (McFadden, 1974). Discrete choice theory is used to model individual preferences in discrete choice situations. This is consistent with the modeling framework that models individuals as agents. Based on discrete choice theory, an individual's utility (or payoff) for alternative a (u_a), and the odds of selecting alternative a over b, OR_{ab}, are given by Equations 3-1 and 3-2, respectively. β_j is the taste coefficient associated with attribute j; x_j, is the variable for attribute j; ε_a is the random unobserved component, and *n* is the number of attributes relevant to the choice. The odds ratio, which is the ratio of the probability of an individual with specific demographic characteristics choosing alternative a over alternative b, under specific conditions, is used as the decision criteria in this work (Equation 3-2). The agent chooses an alternative over the status quo, if its odds ratio is greater than one.

$$U_a = \left(\sum_{j=1}^{n} \beta_j x_j + \varepsilon_a \right) \tag{3-1}$$

$$OR_{ab} = \exp\left(\sum_{j=1}^{n} \beta_j \left(x_j^a - x_j^b \right) \right) \tag{3-2}$$

At each time step, the odds ratio is estimated for all agents participating in the decision. The odds ratio is then used to determine the agents' state with respect to whether they prefer the simulated mining project over the status quo or not. The model then collates that to estimate the level of community acceptance at that time step.

The user needs to provide the model with the desired distributions of the various agent's attributes. During the agent initialization step, the agents are assigned initial values of the demographic attributes based on Monte Carlo sampling. (It is worth mentioning that, although the model is capable of incorporating correlation in the Monte Carlo sampling, the case study in this work does not consider potentially correlated properties since correlation coefficients are not available in Que's work). The demographic attributes of each agent are assigned by randomly sampling from the given distributions to mimic the actual distributions of the attributes. On the contrary, the non-demographic attribute values are assigned to the agents in a deterministic approach based on the particular simulated scenario. This approach assumes that at time zero, all agents perceive the status quo and the option to be evaluated to the same extent. This assumption is a limitation that is imposed by the survey (discrete choice experiment) used to capture individual's preferences. Since all participants in the surveys were given same descriptions of the alternatives and instructions, the discrete choice modeling assumes that any differences in choices are due to individual's preferences (which are assumed to be explained by demographics and project attributes) and not differences in the way the participants perceive the alternatives. Hence, when using the discrete choice model as a utility function, it is inconsistent to assume that the agents have differing perceptions of the alternatives. Nonetheless, the candidate believes the benefits of using a utility function based on actual data on individual's preferences outweigh this limitation.

At each time step, dynamic agent's attributes (those that change with time) are updated. There are three types of these dynamic attributes: attributes that are a direct function of time (e.g. age); attributes that are function of events that happen over time (e.g. number of children); and those attributes that change from interaction with other agents (e.g. an agent's number of "active friends"[2]). Attributes that are a function of time are updated on the function that describes the attribute (e.g. agent's age is updated by adding the time step to the previous age). Attributes that are a function of events that happen over time are updated based on whether those events occur or not in the simulation. Those other attributes that change due to interactions between agents depend on topology and the diffusion process which are discussed in the next two sections.

In this work, the agents have 20 (4 demographic and 16 non-demographic) attributes that are used to estimate the utility function as per (Que, 2015). These agents' attributes were chosen based on a survey of residents of mining and non-mining communities to test the hypothesis that these demographic and non-demographic attributes influence individuals' decision to accept a proposed mining project (Que, 2015).The four demographic attributes are age, gender, level of education and annual

---

[2] "Active friends" is used to refer to those agents connected to an agent that are participating in the decision (i.e. 18 years or older and alive)

income. The 16 non-demographic attributes cover economic, environmental, social and other factors relevant to the problem. Of these 20 attributes, age is the only dynamic attribute that is a function of time. Agent's decision state variable is affected by two events (an “adult” agent dies or a “child” agent becomes 18 years old), which are simulated using Monte Carlo simulation at each time step. The agent's number of active friends changes as the agents interact through the network.

Agents' death is simulated using the death rate distribution over the age of the agents in this model. Monte Carlo sampling is used to determine whether an agent is dead or not at each time step. Dead agents are removed from the pool of decision makers by assigning “0” to their decision state variable. Conversely, those agents who are living (i.e. decision makers) have their decision variable set to “1”.

During the step to initialize agents, the ages of the agents are simulated using Monte Carlo sampling, based on the age distribution provided by the user. To introduce new agents into the decision pool, all agents that have attained 18 years (new entrants) after ages are updated at each time step are identified and added to the decision makers.

3.2.2 Modeling Agents’ Topology. Topology describes agents' relationships and interactions with each other. The two main concerns of modeling agent’s interactions are identifying who is, or could be, interacting and the mechanism of the interaction (Macal & North, 2010). In network topology, agents can interact with other agents through paths in the network. This type of topology is used to model situations like contagion, learning, and diffusion of various behaviors through a social network (Jackson, 2008). In network topology: (1) an agent interacts with a subsection of agents that it is connected to, referred to as the agent's neighbors; and (2) local information is obtained from interactions with an agent's neighbors. Many networks with distinct characteristics have been described in the literature (Newman, 2003a). It is advisable to select a network that is applicable to the particular model (Kiesling et al., 2012).

For this framework, the ABM model uses a static network in which connections are defined at the beginning of the simulation and do not change (Macal & North, 2010). However, a new network is simulated and used for each iteration. The candidate used a static network because the work focuses on changes to the level of acceptance due to information diffusion. This is a limitation and can be addressed in future work by incorporating strategic network formation based on agents' choices and adaptation (Jackson, 2008). The network used in this framework can be any class of networks that describe social networks by which information about mine characteristics and impacts diffuses through a community. Although, such networks have not been comprehensively described in the literature, preliminary descriptions of such networks exist (Boutilier, 2011). However, it is reasonable to hypothesize that one could approximate such networks with other social networks that have been observed to describe information diffusion and a variety of social interactions (Newman, 2003a).

The algorithm that generates the network in the framework is based on a random graph algorithm. The algorithm is modified, however, to account for homophily (i.e. a higher likelihood that individuals will be connected to other individuals who are similar to them). The candidate accounted for homophily in this work because homophily, which is the property of social networks that leads to the observation that individuals tend to be similar to their friends, is one of the most basic properties of social networks (Easley & Kleinberg, 2010). Its basis could be any of the individual's (in this case agent's) attributes, including demographic attributes such as age, gender, race/ethnicity, education and by psychological ones such as intelligence, attitudes, and aspirations (McPherson et al., 2001). In the case study model, the candidate uses the agent's location (postal zip codes) as the basis for simulating homophily. Proximity is the most basic source of homophily as people (agents) are more likely to interact with those who are closer to them geographically than those who are distant (Hipp & Perrin, 2009; Kadushin, 2004; McPherson et al., 2001).

Agents' zip code is assigned using Monte Carlo sampling from the zip code distribution over a given total population. Agents are considered "similar" if the difference between their zip codes is equal to or less than a "proximity" value defined by the user. As with random networks, the candidate started with a goal of a binomial degree distribution (that is, the distribution of number of neighbors/friends is binomial) with probability of a connection, ψ . The candidate then modified the algorithm to adjust the probability of a connection between two agents by a ratio, α $\left(0<\alpha<1\right)$ to ensure a higher likelihood of connection between similar agents relative to dissimilar agents. Hence, the probability of a connection is given by Equation 3-3, where ΔR the difference in zip code, and P is the proximity value provided by the modeler.

$$\text{Probability of connection } = \begin{cases} \alpha\psi & \text{if } \Delta R \leq P \\ (1-\alpha)\psi & \text{if } \Delta R > P \end{cases} \qquad (3\text{-}3)$$

The candidate specified the "proximity" value as zero in the case study in this research. This implies that agents are similar if they have the same zip code. The candidate defined the probability ψ as 50 divided by the number of agents (i.e. average number of friends of 50). Average number of friends of 50 was assumed to be reasonable.

For instance, a social group size of 30 to 50 individuals is considered a typical size of social group such as overnight camps or a band society (Hill & Dunbar, 2002; Zhou et al., 2005). Homophily was ensured by defining $\alpha = 0.75$.

3.2.3. Modeling Changing Perceptions. Changing perceptions are modeled as a diffusion process over a social network (e.g. word of mouth information transfer) in this framework. The most common diffusion models, in the literature, are the Bass, SIR (“Susceptible, infected, removed”) and SIS (“Susceptible, infected, susceptible”) models (Jackson, 2008). The candidate adopted the Bass model for this framework because it is consistent with the objective of this framework. The Bass model postulates that diffusion of innovation as a contagion across network nodes (or agents) is random and the probability of becoming “infected” depends on the number of neighbors that a node has and the state of those neighbors (Jackson, 2008). The model captures the rate at which agents innovate or spontaneously adopt, and the rate at which they imitate other agents or adopt because others in their neighborhood have.

Similarly, the candidate assumes that the probability of a person adopting the new perception of the mine’s sustainability depends on the number of friends that person has and a stochastic process that is a function of the proportion of friends who have adopted the new view. Adoption in this context means the process of agent becoming convinced of the new perception (e.g. change in the environment). The candidate assumes that agent innovation or spontaneous adoption is negligible (i.e. diffusion is primarily by word of mouth) because “word of mouth” is seen to be the predominant mode of diffusion in many cases and has major influences on individuals’ behavior (Buttle, 1998; Rezvani et al., 2012). Thus, this model is limited to situations where there is no significant innovation and other factors such as public education and advertising which may drive changes in attitudes independent of social diffusion. Because this model assumes negligible innovation, initial conditions need to specify the number of agents who have this new view at the beginning of the simulation.

Figure 3.2 illustrates the algorithm used to update the agents' perceptions of the mine's sustainability impacts at each time step. The two key steps of the algorithm are determining: (i) the agent's active friends; and (ii) the probability that an agent will adopt.

The statuses of an agent's friends are determined to ascertain whether they are active or not. If some of an agent's active friends have adopted the new perception, then it is necessary to determine the agent's likelihood of adopting the new perception based on strength of influence from his friends (Figure 3.2). In this work, the agent's adoption decision is guided by the product adoption model in Equation 3-4 (Bonabeau, 2002). In this model, a new perception's (analogous to a new product's) value V to the agent depends on the number of agents who have adopted it, N in a total population of N_T agents. Where ρ is the fraction of the population that has adopted the new perception, θ is a characteristic value and represents a threshold fraction of the population at which the adoption curve takes off, and d is an exponent that determines the steepness of the function. θ and d are taken to be 0.4 and 4, respectively, in the base case as per (Bonabeau, 2002). These input parameters were used to model how movies become hits in an ABM. This adoption model is deemed adequate to model how new perceptions about a mine's attributes become pervasive within a mining community.

$$V(N) = V(\rho) = \frac{(1+\theta^d)\rho^d}{\rho^d + \theta^d} \tag{3-4}$$

V can be estimated for each agent by considering ρ to be the ratio of number of active friends who have adopted the new perception to total number of active friends. This estimate of V is used to model the probability of the agent adopting the new perception in this study. This probability increases as the number of adopting friends increases. Monte Carlo sampling is then used to determine whether the agent will adopt the new perception in the current time step or not.

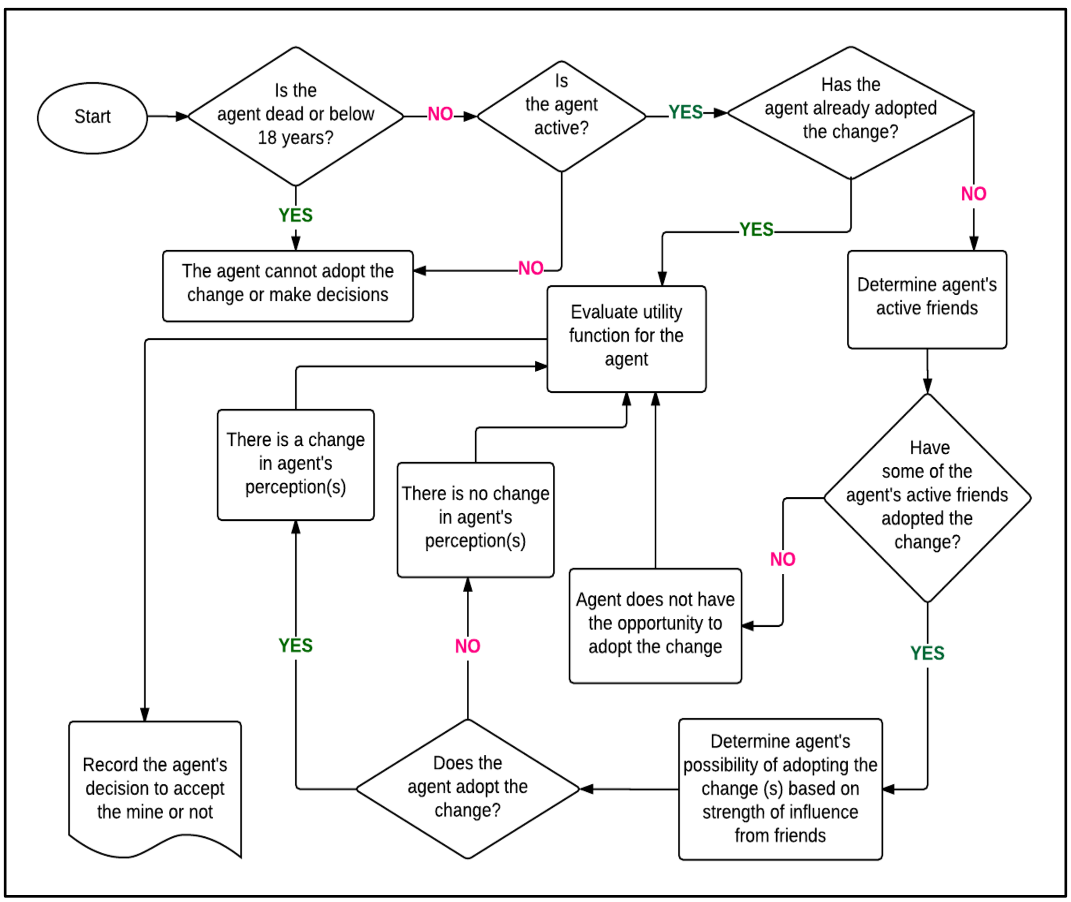

Figure 3.2. Agent Going Through Adoption and Decision Making Process at Each Time Step

3.3. MODEL VALIDATION

ABM validation presents practical and scientific challenges for researchers. As noted by Klugl & Bazzan (2012), it is rare to have the empirical data for full validation. To fully validate an agent-based model with empirical data, researchers need to observe agents' state at each discrete time step in a carefully documented scenario (Windrum et al., 2007). Such data is often unavailable and is not available in this case too. The data available to the candidate only surveyed community residents at a point in time and provides no dynamic data. Hence, the candidate chose to validate the modeling framework with data from Salt Lake City, Utah, USA (Que , 2015), which is used as the initial time step in this simulation. Que (2015) conducted a discrete choice experiment in Salt Lake City to understand the drivers of the local community's acceptance of a mining project.[3] She determined the taste coefficients using a strata conditional logit model (Table 3.2). The candidate used Que's coefficients as the coefficients, β in Equations 3-1 and 3-2 to describe agent motivations based on the four demographic and 16 non-demographic attributes she found to be relevant. To validate the agent based model (at least for predicting at a particular instant in time), the candidate simulated the level of acceptance of the base case option in Que (2015). Data from Que (2015) was used as input to simulate the demographic and non-demographic attributes of the agents. For all attributes, the candidate used the same numeric codes used by Que (2015) to ensure the utility function is valid.

[3] Salt Lake City is home to the Bingham Canyon Mine, a surface mine that produces mainly copper but also some gold, silver and molybdenum.

Table 3.2.Strata Conditional Logit Model for Salt Lake City (Que, 2015)

Attribute	Coefficient
Demographic attributes	
Age	0.0028
Gender	-0.0093
Annual income	0.0021
Education	0.0017
Non- demographic attributes (Economic)	
Job opportunities	1.3886
Income increase	1.2541
Increase in housing costs	-1.7527
Labor shortage for other business	-0.1117
Non- demographic attributes (Environmental)	
Noise pollution	-1.6794
Water pollution and shortage	-0.3471
Air pollution	-1.8216
Land pollution and subsidence	-0.2707
Non- demographic attributes (Social)	
Population increase	-0.2570
Infrastructure improvement	1.1575
Traffic increase	-0.1742
Crime increase	-1.6939
Non-demographic attributes (Governance and others)	
Permit approval decision making mechanism	0.2028
Availability of information	1.2606
Mine buffer	1.2141
Mine life	0.1402

The demographic attributes used in this model are gender, age, level of education and annual income. In the validation experiment, the proportion of male and female agents was equal. Tables 3.3, 3.4 and 3.5 present information regarding respondents' level of education, annual income and age in Que (2015), which are used in this experiment as input for generating agents' demographic attributes.

Table 3.3. Agents' Attributes: Level of Education (Que, 2015)

Code	Level of Education	% Population
1	Less than high school	14
2	High school/GED	18
3	Some college, Vocational, or 2 year college degree	27
4	Bachelor's degree and higher	41

Table 3.4.Agents' Attributes: Annual Income (Que, 2015)

Code	Annual Income	% Population
1	\$5,000-\$20,000	22
2	\$20,000-\$39,000	23
3	\$40,000-\$59,000	18
4	\$60,000-\$200,000	37

Table 3.5. Agents' Attributes: Age (Que, 2015)

Code	Age group (years)	% Population
1	18 to 25	18
2	26 to 34	26
3	35 to 54	31
4	55 to 64	12
5	65 to 120	13

For all non-demographic attributes, Que (2015) used codes 1, 2 and 3, where 2 represented the base case option code. Hence all non-demographic attributes are set to code 2 in the validation experiment. Table 3.6 shows the meaning of code 2 for each of the 16 attributes (Que, 2015).

Using these inputs, the candidate conducted an experiment with 20,000 agents and 20 iterations to predict the level of acceptance for the base case option (no dynamic changes were evaluated in this experiment). This was based on computational cost and a reasonable coefficient of variation (1.6% for the validation experiment) after 20 iterations (replications). The validation results (Figure 3.3) indicate that the mean acceptance for the base case option is 42.4%. In Que's work, 44% of respondents chose this option (Que, 2015). Comparing these two results, the candidate believes that the model results agree with the data used to generate the discrete choice model. The reader should note that the ABM results are limited by the confidence inherent in the discrete choice model. For instance Que's strata conditional logit model has "percent" concordant[4] of 78.5% and the percent discordant and percent tied are decreased to 18.7 and 2.8, respectively (Que, 2015). Thus, the accuracy of the ABM is dependent on the accuracy of the Que's discrete choice model. In other words, the ABM cannot predict any better than this rate of success. The candidate did not attempt to validate the diffusion model because there is no data available in the literature to validate the results. However, there are many instances where diffusion models based on the Bass model have performed well in characterizing changing perceptions (Dodds, 1973; Wu et al., 2015).

[4] Concordance analysis is used to show the degree to which different measuring or rating techniques agree with each other (Kwiecien et al., 2011)

Table 3.6. Interpretation of Base Case Option Simulated in the Validation Experiment (Que, 2015)

Environmental variable	Interpretation
Job opportunities	*600 people employed directly by the mine*
Income increase	*+$300 per month*
Increase in housing cost	*5% increase every year in 10 years*
Labor shortage for other business	*Other businesses take longer to fill vacancies but don't have to pay more*
Noise pollution	*Same as similar mine in the area*
Water pollution and shortage	*Same as similar mine in the area*
Air pollution	*Same as similar mine in the area*
Land pollution and subsidence	*Same as similar mine in the area*
Population increase	*4% annually*
Infrastructure improvement	*Moderate improvement*
Traffic increase	*Same as current rate*
Crime increase	*Same as current rate*
Permit approval decision making mechanism	*Final decision by government agency after significant public input*
Availability of independent and transparent information on potential impacts of mine	*Information reported/verified by government agency*
Mine buffer (Home distance from mine)	*10 miles*
Mine life	*30 years*

The candidate recognizes that further work needs to be done to obtain empirical data to fully validate the model. Also, one could easily argue that the validation in this work simply verifies that the utility function, which is derived from Que's discrete choice model, has been properly incorporated into the model. The candidate believes this is not the case, since the stochastic aspects of the agent-based model do not necessarily rely on any input from Que's work. Regardless, however, the candidate believes further work is necessary to comprehensively validate the modeling framework.

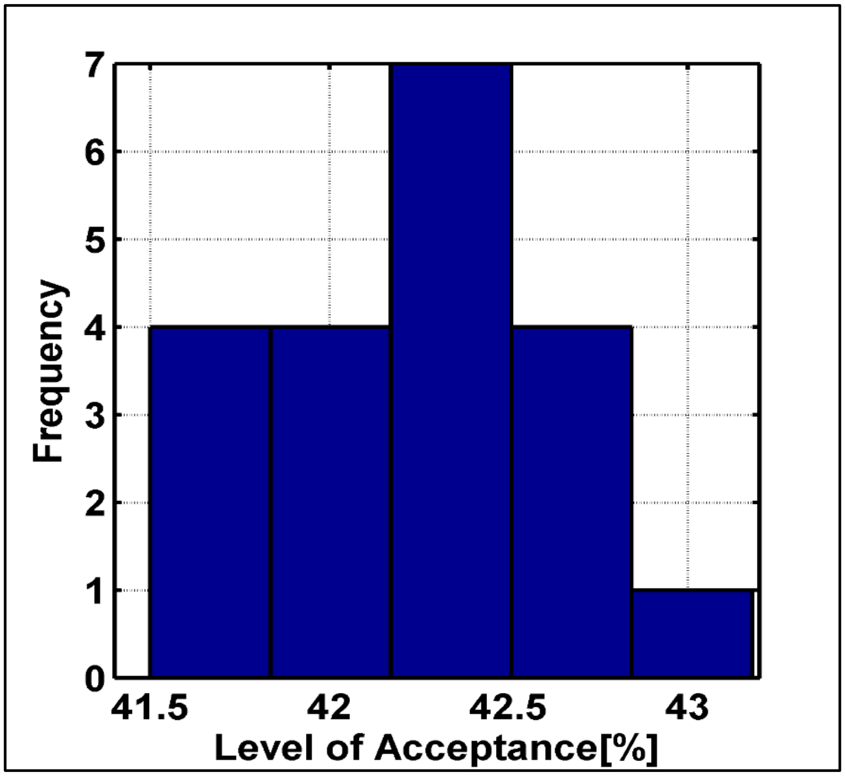

Figure 3.3. Validation Results. Mean and Standard Deviation of the Level of Acceptance was 42.4% and 0.66%, Respectively

.

3.4. CASE STUDY USING SALT LAKE CITY, UTAH, USA

- **Experiments**

The motivation for these experiments was to illustrate how to use the proposed framework to analyze how, in a given mining community, interactions between people, in the presence of changing perceptions of mine impacts, can influence acceptance of the mining project. The candidate ran simulations to evaluate how an improvement in residents' perception of the air pollution situation (this is a highly visible impact in Salt

Lake City as the particulate emissions are visible in the community) can influence their acceptance of the mining project. The air pollution situation is simulated to have improved by 1 on the scale used by Que (2015).[5] The use of relative scale to indicate a change in air pollution situation is appropriate since Que used relative scale in designing the discrete choice model, which provides data for this framework. However, this framework will still work regardless of any given discrete choice model. The initial condition used makes all agents living in a particular zip code the early adopters of the new perception of improvement in the air pollution issue.

The candidate used the same discrete choice model and input data in Tables 3.2, 3.3, 3.4, and 3.5 for these experiments. However, since these experiments involved a dynamic simulation of the effect of information diffusion across the social network, additional input data was required including death rates and a comprehensive age distribution. This age distribution is based on the demographics of Salt Lake City as shown in Table 3.7. Salt Lake City death distribution data for 2013 (Table 3.7) (National Center for Health Statistics, 2014) was also used to simulate agents' death.

In addition, the model requires the rate of communication ("time step" per interaction) as an input. The rate of communication in this context, is the time it takes for meaningful interaction between the agents on an issue probable. The candidate sets the rate of communication to 0.1 years (10 interactions on this subject per year). The candidate assumed this rate of interaction was reasonable to signify frequent interaction. For example, Friedman (2015) considers monthly meetings (12 meetings in a year) for two hours to be optimal to convene a wisdom circle involving members from the same

---

[5] This change means the perception of air pollution changes from "same as similar mine in the area" to "less than similar mine in the area."

neighborhood or part of the town. The rate of communication of 0.1 years was used for the initial experiment to represent the base case.

Table 3.7. Deaths Per 100,000 People by Age Group in Salt Lake City (National Center for Health Statistics, 2014)

Age group (years)[6]	Percentage in population	Number of deaths
0 to 17	22.6	47
18 to 24	13.4	99
25 to 34	20.2	218
35 to 54	24.4	667

The initial experiment only simulates the changing level of acceptance due to diffusion of the new perception over the social network over a four year period. The candidate assumes that this period is short enough to ensure the discrete choice model is still valid. This is a limitation of this work that needs to be explored with future work (i.e. how long is a discrete choice model valid for?).

Two additional experiments were carried out to demonstrate how the model responds to changes in average degree (average number of friends) and the time between meaningful interactions (rate of communication). In the rate of communication experiments, the candidate ran different simulations with the rate of communication taking values of 0.1, 0.2, 0.25 and 0.5 years. In the average number of friends experiment, the candidate varied the average number of friends from 30 to 60 in steps of 10. The goal was to investigate how a more connected network influences the spread of

[6] Age distribution data was obtained from 2009-2013 American Community Survey (American Community Survey, n.d.).

new information and its impact on level of acceptance. In both experiments, the candidate ran four-year simulations. The results of these experiments are discussed in the following sections.

3.5. RESULTS AND DISCUSSIONS

Figures 3.4, 3.5 and 3.6 show the results of the first experiment. The reader may note that the mean level of acceptance has increased from 42.4% in the validation experiment to 44.0% at time zero. This is anticipated because some of the agents adopted the improvement in the air pollution and changed their perceptions about the project and this increased the mean level of acceptance. Generally, the level of acceptance increases as more agents adopt the new perception (improved air pollution situation) over the period. The level of acceptance and the percentage of agents who changed their view of air pollution reach 100% before two and half years.

The results, as shown in Figures 3.4 and 3.5, follow an S-shaped curve, which is a behavior of the Bass model described in the literature. In the Bass model, agents are influenced by a desire to innovate (defined as coefficient of innovation) and by a need to imitate others in the population (coefficient of imitation). The “S” shape occurs under a condition where the ratio of the coefficient of imitation to coefficient of innovation is greater than one (Meade & Islam, 2006). In the model in this work, the ratio is infinite since all the adoption is from imitation (word-of-mouth only).Practically, the S-shaped curve implies a relatively long time to “takeoff” followed by rapid increases in adoption once takeoff has been attained and a slowdown phase as fewer and fewer agents remain to adopt the new information (Boyle, 2010; Mahajan et al., 1990).

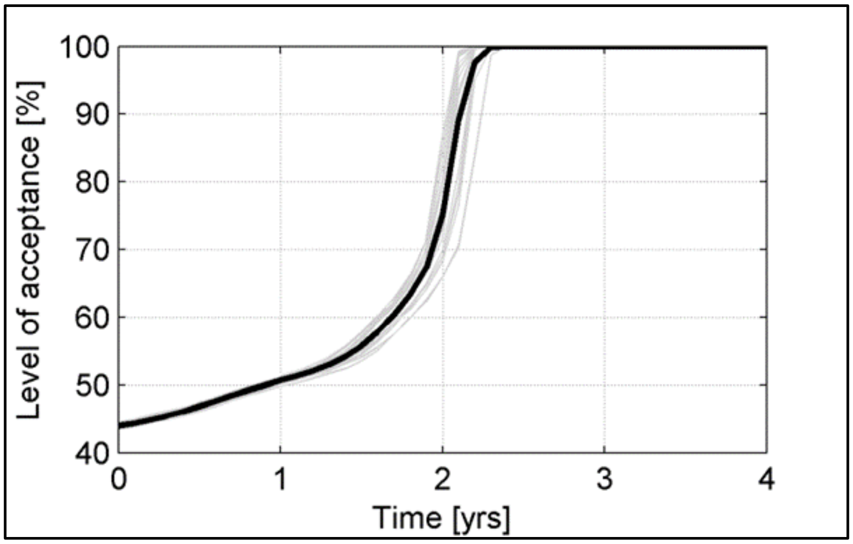

Figure 3.4. Simulation Results: Effect of Changing Perceptions of Improved Air Pollution Impact on Level of Acceptance; Grey Lines Represent Each Replication; Thick Black Line is the Mean

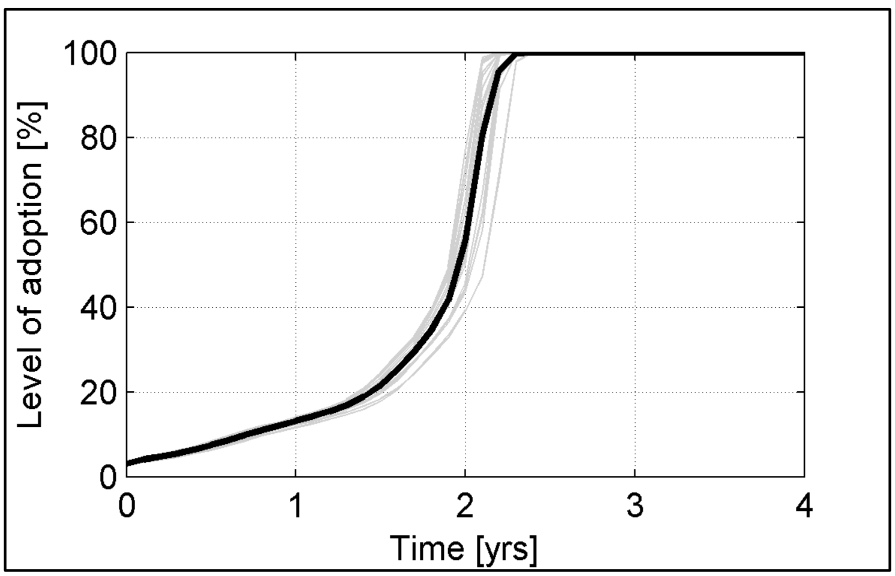

Figure 3.5. Simulation Results: Effect of Changing Perceptions of Improved Air Pollution Impact on Level of Information Diffusion; Grey Lines Represent Each Replication; Thick Black Line is the Mean

The rapid adoption shown in these results may not always be observed in such situations. The results of these simulation experiments are, in part, because the candidate simulated scenarios where adoption is through imitation resulting from unidirectional (i.e.

the model only allows interaction where the early adopters of the new perceptions convince agents who have not yet adopted to change their perceptions) word of mouth (Lilien et al., 2007). It is important to note that incorporating bidirectional word of mouth into the model would affect the results. Also, given different social networks (because of the diversity of host mining communities, e.g., small towns or cities, traditional societies or urban populations) would lead to different results. However, the candidate believes that the case study is a good illustrative example of the framework presented in this research. To study particular dynamics, many other experiments are required to explore the full parameter space to more comprehensively understand the system behavior.

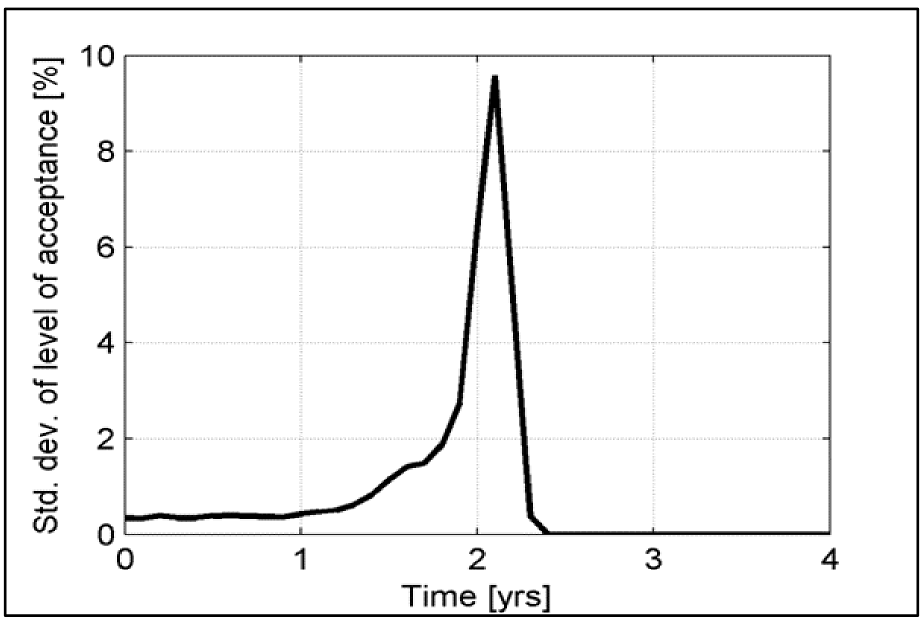

Figure 3.6.Simulation Results: Effect of Changing Perceptions of Improved Air Pollution Impact on Level of Acceptance; Standard Deviation of Level of Acceptance

In this model, the initial slow build up is the result of the fact that very few agents have adopted the new perception of air pollution at this stage of the simulation.

Consequently, most of the potential adopters of this new perception have no neighbor who has the new perception and zero chance of changing their own perception (Figure 3.2) at this stage. Once critical proportions of agents have adopted the new perception, rapid social contagion ensues as the probability is higher that each agent has at least one neighbor with the new perception and therefore some probability of adopting the new perception. The point of inflection, which symbolizes the "takeoff" point is the crucial point in the diffusion process (Laciana et al., 2013). This appears to occur around the point where 20% of the agents have adopted, in the simulated social network. The time it takes to reach this critical stage, is an important simulation output for managers and other stakeholders interested in how changing perceptions of sustainability affects a mine's social license to operate.

Figures 3.4 and 3.5 confirm that the level of acceptance of the mining project is driven primarily by the perception of air pollution impacts. The mean level of acceptance curve follows the same trend as the mean level of adoption of the new perception. The other simulated mechanisms (ageing, maturity of younger agents and death of older agents) have relatively little impact on the level of acceptance. This is consistent with the discrete choice model used as the utility function in two ways. First, the coefficients of the non-demographic factors are much higher than those of the demographic factors. For example, the coefficients for air pollution impacts and age are -1.8216 and 0.0028, respectively. Hence, a unit change in an agent's age (say moving from the 18 to 24 years age group to the 25 to 34 years age group) will increase the odds ratio by a factor of 1.0028 $(e^{0.0028})$. On the contrary, if the same agent were to change its perception of air pollution from 2 to 1 (as simulated here), its odds ratio would increase by a factor of 6.18

$(e^{1.8216})$ (see Equation 3-2). Thus, changing opinions about the mine's impacts will have much more significant effects on level of acceptance (and social license to operate) than changing demographics, in this case. Second, changes in demographics as a result of new entrants into the decision pool (young agents turning 18) and death of older agents (higher probability of death –Table 3.7) have negligible effects on the level of acceptance since it only affects the age of the agents in the decision pool. As discussed here, age is not as important as perception of sustainability impacts. However, this observation cannot be generalized without further evidence that a community's views on impacts are more important explanatory variables than demographic variables.

It is also important to note that the different replications differ the most during the "rapid adoption" phase of the simulation (Figure 3.5).The uncertainty in the diffusion process at this stage manifests as uncertainty in the level of acceptance (Figure 3.4). Figure 3.6 illustrates the evolution of uncertainty surrounding the mean acceptance as the simulation proceeds, using the standard deviation of the level of acceptance. The increased uncertainty during the rapid adoption phase is due to the many possibilities available for the information to diffuse through the network. This higher uncertainty also affects the onset of the rapid adoption phase, which is a critical parameter. For example, using 20% as the critical point for "takeoff," the higher uncertainty implies that after 1.5 years (corresponding to a mean level of adoption of 20%), the standard deviation of the level of acceptance is 9.58%. Also, for the 20 replications, the level of acceptance after 1.5 years varies from 55.8% to 57.9%.

The results from the rate of communication experiments are shown in Figures 3.7 and 3.8. The results show, as expected, that over the 4-year simulation period, there is an increase in level of acceptance as the proportions of agents that have the improved view of air pollution increase with time for all rates of communication. However, also as expected, the rate at which the new perception diffuses through the community is lower with rate of communications of greater interval. This trend is reflected in the rate of increase in the level of acceptance, as well. For example, the simulation with rate of communication of 0.1 years resulted in 100% of the agents, on average, adopting the improved view of air pollution (consequently, the mean level of acceptance of 100%) before 2.5 years. However, for rate of communication of 0.2 years, only 15% of the agents, on average, adopt the improved view of air pollution (the corresponding mean level of acceptance is 53%) at the end of 2.5 years. As explained in the previous section, the rate of communication defines the time it takes for meaningful interaction between the agents on the issue (in this case, air pollution), probable. Increasing the time between interactions (decreasing the rate of communication) means less communication between agents on this issue, which will ultimately affect the rate at which the new perception spreads. This will eventually affect how quickly the level of acceptance changes. The rate at which new information is adopted is proportional to the number of meaningful interactions between adopters and potential adopters (Midgley, 1976). This implies that mining community engagement that facilitates discussion of the issue in the local community may speed up changes in perception and level of acceptance in the presence of new information. More importantly, the rate of communication is a key driver of rate of change. Hence mines that can drive communication about positive attributes will increase the level of acceptance at a higher rate.

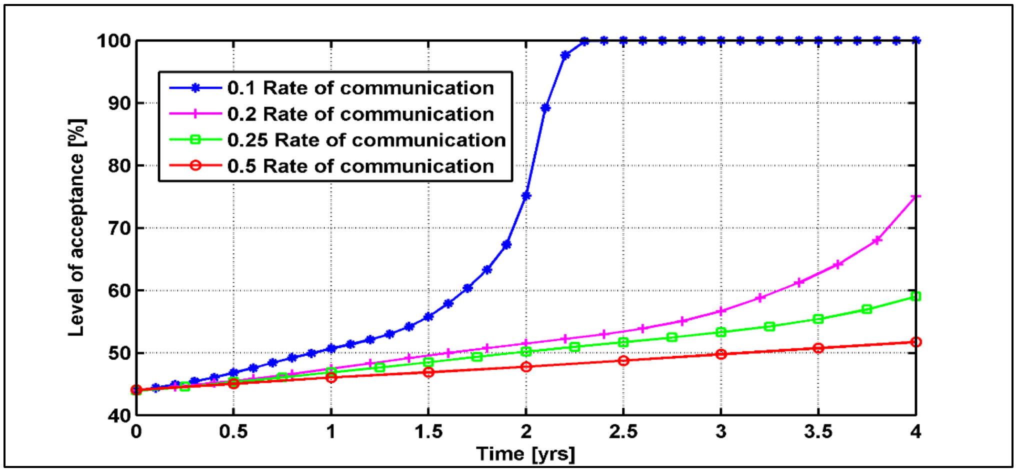

Figure 3.7. Effect of Varying Rate of Communication on Level of Acceptance

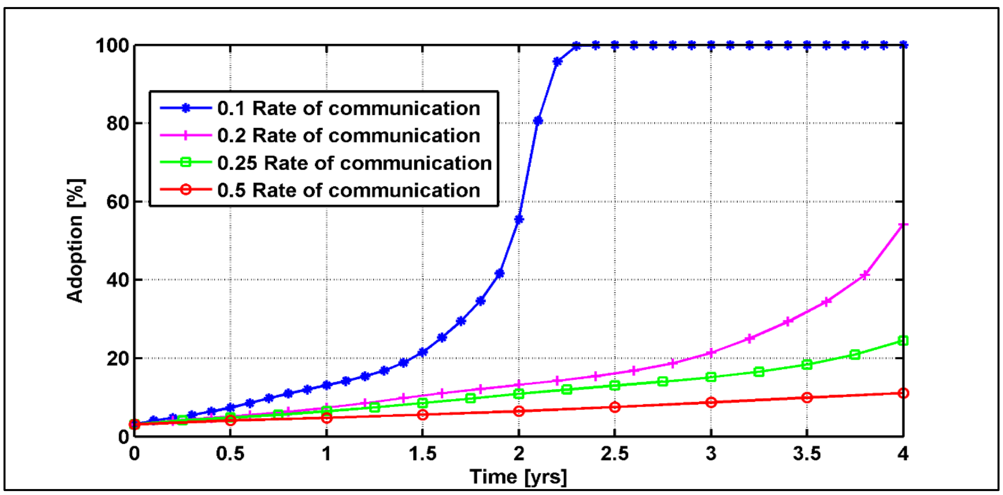

Figure 3.8. Effect of Varying Rate of Communication on Adoption of New Perceptions

Figures 3.9 and 3.10 present simulation results from the average number of friends experiments. The results indicate that the simulated networks with lower mean degrees (average number of agent's friends) have faster information diffusion and higher rates of change of mean level of acceptance. For example, for an average of 30 friends per agent, the ratio of agents, on average, who have adopted the new perception and mean level of acceptance reach 100% after the 23rd interaction while for an average of 60 friends per agent, 100% is reached after the 26th interaction. This is because with higher number of friends value to the agent, of adopting the new perception, *V*, for each friend who adopts is lower since the value depends on the ratio, rather than the number of friends (Equation 3-3). Hence, higher number of friends leads to slower rate of increase in adoption of the new perception past the takeoff point.

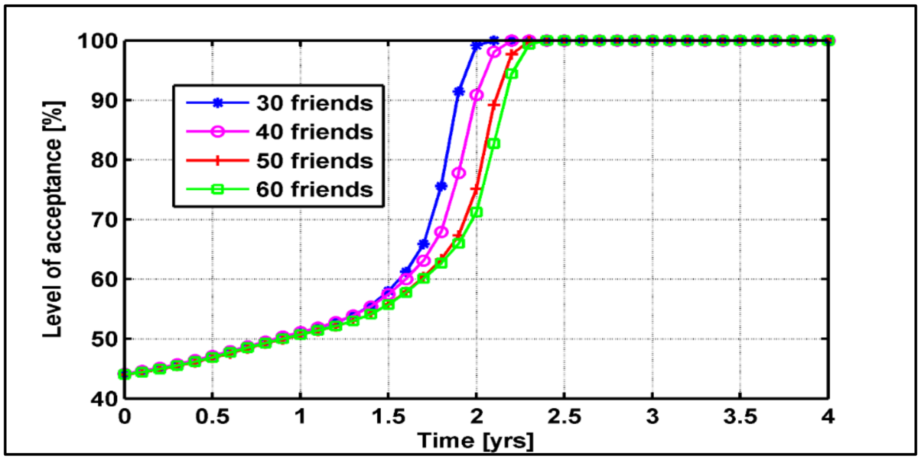

Figure 3.9. Effect of Varying Number of Friends on Level of Acceptance

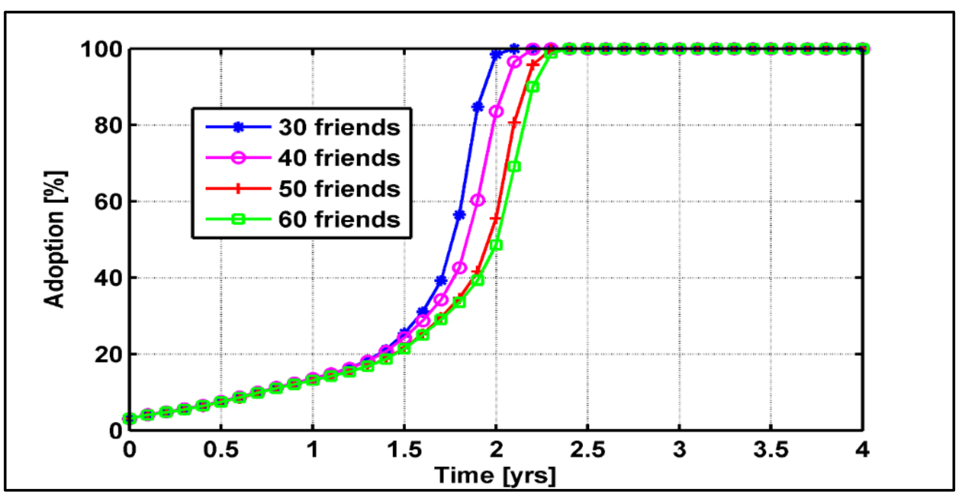

Figure 3.10. Effect of Varying Number of Friends on Adoption of New Perceptions

Nevertheless, the takeoff point still occurs approximately at the same time regardless of average number of friends. This shows that the time to takeoff is independent of the connectedness of the network (average degree). As explained earlier, prior to takeoff the adoption process is primarily driven by the small probabilities that exist just because an agent has at least one friend who has adopted the new perception. Rapid adoption begins when most agents have at least one friend who has adopted and the increased adoption rate is the result of higher and higher probabilities of adoption as the ratio of an agent's friends who have adopted increases. Hence, it is not surprising that the time to takeoff is not affected by the average number of friends.

- **Further Discussion**

As noted earlier, the work presented in this section attempts to provide a framework for mine managers and other stakeholders to anticipate changes that can occur in community acceptance over time due to changes in perceptions. These changing perceptions occur due to engineering design choices, changing community demographics, and environmental performance of the mine. This new method provides a tool to assess design alternatives and various scenarios to understand the associated risks and sustainability outcomes. Although the current model (and case study) has limitations, it illustrates a pathway for using ABM to assess potential effects of specific changes in perception on social license to operate. Specifically, this work shows that using an agent-based model like the one presented in this study with agent utility function derived from valid discrete choice models can be used to explore the interactions between information diffusion and community acceptance.

The model has some limitations that require future work including the fact that the: (1) social network used in this work is only assumed to be representative of the mining community and has not been observed in the community; (2) model does not account for different roles (e.g. active or passive, resistant or receptive, and innovators or followers) for individuals during information diffusion; and (3) model has not been fully validated with empirical data from a mining community or communities. Also, the model assumes that the analyst can isolate the "local community." The system is thus bounded to a particular community and assumes no significant interaction between individuals in the community under study and in other communities that can impact perceptions. Notwithstanding, the candidate believes the general framework presents a novel contribution that allows these limitations to be addressed in future work.

Readers should note that the case study results are, at best, applicable to the particular instance. The results do not represent, as far as the candidate knows, a general trend. In fact, the whole point of the framework presented in this section is to help stakeholders explore different scenarios to understand potential outcomes of changes in perception due to engineering design choices, changing community demographics, and the environmental performance of the mine so as to incorporate those possible outcomes into design, policy or government decisions. By incorporating appropriate utility function, social network model and other input parameters for a particular situation, an analyst is likely to generate results that differ from what is presented in this case study. However, those results will provide insights that are useful for decision-making in that context.

Additionally, the model and framework presented here can be applied beyond mining in such applications as oil and gas projects and other large scale engineering projects such as construction of fossil fuel power plants and hydro-electric power stations. The framework is applicable in situations where the project has a relatively long duration (e.g. more than five years), significant environmental and socio-economic impacts, and distinct phases (e.g. construction, operation and decommissioning) with different impacts.

3.6. SUMMARY OF THE SECTION

This section presents a framework for modeling the effect of information diffusion on dynamic community acceptance of mining using agent-based modeling (ABM). The model evaluates information diffusion due to word-of-mouth social contagion. A case study of mining activity in Salt Lake City, Utah, USA is used to illustrate the framework. The case study relies on discrete choice modeling by Que (2015) and simulates only unidirectional (from adopters to receptive agents) social contagion. The results show that changes in agents' perception of air pollution have a significant effect on acceptance of mining while demographic factors included in this case study (age, gender, income and education) do not have a significant effect. For the simulated social network, the onset of rapid social contagion (takeoff) appears to occur when about 20% of the agents in the network have adopted the new perception. However, once takeoff occurs, the rate at which information diffuses decreases with increase in average degree of the network. Finally, the rate of diffusion is proportional to the number of relevant agent’s interactions per unit time. Consequently, community engagement and other interventions that increase discussion of the issues around a mining project are likely to affect the rate at which information (on the positive or negative impacts of the mine) diffuses through the community and how that affects the mine's social license to operate. Essentially, the rate of communication is a key driver of the rate of change. Therefore, mines that can drive communication about positive attributes will more rapidly increase the level of acceptance.

The framework presented in this section can be used to understand the effect of information diffusion and social interactions on community acceptance. The framework can be applied to other resource extraction projects and to large engineering projects in general. Although, the case study uses a utility function that includes 20 demographic and non-demographic factors, the list of factors will necessarily be facts and circumstances determination. Besides the utility function, however, there are other aspects relevant to understanding the changes in community acceptance over time that are not accounted for in the current work. Those aspects include the role of the agents in the diffusion process (active or passive, resistant or receptive, and innovators or followers) and diversity of social networks, including those with hierarchies. These aspects can be incorporated into the model as part of future work. Finally, future work should attempt to validate the diffusion process and its effect on preferences for mining projects.

4. RESPONSIVENESS OF MINING COMMUNITY ACCEPTANCE MODEL TO KEY PARAMETER CHANGES

4.1. INTRODUCTION TO SENSITIVITY OF MINING COMMUNITY ACCEPTANCE MODEL

Section 3 focuses on application of agent-based modeling together with social network concepts to model changes in perceptions as a result of word-of-mouth. Similar work has been done by others (Sobkowicz, 2009; Suo & Chen, 2008). However, these agent-based models are responsive to several key input parameters such as network parameters, diffusion model parameters and initial conditions. In practice, acquiring these parameters can be cumbersome and expensive while estimating them based on assumptions can lead to uncertainties in the modeling results. In an attempt to understand the uncertainties surrounding the modeling results when estimates of these parameters are used in the model, researchers should ascertain the sensitivity of the model results to these parameters.

This section investigates the responsiveness of the agent-based model (ABM) presented in section 3 to key input parameters. The key input parameters explored in this study are average degree (number of friends), close neighbor ratio (a parameter used in the ABM to model homophily) and number of early adopters ("innovators"). The candidate used a two-level full factorial experiment to investigate the responsiveness of the model to these parameters (Saltelli & Annoni, 2010).

Sensitivity analysis is important to make informed decisions to balance the cost of studies to obtain accurate estimates of key parameters and the uncertainty related to estimates based on assumptions. The candidate is not aware of any work that evaluates the sensitivity of agent-based models of changes in community perceptions of large projects (including mining projects) due to changes in perception of environmental, social and economic impacts of the projects. This work contributes to further discussion of the uncertainties surrounding such ABM results and informs future research and models.

4.2. SENSITIVITY ANALYSIS OF MODELS

Sensitivity analysis of agent-based models is challenging because these models are non-linear, multi-level and have emergent properties (ten Broeke et al., 2016). Some of the approaches for performing sensitivity analysis in the literature are: one-factor-at-a-time (OAT), local and global sensitivity analysis (Saltelli & Annoni, 2010; ten Broeke et al., 2016; Thiele et al., 2014). Several researchers have discussed the differences and applications of these sensitivity analysis approaches. Below are some of the differences and applications of these sensitivity analysis approaches as discussed by Saltelli & Annoni (2010):

One-factor-at-a-time (OAT) approach is the most popular sensitivity analysis practice. This consists of analyzing the effect of varying one model input factor at a time while keeping all other constant. However, sensitivity analysis approaches should ideally be able to deal with a model irrespective of assumptions about a model's linearity and additivity, taking into account interaction effects among input uncertainties, and evaluate the effect of an input while all other inputs are made to change as well. OAT application is based on assumptions of model linearity, which appear unjustified in reviewed cases. Thus, OAT approach is applicable so long as the model is linear and non-additive. Also OAT cannot detect interactions among factors because such identification is predicated on the simultaneous movement of more than one factor. The insufficiency of OAT is not limited to sensitivity analysis, e.g. to the quest for the most influential model input factors, but to uncertainty analysis as well. Basic statistics about the model output (inference), such as its maximum, or mode, can be totally misinterpreted through OAT.

On the other hand, *local sensitivity analysis* is sensitivity analysis where the importance of the factors is investigated by derivative (of various order) of the output with respect to that factor. The term ‘local’ refers to the fact that all derivatives are taken at a single point, known as ‘baseline’ or ‘nominal value’ point, in the hyperspace of the input factors. For example, in approximating a model output in the neighborhood of a set of pre-established boundary conditions, it may not be necessary to average information over the entire parameter space and local approaches around the nominal values can still be informative. In principle, local analyses cannot be applied for the robustness of model based inference except the model is verified to be linear (for the case of first order derivatives) or at least additive (for the case of higher and cross order derivatives). In other words, derivatives are informative at the base point where they are computed, but do not provide for an exploration of the rest of the space of the input factors unless some conditions (such as linearity or additivity) are satisfied.

With *global sensitivity analysis*, a neighborhood of alternative assumptions is chosen and the corresponding interval of inferences is identified. Conclusions are judged to be sturdy only if the neighborhood of assumptions is extensive enough to be credible and the corresponding interval of inferences is narrow enough to be useful. This method of analysis indicates that even varying the input assumptions within some plausible ranges some desired inference holds. Saltelli et al (2004) report that a global sensitivity measure must be able to appreciate the so-called interaction effect, which is especially significant for non-linear, non-additive models. Also, global sensitivity analysis permits the identification of the elements and groups characterizing the interaction structure, but not the topological configuration of that structure.

In agent-based modeling, the interactions between the agents are non-linear (Scholl, 2001; ten Broeke et al., 2016). For this reason, global sensitivity analysis, which relies on statistical theory is the most appropriate for ABM (Saltelli et al., 2008; Saltelli & Annoni, 2010) .

4.3. SENSITIVITY ANALYSIS OF THE ABM

The main objective of this section is to evaluate the responsiveness of the model discussed in section 3 to key input parameters. In order to select these key input parameters, the candidate initially conducted screening experiments on all the ABM parameters to analyze how these input parameters respond to the model output (level of acceptance). The results from the screening experiments show that changes in the number of friends, close neighbor ratio, and number of early adopters have significant effects on the results of the ABM model. Hence, the motivation to carry out the sensitivity analysis on these key input parameters.

Given that the level of acceptance, which is the output varies as the simulation continues, a time-based sensitivity analysis is appropriate (Ligmann-Zielinska & Sun, 2010). In such an approach, the output at each time step is treated as a separate output and sensitivity indices are estimated for each *output*. To estimate the effect of changes in the input on the output, the candidate used a design of experiments method employed by other researchers in the literature (Anderson & Whitcomb, 2015; Saltelli & Annoni, 2010). The candidate designed a two level full factorial experiment for the three parameters. Table 4.1 shows the factors and their levels used in the experiment.

Table 4.1. Values of Levels of the Key Factors (Parameters)

Factor	Level	Value	Reference
Number of friends (A)	0	30 friends	(Hill & Dunbar, 2002; Zhou et al., 2005)
	1	50 friends	
Close neighbor ratio (B)	0	0.55	Based on reasonable assumptions and preliminary experiments
	1	0.75	
Number of early adopters (C)	0	35%	(Bass, 2004; Cho et al., 2012; Rizzo & Porfiri, 2016; Rogers, 2002) and reasonable assumptions
	1	69.4%	

As explained earlier, the literature has considered a group size of 30 to 50 individuals as a typical size of social group such as overnight camps or a band society (Hill & Dunbar, 2002; Zhou et al., 2005). This work used these numbers as the limits of what could be considered an influential group that the agent (individual) belongs to.

In the case of close neighbor ratio, the candidate set minimum value to 0.55 to ensure homophily and maximum value to 0.75 based on preliminary experiments (Figure 4.1). The ratio has to be greater than 0.5 to ensure higher probability of connections between "similar" agents as discussed in section 3.2.2. The candidate set a maximum value of 0.75 for close neighbor ratio by conducting screening experiments using 20,000 agents and 20 iterations, and keeping all the factors for the base case the same while varying the close neighbor ratio from 0.55 to 0.85 in the interval of 0.1. The preliminary experimental results indicate that beyond 0.75, the dynamic behavior of the mean level of acceptance changes (Figure 4.1). This is probably due to the extreme homophily modeled by 0.85, which likely leads to small-world networks.

Regarding number of early adopters in this work, 69.4% of the agents in a particular zip code where the information diffusion is initiated are considered innovators (“early adopters”). The 69.4% of agents in this zip code is equivalent to 2.5% of the total number of agents (total population) considered to be the number for innovators or “early adopter” according to literature. However, half of this percentage (i.e. 35% of agents in that particular zip code or 1.25% of the entire population) was assumed to be reasonably enough for the low level.

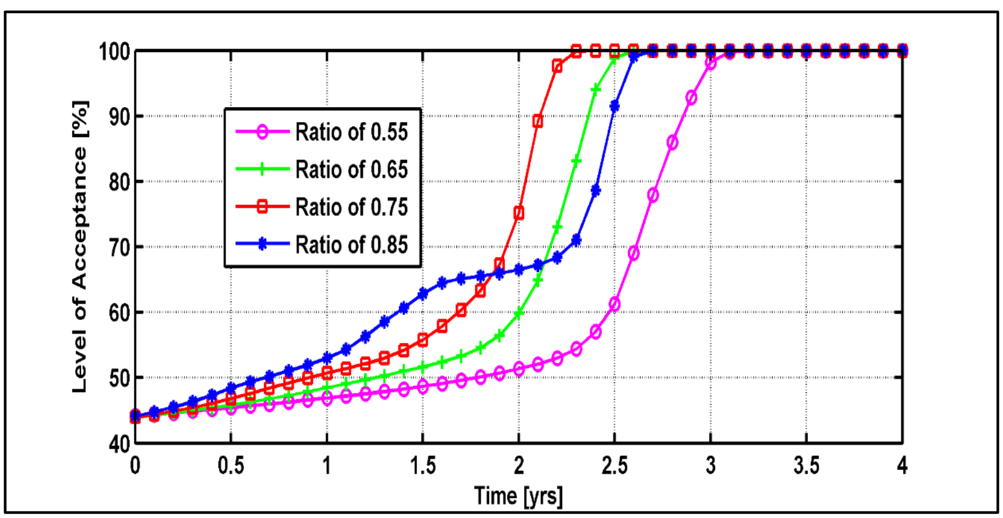

Figure 4.1. Effects of Varying Close Neighbor Ratio on Level of Acceptance

The experiment simulates all possible combinations of the factor levels (Table 4.2). From the output of these simulation runs, the primary (main), secondary and tertiary effects of each parameter can be estimated using well established approaches (Anderson & Whitcomb, 2015; Saltelli & Annoni, 2010). Assume, for example, that *Z* is the output (level of acceptance at a particular time instance) for given levels of the three factors (Table 4.1).

Also assume that Z^{F1} represents the output when a particular factor *F* is set to level 1 and Z^{F0} represents the output when the same factor is set to level 0. Similarly, let nF_1 and nF_0 represent the number of experiments where the factor is set to 1 and 0, respectively. Then Equation 4-1 can be used to estimate the main effect of factor *F*. Similar equations exist for estimating the secondary and tertiary effects of the factors (Anderson & Whitcomb, 2015). The secondary effects estimate the effect of interactions between two factors while the tertiary effects estimate the effect of interactions between three factors.

$$Eff(F) = \frac{\sum Z^{F1}}{nF^{1}} - \frac{\sum Z^{F0}}{nF^{0}} \tag{4-1}$$

Although, the estimates of primary, secondary and tertiary effects can result in positive and negative numbers (Equation 4-1), the results only show the absolute values of these estimates to facilitate easy comparison of the scale of the effects. The results of the sensitivity analysis are discussed in the next section.

Table 4.2. Combinations of Factors in Full Factorial Design

Exp. #	Level
1	(0,0,0)
2	(1,0,0)
3	(0,1,0)
4	(1,1,0)
5	(0,0,1)
6	(1,0,1)
7	(0,1,1)
8	(1,1,1)

4.4. RESULTS AND DISCUSSIONS

The results of the sensitivity analysis are shown in Figures 4.2 and 4.3. Figure 4.2 shows the level of acceptance for all the experiments while Figure 4.3 shows the estimated effects from the results in Figure 4.2. The reader should note that points in Figure 4.3 where a particular effect "pinches" out indicate a transition from negative to positive or positive to negative effects (the plot shows absolute values of the estimated effects). The total estimated effects (sensitivity metrics) gradually rise from almost zero at the beginning of the simulation to a maximum, just over 100, at 2.9 years. Subsequently, the uncertainty decreases slightly and stays near constant for the rest of the simulation. The level of acceptance (the output of the model) is near constant at the beginning of the simulation for all the experiments (Figure 4.2). Hence, the model output is not sensitive to the three factors. However, as the simulation proceeds, the effect of the three investigated factors on the output increases over time. This is because the level of acceptance over time, which is a function of agent's interaction and information diffusion, is affected by the three factors. In particular, as shown in Figure 4.2, the onset and duration of the rapid adoption phase varies among the experiments in these experiments, depending on the input values for the three factors. The sensitivity results in Figure 4.3 follow a similar trend (i.e. the three factors have the most effect during the period between 1.5 to 3.5 years). After 3.5 years, however, with the exception of the first two experiments (Table 4.2), all the simulations have a constant level of acceptance (100%) as the entire community has adopted the new perception. This is what causes the reduction in the estimated effects and, thus, the model sensitivity to the three factors.

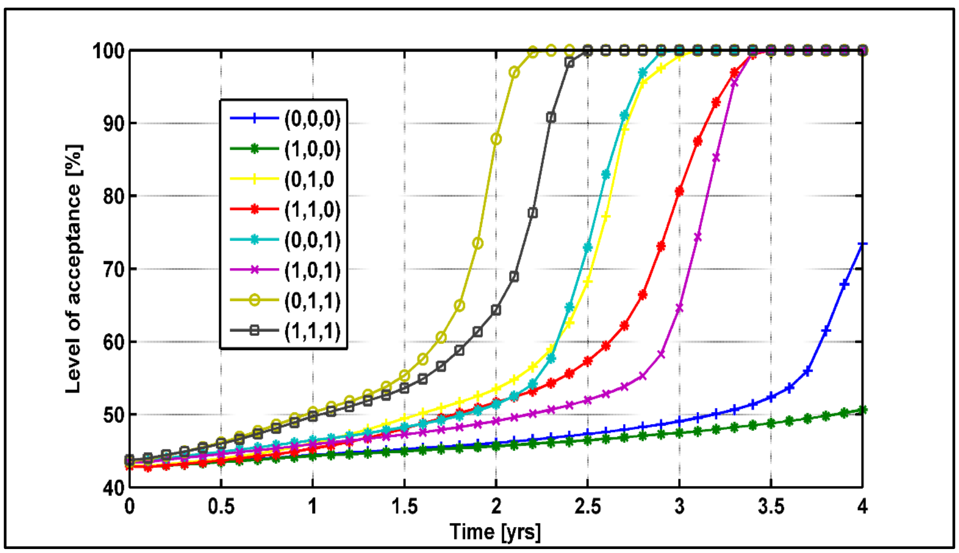

Figure 4.2. Simulation Results for the Full Factorial Experiment

From Figure 4.3, one observes that *close neighbor ratio* (B) and *number of early adopters* (C) are relatively more significant factors than *number of friends* (A). The main effects of close neighbor ratio and number of early adopters are significant contributors to the total sensitivity of the level of acceptance to the three factors. Additionally, the interaction of these two factors is more significant compared to any other interaction, including interactions of all the three factors. This means the model's prediction of the level of acceptance is more sensitive to changes in close neighbor ratio and number of early adopters than to changes in number of friends. It is particularly important to note that, of the two network parameters, one (close neighbor ratio) is much more significant than the other (number of friends).

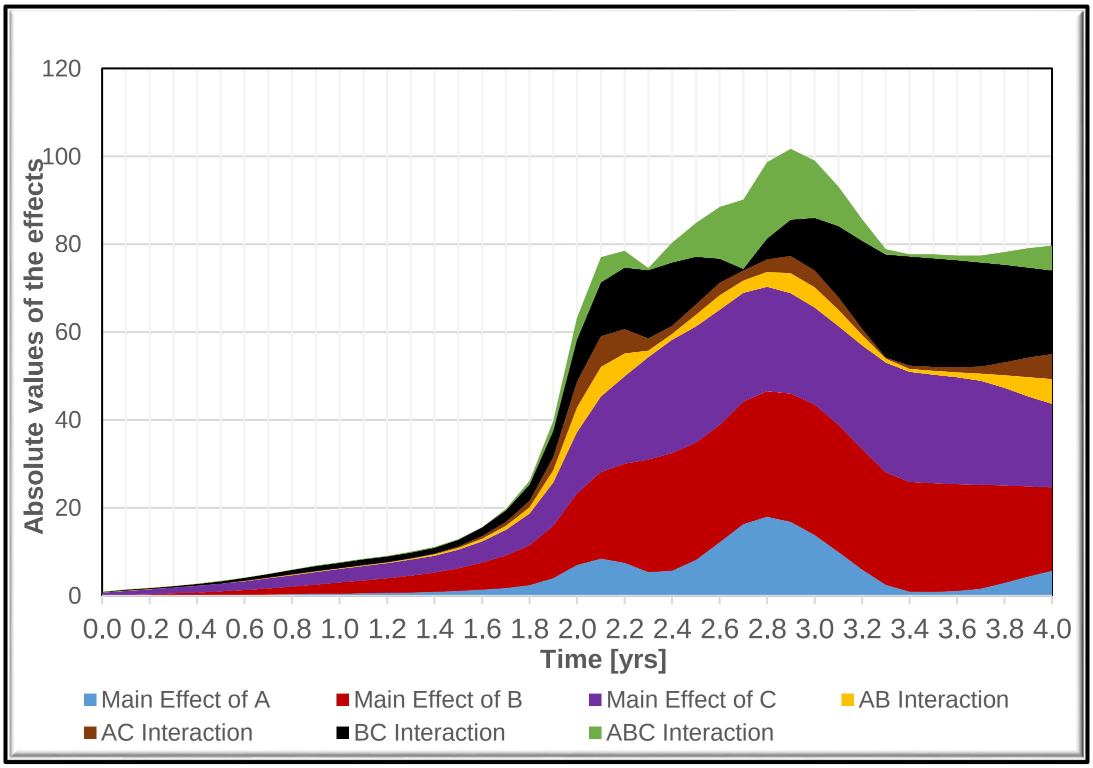

Figure 4.3. Main Effects and Interactions of All the Factors

This is because close neighbor ratio, which is used to model homophily in the social network, influences the degree of clustering in the social network. It is known that innovations (a perception of improved air pollution, in this case) diffuse quicker in more clustered networks than in random networks due to individual's exposure to more social influence (Kiesling et al., 2012). The candidate confirmed the relationship between close neighbor ratio and clustering by analyzing the clustering coefficients of simulated networks with different close neighbor ratios using open-source MatLab routines for network analysis (Bounova & de Weck, 2012). In this analysis, the candidate estimated clustering coefficients of networks simulated with the network algorithm in this work using close neighbor ratios of 0.55, 0.65 and 0.75. The networks had 2,000 nodes (agents) and average degree (number of friends) of 50 to reduce the computational cost. The estimated mean clustering coefficients, for 10 networks each, were *0.0251, 0.0372* and *0.0536* for close neighbor ratios of 0.55, 0.65 and 0.75, respectively. The candidate confirmed that increasing close neighbor ratio leads to a more clustered network. As the network becomes more clustered, diffusion as a result of social influence occurs at a faster rate, which increases level of acceptance.

On the other hand, the number of friends (average number of agent's friends) affects the diffusion process in two ways. First, the higher the number of friends for an agent, the higher the probability that it is connected to some other agent who has already adopted the new perception. Second, the higher the number of friends, the lower the effect of each single connected agent in influencing the agent's decision to adopt the new perception (Equation 3.4 in section 3.2.3), which slows down diffusion. The combined effect of these two mechanisms on the diffusion process appears to result in the model's lower sensitivity to the average number of friends than to the close neighbor ratio (within the ranges of the two factors).

Unlike the two network parameters, the number of early adopters (innovators) is an initial condition for the simulation. The number of early adopters plays a role analogous to gatekeeping in launching a new idea (Rogers, 1995). The "new idea" here is the change in perception (in this case, improvement in the air pollution impact). Basically, innovators are more influential at the beginning of the adoption process. Thus the model is, relatively, most sensitive to the number of early adopters at the beginning of the simulation. As the simulation progresses, the magnitude of the sensitivity index for number of early adopters increases but the overall contribution towards uncertainty is surpassed by the contribution of the close neighbor ratio (Figure 4.3).

The candidate investigated further the combined effects of *close neighbor ratio* and *number of early adopters* on the level of acceptance over time to clarify the relationship and effect on the output. The candidate conducted experiments with four different levels of *close neighbor ratio*, “B” and *number of early adopters* “C”. The inputs for close neighbor ratio were 0.60 to 0.75 with 0.05 step size, and that for number of early adopters were 40% to 55% with 5% step size. These input figures are within the limits of the ranges used in the sensitivity analysis and provide the best insight based on candidate’s observations. Table 4.3 shows the 16 experimental runs for all possible combinations of the factor levels, which were set to 1 to 4 in order of increasing values. The results of these experiments (Figure 4.4) show that the level of acceptance increases as the close number ratio increases with a given number of early adopters.

Figure 4.4 shows how the two factors affect level of acceptance over time. It shows that as the close neighbor ratio (thus homophily) increases, the rate of adoption is faster leading to a faster rise in the level of acceptance. The candidate examined the interaction between the two factors and the level of acceptance at each of the 41 time steps. The reader can observe a wide range of effects ranging from no change in level of acceptance with changes in the two factors at time $t = 0$, to wide variation in level of acceptance during the rapid adoption phase to reduced level of variation towards the end of the simulation where most replications have 100% level of acceptance.

Table 4.3. Combinations of Factors for the Sensitivity Experiment

Experiment #	Level
1	1,1
2	1,2
3	1,3
4	1,4
5	2,1
6	2,2
7	2,3
8	2,4
9	3,1
10	3,2
11	3,3
12	3,4
13	4,1
14	4,2
15	4,3
16	4,4

Figures 4.5 and 4.6 show the level of acceptance at t = 2 years and t = 3.5 years respectively, which illustrate some of the observed trends. The candidate selected 2 and 3.5 years because within this time, the level of acceptance significantly varies with varying close neighbor ratio and number of early adopters. At t = 2 years, level of

acceptance increases as close neighbor ratio and number of early adopters increase (Figure 4.5). At t = 3.5 years, the relation is a bit more nuanced. Though the level of acceptance increases as *close neighbor ratio* and *number of early adopters* increase, with *numbers of early adopters* set at 50% and 55%, level of acceptance by 3.5 years in the simulation is approximately 100% regardless of the *close neighbor ratio*. Hence, the sensitivity of the output in later years is diminished when the combined effect of the two variables significantly increases the rate of information diffusion and, thus, the rate at which the level of acceptance increases.

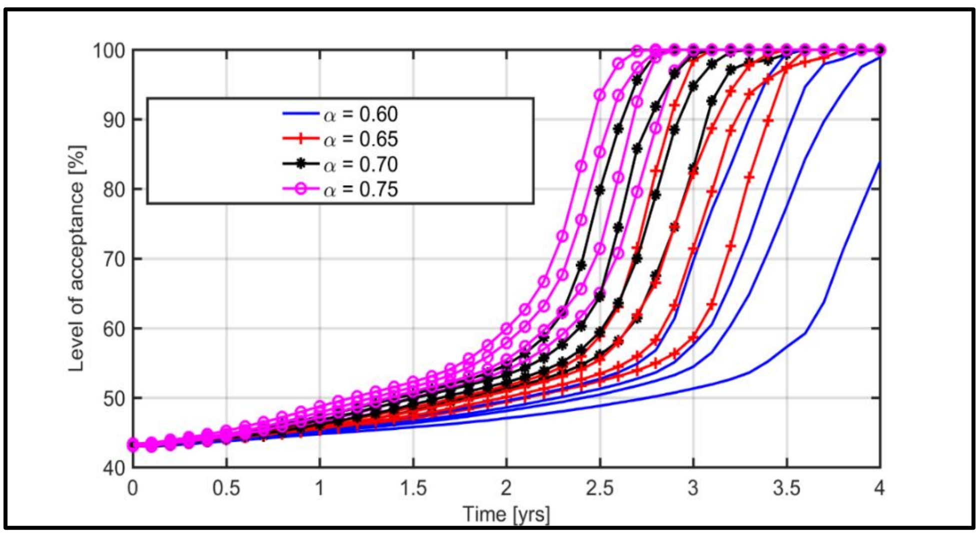

Figure 4.4. Combined Effects of Close Neighbor Ratio and Number of Early Adopters on Level of Acceptance

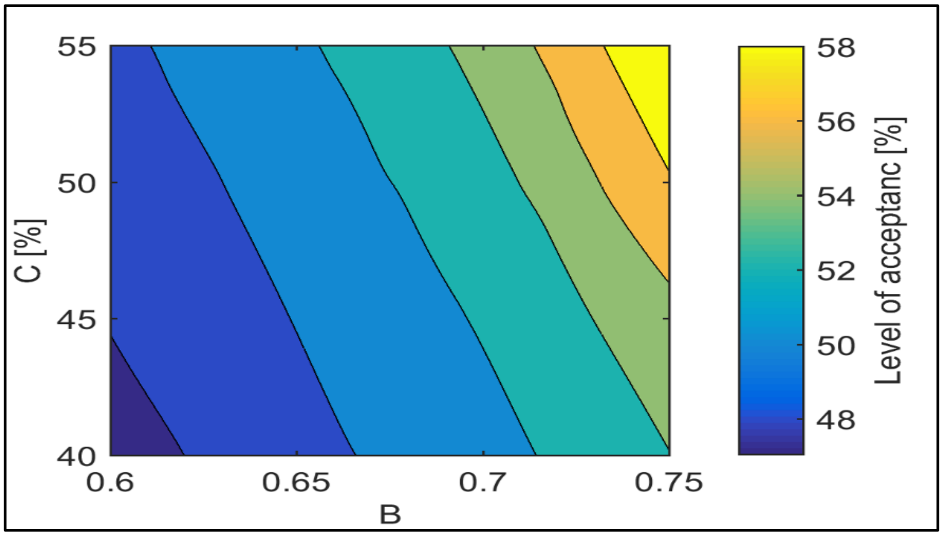

Figure 4.5. Effect of Close Number Ratio (B) and Number of Early Adopters (C) on Level of Acceptance (%): t = 2 Years

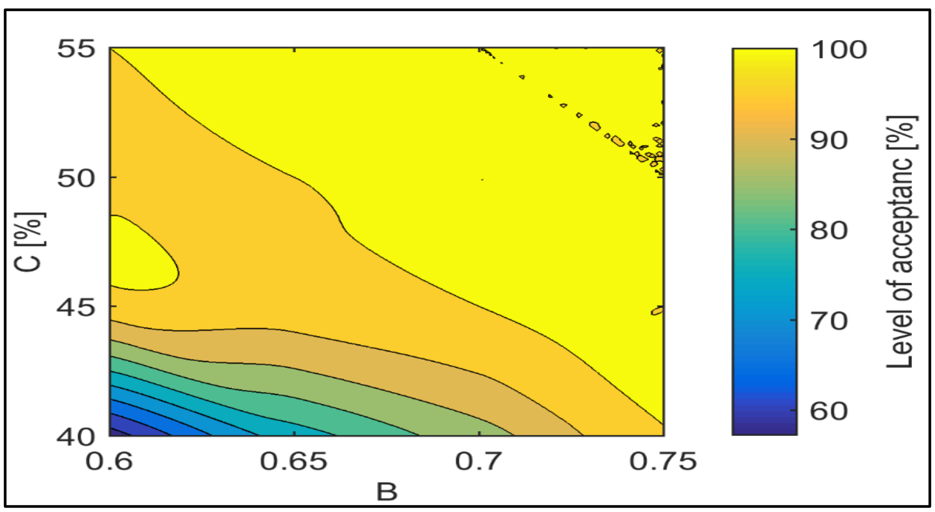

Figure 4.6. Effect of Close Number Ratio (B) and Number of Early Adopters (C) on Level of Acceptance (%): t = 3.5 Years

When using this model to understand the effect of information diffusion on changes in the level of community acceptance of mining, critical attention should be paid to the degree of homophily in the social network (close neighbor ratio) and number of early adopters (initial condition). The model is very sensitive to these factors and the reliability of the results depends on the accuracy of the estimates of these important input variables. It is therefore advisable that mine managers consider the costs and benefits of acquiring data to estimate these key parameters accurately so as to minimize uncertainties around their conclusions.

The information and estimates of number of early adopters are well documented in the literature (Bass, 2004; Cho et al., 2012; Rizzo & Porfiri, 2016; Rogers, 2002). However, the information and estimates concerning the network parameters (number of friends and close neighbor ratio) can be obtained reliably only through a survey. For instance, during community engagement, individuals in the local mining community can be interviewed to document the people they are likely to discuss the relevant issue (relating to this mine) who are likely to affect their perceptions of the mine. Additional questions relating to the residence of those individuals would allow researchers to document the degree to which the type of homophily modeled in this work exists in the community. This will guide mine managers to estimate the number of friends and close neighbor ratio. Nonetheless, such a survey could be expensive, time consuming, and present difficulties in obtaining a good representative sample and reliable responses. Further research should focus on economic and reliable means of estimating these important input variables.

As previously discussed, the ABM in this study attempts to provide a framework for mine managers and other stakeholders to anticipate changes that can happen in community acceptance due to changes in opinions. These changing opinions occur due to changes in the society and individual perceptions about these mines because of the mines' environmental and social impacts. Hence, agent based models built based on this framework can be used by stakeholders to evaluate different scenarios and explore the likely effects of these scenarios in order to incorporate them into design, policy or government decisions. The results of the sensitivity analysis in this work will help stakeholders identify the key parameters of the model that contribute to uncertainty in the model output. This will guide modelers and decision makers on where to expend resources in order to obtain more reliable results.

As already stated, the ABM model presented in this research can be useful beyond mining as it is applicable to other fields including oil and gas and other large scale engineering projects such as construction of power stations. The framework can be applied in cases where the project has a relatively long duration (e.g. more than five years), substantial environmental and socio-economic impacts, and different stages (e.g. construction, operation and decommissioning) with diverse impacts.

4.5. SUMMARY OF THE SECTION

This section investigates the responsiveness of mining community acceptance model, presented in section 3 to key parameter changes. The parameters investigated were average degree (average number of friends) of the social network, close neighbor ratio (a measure of homophily in the social network) and number of early adopters ("innovators"). The results indicate that the model is relatively more responsive to close neighbor ratio (homophily) and number of early adopters than average degree (number of friends). Therefore, the candidate recommends that mine managers using this model to understand the effect of word-of-mouth information diffusion on the level of community acceptance of their projects pay particular attention to the estimates of close neighbor ratio and number of early adopters. This will minimize the uncertainty surrounding the inferences they draw from their simulation experiments. The literature on early adopters is mature and offers a reliable means to estimate the range of the number of early adopters. This is not the case for the social networks in mining communities, and that it will require more effort to reliably estimate the extent of homophily in the social networks. The candidate recommends that future work addresses approaches to adequately characterize this, given its importance.

The proposed ABM framework will assist stakeholders to understand the effects of various scenarios on the rate of change of community acceptance so that they can incorporate them into design, policy or government decisions. The sensitivity analysis results have identified the ABM's key parameters and how they affect the model output. This provides a useful guide for modelers and decision markers to determine how to spend scarce resources to improve the uncertainty of the results.

5. EFFECT OF SOCIAL NETWORKS ON INFORMATION DIFFUSION AND COMMUNITY ACCEPTANCE

5.1. INTRODUCTION TO EFFECT OF SOCIAL NETWORKS ON COMMUNITY ACCEPTANCE

Differences in social networks affect information diffusion in real and simulated societies (Suo & Chen, 2008). A person’s social network structure does not only constrain or enable current attitudes and practices but can also influence their ability to change their behavior in future (D' Andreta, 2011). Homophily, which is the principle that a contact between similar people happens at a higher rate than among dissimilar people (McPherson et al., 2001), is one of the most basic characteristics of social networks (Easley & Kleinberg, 2010). Early network studies indicated considerable homophily by demographic characteristics such as age, gender, race/ethnicity, and education and by psychological characteristics like intelligence, attitudes, and aspirations (McPherson et al., 2001). To the best of the candidate’s knowledge, there has been no work that explores the effect of homophily in social networks on agent-based models for understanding changes in community acceptance (of mining projects).

This section explores the effect of social network on the results of the agent-based model (ABM) presented in section 3. It investigates the effect of homophily on information diffusion and its effect on community acceptance over time. Specifically, this study examines how the model results are affected by three social networks; social network with homophily based on physical distance (propinquity) and social distance (social attributes), and social network without homophily (a random network). Also, this study discusses the linkage between these social networks and characteristic mining communities.

The results of this study would provide stakeholders with a better understanding of how the rate of change in project acceptance may differ from community to community due to differences in social networks. This will help stakeholders to make more informed decisions during project planning and design, and community engagement to facilitate gaining and maintaining social license to operate to promote mining project sustainability. In addition, this study contributes to further discussion of the uncertainty surrounding such ABM results, and informs future research and models.

5.2. INVESTIGATING SOCIAL NETWORKS

As stated earlier, the analysis in this section examined the effect of social networks with homophily based on propinquity and social distance (social attributes), and one without homophily on the ABM results. Social network with homophily based on propinquity, which was used as base case scenario for this research, was modeled as described in section 3.2.2.

The candidate modeled the social network with homophily based on social distance (social attributes) using the agent's social attributes (age, gender, education and income). To achieve an average degree (the number of agents connected to an agent) of d (d represents only an initial user-provided estimate for the average degree) in an agent network with N agents, the probability of a connection between each pair of agents has to be d/N. To model homophily based on social attributes, the network algorithm should adjust this probability to make it higher or lower for some pairs of agents depending on their similarity (Equation 5-1). As per Equation 4, the probability of a connection between agents i and j, p_{ij} is obtained by adjusting the average probability by a factor, μ_{ij} which is a mapping of the inverse of the degree of similarity between agents to the uniform distribution between 0.5 and 1.5 $\left\{\mu_{ij} : \left|\mathrm{a}_i - \mathrm{a}_j\right|^{-1} \to \text{unif}\left\{0.5, 1.5\right\}\right\}$, normalized by the average factor, $\overline{\mu}$. The degree to which agents are similar is established by the norm of the difference between their social attribute vectors $\left(\left|\mathrm{a}_i - \mathrm{a}_j\right|\right)$

$$P_{ij} = \frac{\hat{d}}{N} \frac{\mu_{ij}}{\overline{\mu}} \tag{5-1}$$

In the case of social network without homophily, the candidate used the open-source algorithm by Bounova & de Weck (2012) for a random directed graph. In this network, the probability of a connection between any pair of agents is the same.

The candidate ran three simulation experiments (one for each of the networks) of 20 iterations each using 20,000 agents and average degree of 50. Note that the modeled social networks do not explicitly incorporate transitive triples (the situation where a link between agents i and k, and j and k, means that there is higher probability of a link between i and j) because the candidate did not want to confound the results. Therefore, these social networks do not account for triadic interaction between agents (any such interaction is just coincidence). For initial conditions, the model randomly selects 4% and 5% of the entire agent population as early adopters for each simulation. This differs from the initial conditions in the experiments in section 3. In those experiments, the initial condition assumes all agents in a particular zip code were the initial adopters. This approach was reasonable when the network incorporated homophily due to physical distance. The initial conditions in this section are necessary to provide the same initial conditions for experiments with all three networks.

5.3. RESULTS AND DISCUSSIONS

Figures 5.1 and 5.2 show the experimental results. Figure 5.1 shows the level of acceptance over the simulation period for the various networks. The rate of change of level of acceptance remains almost the same for the three social networks at the beginning of the simulation. For instance, with 4% early adopters, the level of acceptance for the three networks was the same for approximately 2.5 years. After that, the network with homophily based on social attributes recorded the slowest rate of adoption (Figure 5.1), leading to lowest level of acceptance at the end of the simulation period. However, the other two networks (network with homophily based on propinquity, and network without homophily) virtually recorded the same level of acceptance throughout the simulation (Figure 5.2). Similarly, with 5% early adopters, there was no difference in the level of acceptance until just before 1.5 years. After that, the network with homophily based on social attributes reported the slowest rate of adoption (Figure 5.1) resulting in the lowest level of acceptance at the end of the simulation (Figure 5.2) while the network with homophily based on propinquity recorded the fastest rate of adoption followed by network with no homophily. The candidate observes that the initial adoption process leading to level of acceptance are the same for all the networks. As the adoption process continues, the connectivity of the agents is different for each of the social networks resulting in different evolutions for the level of adoption and acceptance. The different levels of adoption and acceptance can be due to differences in degree, degree distribution and clustering coefficients of the networks. This is because degree, degree distribution and clustering coefficients affect information diffusion processes (Buskens & Yamaguchi, 1999; Dover, 2011; Peres, 2014).

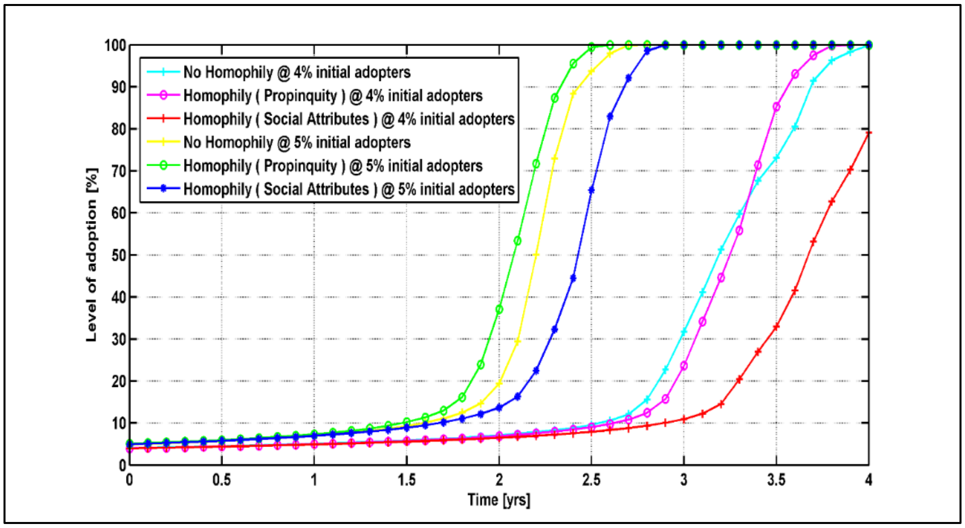

Figure 5.1. Effects of Changing Social Networks on Level of Adoption

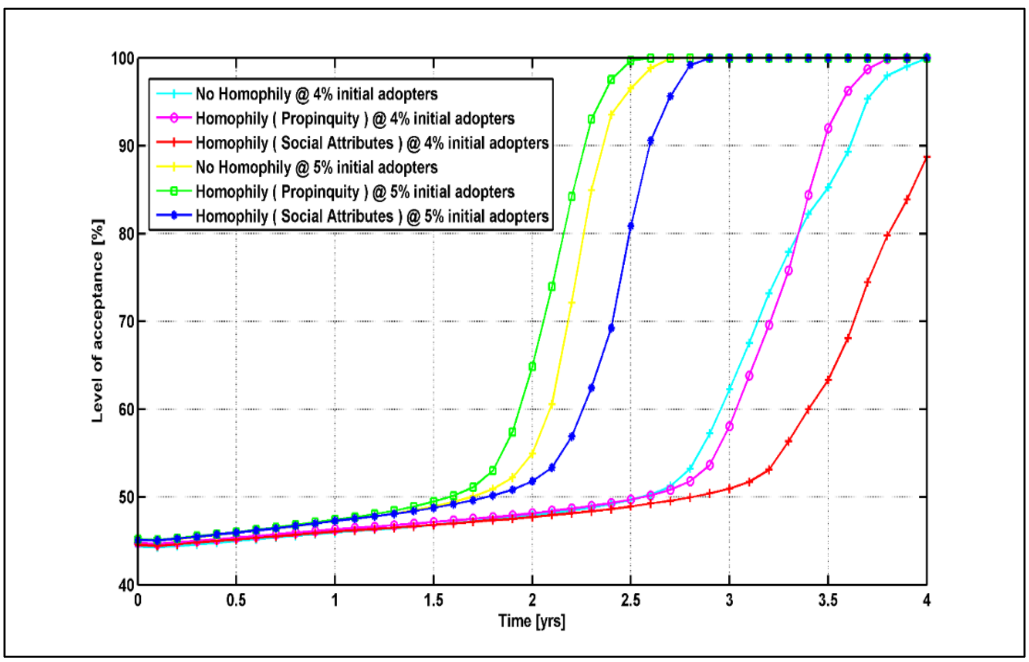

Figure 5.2. Effects of Changing Social Networks on Level of Acceptance

In order to understand why the three networks resulted in different diffusion rates, the candidate examined the differences in their degree distributions and their clustering coefficients using an experiment that extracted 10 networks. These networks consisted of

2,000 agents (nodes) and average degree (number of friends) of 50 to reduce the computational cost. The results of the experiment are shown in Table 5.1. From the results, the average degree and degree distributions of the networks were virtually the same as indicated in Table 5.1 and Figures 5.3, 5.4 and 5.5.

Table 5.1. Comparing Degree Distribution of the Various Social Networks

Network #	Type	Mean	Standard Deviation	Skewness
1	No Homophily	49.808	7.185	0.190
	Homophily by Propinquity	49.995	6.789	0.176
	Homophily by Social Attributes	50.260	6.974	0.142
2	No Homophily	49.981	6.943	0.111
	Homophily by Propinquity	50.024	6.744	0.184
	Homophily by Social Attributes	50.663	7.009	0.128
3	No Homophily	49.973	6.995	0.098
	Homophily by Propinquity	49.984	6.802	0.174
	Homophily by Social Attributes	49.900	6.686	0.106
4	No Homophily	50.181	6.971	0.137
	Homophily by Propinquity	50.205	6.810	0.116
	Homophily by Social Attributes	49.860	7.014	0.156
5	No Homophily	50.106	6.858	0.101
	Homophily by Propinquity	49.844	6.734	0.128
	Homophily by Social Attributes	50.210	7.034	0.072
6	No Homophily	50.111	6.865	0.076
	Homophily by Propinquity	50.067	6.679	0.194
	Homophily by Social Attributes	49.713	6.893	-0.024

Table 5.1. Comparing Degree Distribution of the Various Social Networks (cont.)

Network #	Type	Mean	Standard Deviation	Skewness
7	No Homophily	49.779	6.988	0.143
	Homophily by Propinquity	50.215	6.711	0.138
	Homophily by Social Attributes	49.659	6.919	0.192
8	No Homophily	49.908	6.958	0.178
	Homophily by Propinquity	49.972	6.911	0.115
	Homophily by Social Attributes	49.769	6.871	0.126
9	No Homophily	49.928	7.083	0.149
	Homophily by Propinquity	50.192	6.870	0.220
	Homophily by Social Attributes	49.585	6.879	0.127
10	No Homophily	49.829	6.900	0.159
	Homophily by Propinquity	50.104	6.583	0.129
	Homophily by Social Attributes	49.815	6.936	0.119
Average	No Homophily	49.960	6.975	0.134
	Homophily by Propinquity	50.060	6.763	0.157
	Homophily by Social Attributes	49.943	6.921	0.114

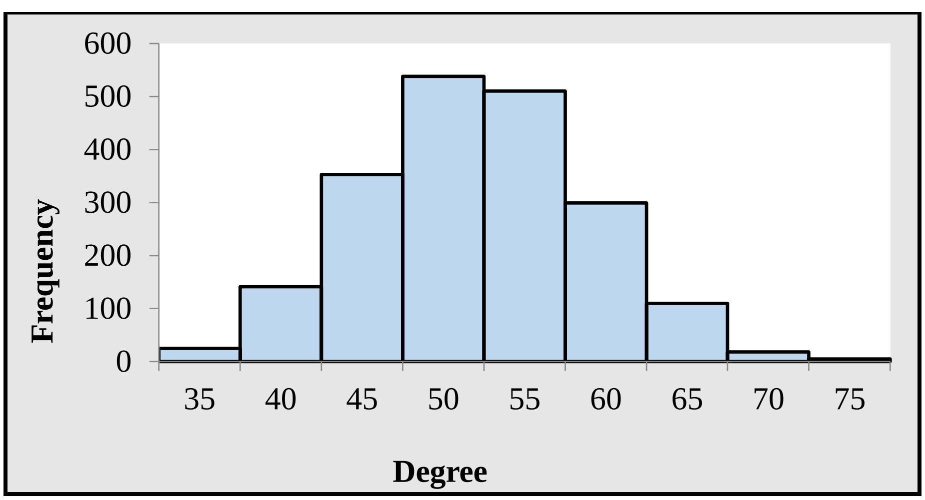

Figure 5.3. Degree Distribution in Sample Social Network with no Homophily

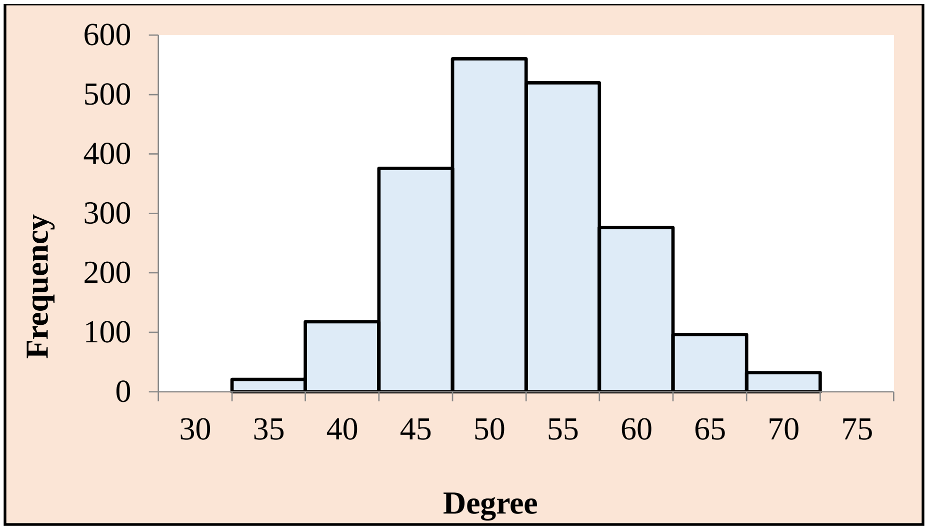

Figure 5.4. Degree Distribution in Sample Social Network with Homophily Based on Propinquity

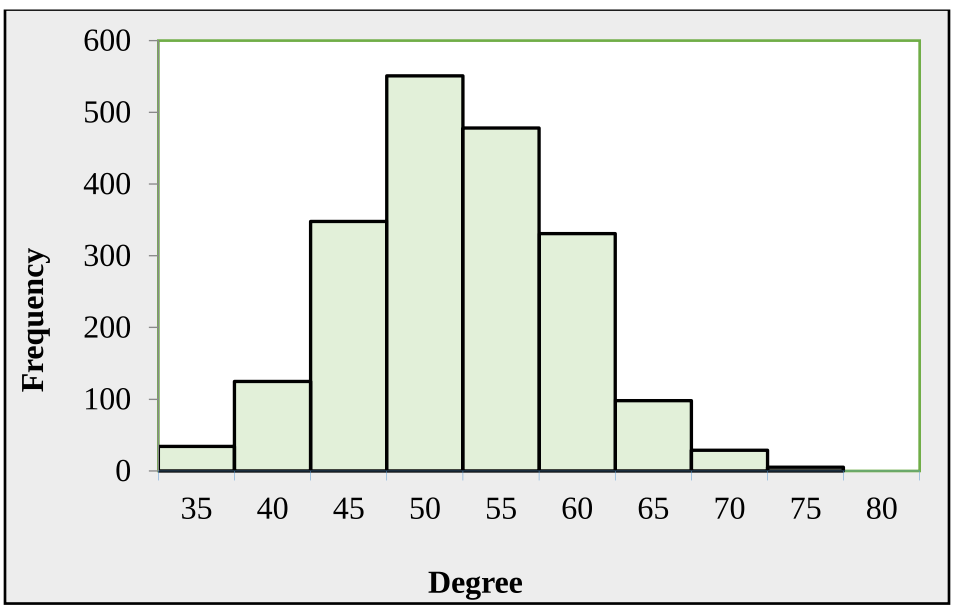

Figure 5.5. Degree Distribution in Sample Social Network with Homophily Based on Social Attributes

However, the clustering coefficients for these networks were significantly different as shown in the Table 5.2. Level of clustering in a network is measured by the clustering coefficient (Newman, 2003b). From Table 5.2, network with homophily based on social attributes recorded the highest mean clustering coefficient of *0.0249*, followed by network with no homophily *(0.0063)* while network with homophily based on propinquity recorded the least mean clustering coefficient of *0.0007*. These differences are one order of magnitude in each case.

The candidate believes that the difference in the clustering coefficients of these networks led to the differences in their diffusion rates. The clustering coefficient serves as a measure of a network's transitivity. In other words, the clustering coefficient shows the probability that a person in a given network is a friend with the friends of his or her friends (Peres, 2014). Clustering coefficient, and for that matter clustering, affects diffusion process by impeding the diffusion process. That is, the redundancies generated by high clustering impede diffusion (Coupechoux & Lelarge, 2014; Peres, 2014). Newman (2003b) observed that in epidemics, increasing clustering decreases the size of an epidemic for an epidemic process on the network.

Hence, it is not surprising that social network with homophily based on social attributes recorded the slowest level of adoption leading to the least level of acceptance at the end of the simulation period. This is because such a network possesses the highest clustering coefficients, which implies the highest relative average local clustering as compared to the other networks (network with homophily based on propinquity and network without homophily). Likewise, the network with homophily based on propinquity resulted in the fastest level of adoption leading to the highest level of acceptance at the end of the simulation period due to its lowest average local clustering. The candidate concludes that the different types of homophily led to differences in average local clustering, which eventually resulted in differences in diffusion rates.

Table 5.2. Average Local Clustering, C_2, (Bounova & de Weck, 2012) for the Various Networks

Network #	Clustering Coefficients		
	No Homophily	Homophily by Propinquity	Homophily by Social Attributes
1	0.00624	0.00076	0.02484
2	0.00625	0.00073	0.02494
3	0.00623	0.00075	0.02489
4	0.00625	0.00068	0.02484
5	0.00625	0.00073	0.02481
6	0.00629	0.00075	0.02496
7	0.00628	0.00072	0.02489
8	0.00630	0.00076	0.02514
9	0.00632	0.00079	0.02525
10	0.00630	0.00070	0.02481
Average	0.0063	0.0007	0.0249

For these results to inform management decisions, there is a need to consider connection between these networks and typical mining communities. The candidate considers the two types of mining communities defined by Evans & Kemp (2011): local/host community and affected community. Local community refers to those living in the immediate vicinity of a mine, who may have cultural affinity, claim or direct ownership of the area. On the other hand, affected community describes the communities affected by a mining company’s activities. Local communities tend to be rural areas as compared to affected communities which can be in urban and dispersed settings. Given this description, the candidate links the modeled social networks to the types of mining communities in the following discussion.

The social network with homophily based on *propinquity* is most likely to describe the social network by which information about a mine's impact diffuses through a rural *local mining community*. Rural communities tend to be more homogenous and kinship and neighborhood solidarities rather than friendship drive relationships (Beggs et al., 1996; Toth Jr et al., 2002). For example, oil sands projects in Nigeria are located in largely rural communities that are quiet homogenous with individuals who are unified in their concerns (Chindo, 2011).

On the contrary, the social network with homophily based on *social distance (social and demographic attributes)* is more likely to describe a more urban *affected mining community's* social network. In urban communities, individuals tend to form ties based on social similarities rather than propinquity. For instance, D'Andreta (2011) emphasizes that modern urban societies are made up of networks that are disjointed, spare and dispersed across physical space as opposed to networks in rural communities.

In addition, the candidate hypothesizes that the social network *without homophily,* which is more a dispersed social network, is also more likely to describe an urban "affected mining community" for the same reasons discussed above.

This study should provide stakeholders with a better understanding of how homophily in the social network of mining communities affects the rate of change in project acceptance due to information diffusion. This should help stakeholders to make more informed decisions during project planning and design, and community engagement to facilitate gaining and maintaining social license to operate for mining projects to uphold project's sustainability. This study shows that when applying ABM to understand the effect of information diffusion on changes in the level of community acceptance of mining, the user must pay attention to the simulated community's social network.

Some studies have sought to understand how various social networks relate to urban and rural communities (D'Andreta, 2011; Hipp & Perrin, 2009; Toth Jr et al., 2002). However, there is no work on differences in social network (due to homophily) of mining communities in the literature. As indicated earlier, Boutilier (2011) is the only author the candidate could find that discussed social networks in mining communities. However, he provided only qualitative description of social networks he has observed in his work. Further work is required to characterize social networks in mining communities.

5.4. SUMMARY OF THE SECTION

The work in this section evaluates the effect of homophily in social networks on the results of the mining community acceptance model, presented in section 3. The effect of homophily was explored by evaluating a network with homophily based on social distance (all agent demographic attributes), network with homophily based on physical distance (propinquity) and network without homophily. The results show that homophily significantly affects the rate of change in community acceptance. The social network with homophily based on propinquity resulted in fastest information diffusion and, therefore, highest rate of change in level of community acceptance of mining followed by the network without homophily, and network with homophily based on social distance. The results of this work indicate that it is important to understand the nature of homophily in social networks in mining communities. Consequently, mine managers can reduce uncertainty surrounding the inferences they draw from simulation experiments using agent-based models by obtaining reliable information about the mining communities' social network. The candidate recommends that future research characterizes homophily in the social networks of mining communities. This work should provide stakeholders with a better understanding of the effect of homophily in social networks on the rate of change in project acceptance.

6. CONCLUSIONS, RECOMMENDATIONS AND FUTURE WORK

6.1. SUMMARY AND CONCLUSIONS

Community engagement is important for ensuring sustainable mining. Current qualitative community analysis approaches do not fully provide enough understanding into the community's trepidations, expectations, and, particularly, variations in level of acceptance due to changes in demographics and perceptions of the project's sustainability. The level of social license to operate changes over time, based on people's ongoing experiences of an operation and changes in their perceptions and opinions, and the procedure by which social license is expressed is contextually specific, dynamic and non-linear. There are many factors that affect community acceptance, which include the impacts of the mine on the environment and host community, the mine owner (the corporate reputation etc.) and governance issues, and demographics of the community. Researchers have used discrete choice theory to model individuals' preferences regarding mining projects. Such work indicates that discrete choice theory can be used to formulate rigorous utility functions for agent based model (ABM) of community acceptance. Agent based models are a potential tool for modeling agents' decisions to innovate or to imitate innovation as well as their strategies for collaboration. Social networks channel information about innovations to some potential adopters who might adopt these innovations and prevent others from getting such information who are, therefore, not in a position to adopt them. Thus, the structure of a social network can favor or inhibit the diffusion of innovations in the network. A review of the literature shows that several agent-based models use some type of discrete choice model in the agents' decision process.

The goal of this PhD study was to combine ABM, discrete choice experiment (DCE) and social networks structure to model community acceptance of mining while addressing the following challenges: (1) how to define valid agent utility functions using discrete choice theory; and (2) how to describe the interaction between perceptions of sustainability and community acceptance using an ABM diffusion model through social network. The specific research objectives were to:

(1) Formulate agent utility functions for ABM, based on discrete choice theory;

(2) Apply ABM to account for the effect of information diffusion on community acceptance; and

(3) Explain the relationship between initial conditions, topology, and rate of interactions, on one hand, and community acceptance on the other hand.

To achieve these objectives, this study relies on discrete choice theory, agent-based modeling, innovation and diffusion theory, and stochastic processes. Discrete choice models of individual acceptance of mining projects were used to formulate utility functions for this research. To account for the effect of information diffusion on community acceptance through social network, an agent-based model was developed to study changes in community acceptance over time, as a function of changing demographics and perceived sustainability impacts. The model's utility function was validated with data from Salt Lake City, Utah, USA, a mining community.

Based on the work in this dissertation, the following conclusions can be drawn:

1. For the first two research objectives:

1) A framework for modeling the effect of information diffusion on dynamic community acceptance of mining using agent-based modeling (ABM) was

developed. The model evaluates information diffusion due to word-of-mouth social contagion. A case study of mining activity in Salt Lake City, Utah, USA was used to illustrate the framework. The case study relies on discrete choice modeling by Que (2015) and simulates only unidirectional (from adopters to receptive agents) social contagion.

2) Changes in agents' perception of non-demographic factors (e.g. air pollution) have a significant effect on acceptance of mining while demographic factors included in this case study (age, gender, income and education) do not have a significant effect. For the simulated social network, the onset of rapid social contagion (takeoff) appears to occur when about 20% of the agents in the network have adopted the new perception. However, once takeoff occurs, the rate at which information diffuses decreases with increase in average degree of the network. Finally, the rate of diffusion is proportional to the number of relevant agent’s interactions per unit time. As a result, community engagement and other interventions that increase discussion of the issues around a mining project are likely to affect the rate at which information (on the positive or negative impacts of the mine) diffuses through the community and how that affects the mine's social license to operate.

3) The modeled framework can be used to understand the effect of information diffusion and social interactions on community acceptance. The framework can be applied to other resource extraction projects and to large engineering projects in general. Although, the case study uses a utility function that includes 20 demographic and non-demographic factors, the list of factors will necessarily be a

facts and circumstances determination. Besides the utility function, however, there are other aspects relevant to understanding the changes in community acceptance over time that are not accounted for in this research. Those aspects include the role of the agents in the diffusion process (active or passive, resistant or receptive, and innovators or followers) and diversity of social networks, including those with hierarchies.

2. For the third research objective:

1) The candidate investigated the responsiveness of mining community acceptance model discussed under objectives one and two to key input parameter changes. The input parameters investigated were average degree (average number of friends) of the social network, close neighbor ratio (a measure of homophily in the social network) and number of early adopters ("innovators").
2) The model is relatively more responsive to close neighbor ratio (homophily) and number of early adopters than average degree (number of friends). Therefore, the candidate recommends that mine managers using this model to understand the effect of word-of-mouth information diffusion on the level of community acceptance of their projects pay particular attention to the estimates of close neighbor ratio and number of early adopters. This will minimize the uncertainty surrounding the inferences they draw from agent-based simulation experiments. The literature on early adopters is established and offers a reliable means to estimate the range of the number of early adopters. This is not the case for the social networks in mining communities that will require more effort to reliably estimate the extent of homophily in the social networks.

3) The candidate also investigated the effect of homophily in social networks on information diffusion and how it affects acceptance of mining. He did this by evaluating a network with homophily based on social distance (all agent demographic attributes), network with homophily based on physical distance (propinquity) and network without homophily.
4) Homophily significantly affects the rate of change in community acceptance. The social network with homophily based on propinquity resulted in fastest information diffusion and, therefore, highest rate of change in level of community acceptance of mining followed by the network without homophily, and network with homophily based on social distance.
5) The difference in the rate of change is due to changes in average local clustering of the different networks. Level of average local clustering in a network, which is measured by the clustering coefficient (Newman, 2003b) measures a network's transitivity. In other words, the clustering coefficient shows the probability that a person in a given network is a friend with the friends of his or her friends (Peres, 2014). Clustering coefficient or clustering, affects diffusion process by hindering the diffusion process. That is, the redundancies generated by high clustering impede diffusion (Coupechoux & Lelarge, 2014; Peres, 2014).
6) In order to guide management decisions, the candidate studied connection between these different networks, and host and affected mining communities by considering the two types of mining communities defined by Evans & Kemp (2011): local/host community and affected community. The social network with homophily based on *propinquity* is most likely to describe the social network by

which information about a mine's impact diffuses through a rural *local mining community*. This is because rural communities tend to be more homogenous and kinship and neighborhood solidarities rather than friendship drive relationships (Beggs et al., 1996; Toth Jr et al., 2002). However, the social network with homophily based on *social distance (social and demographic attributes)* is more likely to describe a more urban *affected mining community's* social network. This is because in urban communities, individuals tend to form ties based on social similarities rather than propinquity. Besides, the candidate posits that the social network *without homophily,* which is more a dispersed social network, is also more likely to describe an urban "affected mining community". This is due to the fact that modern urban societies are made up of networks that are disjointed, spare and dispersed across physical space as opposed to networks in rural communities (D'Andreta, 2011).

7) It is essential to understand the nature of homophily in social networks in mining communities. Consequently, mine managers can reduce uncertainty surrounding the inferences they draw from simulation experiments using agent-based models by obtaining reliable information about the mining communities' social network. This study should provide stakeholders with a better understanding of the effect of homophily in social networks on the rate of change in project acceptance.

6.2. CONTRIBUTIONS OF THE PHD RESEARCH

1. *Contribution to improving understanding of changes in community acceptance of mining project over time using agent based modeling, discrete choice theory and diffusion model through social network*

This dissertation is a pioneering attempt to apply agent based model (ABM) and discrete choice theory in combination with diffusion models through social network to quantitatively understand community acceptance of mining projects over time. The application of discrete choice theory will advance the science of ABM application to mining community/stakeholder modeling by incorporating sound decision theory to describe individual motivation to support or oppose a mining project. This study is at the intersection of mining community/stakeholder analysis, discrete choice theory and complex-adaptive system modeling using ABM and diffusion model through social network. A good framework such as what is proposed by this dissertation would ensure that mine design and permitting, and policy decisions by stakeholders are less challenging than it is, currently. A dependable model, capable of quantitatively assessing changes in community acceptance over time will help stakeholders do an improved job in evaluating alternatives and, therefore, make informed decisions.

This dissertation sought to answer four important questions: (1) How does new information change community acceptance over time? (2) Can an agent-based modeling framework that uses discrete choice theory be proposed to study this dynamic community acceptance? (3) If so, what are the essential input parameters that the model is most sensitive to? (4) What is the effect of social network on the dynamics of information diffusion and community acceptance?

With regards to questions 1 and 2, section 3 of this dissertation presented a framework for studying how new information can change community acceptance over time through word-of-mouth diffusion. Changes in agents' perception of non-demographic factors (e.g. air pollution) have a significant effect on acceptance of mining while demographic factors included in this case study (age, gender, income and education) do not have a significant effect. For the simulated social network, the onset of rapid social contagion (takeoff) appears to occur when about 20% of the agents in the network have adopted the new perception. However, once takeoff occurs, the rate at which information diffuses decreases with increase in average degree of the network. Finally, the rate of diffusion is proportional to the number of relevant agent's interactions per unit time. As a result, community engagement and other interventions that increase discussion of the issues around a mining project are likely to affect the rate at which information (on the positive or negative impacts of the mine) diffuses through the community and how that affects the mine's social license to operate.

In response to question 3, section 4 shows that the model, with the base social network, is more sensitive to close neighbor ratio (homophily) and number of early adopters than average degree (number of friends). These three input parameters were found to be the most important input parameters for the model. Consequently, the candidate recommends that mine managers using this model to understand the effect of word-of-mouth information diffusion on the level of community acceptance of their projects give specific attention to the estimates of close neighbor ratio and number of early adopters. This will reduce the uncertainty associated with the inferences they draw from agent-based simulation experiments. The literature on early adopters is established and offers a reliable approach to estimate the range of the number of early adopters. On the other hand, it will require more effort to reliably estimate the extent of homophily in the social networks in mining communities.

With regards to question 4, section 5 shows that the model is very sensitive to the social network. The candidate examined three different networks: a network with no homophily, one with homophily due to propinquity (physical distance) and one with homophily due to social attributes (social distance). The results show that, at least for the social networks evaluated, the dynamics of information diffusion are sensitive to differences in average local clustering in these networks. All the simulated networks led to similar average degree and degree distribution. However, the difference in the rate of change resulted from changes in average local clustering of the different networks. Level of average local clustering in a network, which is measured by the clustering coefficient (Newman, 2003b) is a measure of a network’s transitivity. That is the clustering coefficient shows the probability that an individual in a specified network is a friend with the friends of his or her friends (Peres, 2014). Clustering coefficient or clustering, affects diffusion process by hindering it. That is, the redundancies generated by high clustering impede diffusion (Coupechoux & Lelarge, 2014; Peres, 2014).

2. *Contribution to knowledge on determining utility function using odds ratio.*

In order to use ABM successfully in this application, this dissertation provides a novel utility function using odds ratio, which is based on sound decision theory. The candidate used the odds ratio as the utility function. The application of odds ratio has been wide in decision applications, especially in the field of medicine for selecting options and making decision. In some cases, it assists patients decide whether to accept or waive painful or expensive treatments, and thus, enables health care providers to make treatment decisions (Mchugh, 2009). By the application of odds ratio as utility function in this dissertation, other researchers can apply the same concept in defining utility functions for similar applications.

3. *Contribution to knowledge on application of ABM, discrete choice theory and diffusion model in mining sustainability*

This dissertation is the first attempt, to the best of the candidate's knowledge to apply ABM, discrete choice theory and diffusion model in mining sustainability. Regardless of the examples of the application of ABM and discrete choice experiments, independently, to model consumer's and individual's preferences (Brock & Durlauf, 2001; Gramming et al., 2005; McFadden, 1974; Zhang et al., 2011), the merger of the two approaches to model community acceptance of mining project has not been given any attention. In fact, ABM applications in resource exploitation entirely have not been supported by rigorous utility functions based on sound social science. This dissertation built an agent-based model that relied on discrete choice models to formulate agent utility functions. Instead of using the discrete choice model itself (which provides the utilities of different choice alternatives), this work uses the odds ratio. This allows the candidate to build a model for community acceptance, which is not a decision on multiple options but a binary decision (accept this option or not). Also, this work is the first exploration of the effect of social networks (characteristics such as homophily and degrees) on word-of-mouth information and how that affects community acceptance and social license to operate. This work has provided a framework to study these issues in depth. Other researchers can build on this work to better document social networks and diffusion models to better study the dynamics of community acceptance.

4. *Contribution to knowledge on understanding the importance of information diffusion in mining community engagement*

This dissertation in addition to other work such as Bahr (2015) shows the importance of information diffusion in mining community engagement. Most of the existing approaches for mining community engagement have largely ignored the effect of information diffusion in the mining community engagement process. This work shows in a fundamental way that word-of-mouth information diffusion on a mine's sustainability performance can be much more important in short-term changes in community acceptance than change in demographics. Also, this work shows that the extent of this effect depends on the social network and the number of early adopters among others. This dissertation will help give more understanding into how information diffusion can influence mining community engagement. Such an understanding is necessary to guide stakeholders and mine managers to strategically ensure more effective mining community engagement.

6.3. RECOMMENDATIONS FOR FUTURE WORK

The following recommendations for future research will improve the current study and enhance the knowledge of local community acceptance of mining over time and mining sustainability in general:

1. *Incorporating a documented mining community social network*

   Social networks used in this dissertation are only considered to be representative of the mining community and have not been observed in the study community. There is no available data on the type of social network in a specific mining community in the literature although some researchers have qualitatively discussed social networks in the mining communities. The information and estimates concerning the social network parameters (number of friends and close neighbor ratio) can reliably be obtained through a survey. For instance, during community engagement, individuals in the local mining community can be interviewed to document the people they are likely to discuss the relevant issue (relating to this mine) who are likely to affect their opinions of the mine. Further questions relating to the residence of those individuals would allow researchers to document the degree to which the type of homophily modeled in this study exists in the community. This will guide mine managers to accurately estimate the number of friends and close neighbor ratio, which will enhance the results of this study.

2. *ABM accounting for possibility of individuals' different roles during information diffusion*

The ABM model in this study does not account for the possibility of different roles of individual such as active or passive, resistant or receptive, and innovators or followers during information diffusion. The assumption of the ABM is that all agents have similar roles in the information diffusion process. That is all agents are open to new information and can influence others. It was also assumed that agent innovation or spontaneous adoption is negligible, which means diffusion is primarily by word of mouth. Thus, the ABM is limited to situations where there is no significant innovation, and that other factors such as public education and advertising which may motivate changes in attitudes independent of social diffusion. Individuals' different roles can be modeled by incorporating bidirectional word of mouth method of diffusion into the model. Vigorously developed ABM can account for the possibility of different roles of individual during information diffusion. Also it can allow diffusion by other means including public education and advertising.

3. *Empirical validation of the ABM*

    The ABM in this study has not been completely validated with empirical data from a mining community or communities. In addition, the model assumes that the "local community" can be defined and isolated. This suggests that the system is thus bounded to a particular community and there is no significant interaction between individuals in the community under study and in other communities that can impact perceptions. Validating the dynamic aspects of the ABM with empirical data is challenging. However, acquiring empirical data through community engagement, surveys and other processes can be useful in validation. As suggested in the literature, to fully validate an agent-based model with empirical data, researchers need to observe agents' state at each discrete time step in a carefully documented scenario. Such a validation will promote more useful ABM.

4. *Assessing Changes in Public Acceptance Through Online Social Media for Mine Intelligence*

    The information diffusion model described by the ABM could be extended to incorporate urgent diffusion events. Urgent diffusion events are events in which the spread of information across the population from outside sources is faster than the spread of information across the population through that population's own social network. Measuring the spread of information diffusion was difficult when the population was not observable, but, with the development of social media, it is currently easy to measure trending topics and to monitor how information is spreading throughout an entire network (Rand et al., 2015). Similarly, the ABM model in this research could model an online social media as the "mining community" in order to predict information diffusion across social media for mine intelligence. This would help mine managers and stakeholders to effectively and in a timely manner respond to developing mining community issues so as to promote community acceptance and social license to operate to ensure mining sustainability.

BIBLIOGRAPHY

Abdollahian, M., Yang, Z., Coan, T., & Yesilada, B. (2013). Human development dynamics: an agent based simulation of macro social systems and individual heterogeneous evolutionary games. *Complex Adaptive Sytems Modeling*, *1*(18), 1–14. https://doi.org/10.1186/2194-3206-1-18.

Aboagye, S. (2014). Mining and Resettlement of Communities in Ghana: Exposing the Harm Caused by Forced Displacement and Relocation. *MININGWATCH CANADA*.

Abrahamson, E., Rosenkopf, L., & Adler, P. S. (1997). Social Network Effects on the Extent of Innovation Diffusion : A Computer Simulation Social Network of Effects on the Extent Innovation Diffusion : Computer Simulation, *8*(3), 289–309.

Agnetis, A., Mirchandani, P. B., Pacciarelli, D., & Pacifici, A. (2004). Scheduling problems with two competing agents. *Operations Research*, *52*(2), 229–242. https://doi.org/10.1287/opre.1030.0092.

Aguirre R, & Nyerges, T. (2014). An Agent-Based Model of Public Participation in Sustainability Management. *Journal of Artificial Societies and Social Simulation*, *17*(1).

Ahrweiler, P., Pyka, A., & Gilbert, N. (2011). A New Model for University Industry Links in Knowledge Based Economies. *Journal of Product Innovation Management*, *28*(2), 218–235. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1540-5885.2010.00793.x/full.

Akanle, O. M., & Zhang, D. Z. (2008). Agent-based model for optimising supply-chain configurations. *International Journal of Production Economics*, *115*(2), 444–460. https://doi.org/10.1016/j.ijpe.2008.02.019.

Akcil, A., & Koldas, S. (2006). Acid Mine Drainage (AMD): causes, treatment and case studies. *Journal of Cleaner Production*, *14*(12–13 SPEC. ISS.), 1139–1145. https://doi.org/10.1016/j.jclepro.2004.09.006.

Ala-Härkönen, M. (1993). The dawn of organizational learning in the mining industry. *Resources Policy*, *19*(3). https://doi.org/10.1016/0301-4207(93)90006-9.

Anderson, M., & Whitcomb, P. (2015). Chapter 3 is excerpted from DOE Simplified: Practical Tools for Effective Experimentation, 2nd Edition. In *DOE Simplified: Practical Tools for Effective Experimentation* (2nd ed.).

Arentze, T. A., Kowald, M., & Axhausen, K. W. (2013). An agent-based random-utility-maximization model to generate social networks with transitivity in geographic space. *Social Networks*, *35*(3), 451–459. https://doi.org/10.1016/j.socnet.2013.05.002.

Azapagic, A. (2004). Developing a framework for sustainable development indicators for the mining and minerals industry. *Journal of Cleaner Production*, *12*(6), 639–662. https://doi.org/10.1016/S0959-6526(03)00075-1.

Bahr, K. (2015). *An Agent-Based Approach to Social License Durability*. Colorado School of Mines.

Bakshy, E., Rosenn, I., Marlow, C., & Adamic, L. (2012). The Role of Social Networks in Information Diffusion. In *Proceedings of the 21st international conference on World Wide Web SE - WWW '12*. Lyon, France: International World Wide Web Conference Committee. Retrieved from citeulike-article-id:10576980%5Cnhttp://dx.doi.org/10.1145/2187836.2187907.

Ballard, C., & Banks, G. (2003). Resource Wars: The Anthropology of Mining. *Annual Review of Anthropology*, *32*, 287–313.

Barczak, T. M. (1992). *The history and future of longwall mining in the United States (Bureau of Mines Information Circular - I.C. 9316).* Washington, DC.

Bass, F. (2004). A New Product Growth for Model Consumer Durables. *Management Science*, *50*(12), 1825–1832.

Beggs, J. J., Haines, V. A., & Hurlbert, J. S. (1996). Revisiting the Rural-Urban Contrast : Personal. *Rural Sociology, 61*(2), 306–325.

Berger, T. (2001). Agent-based spatial models applied to agriculture: A simulation tool for technology diffusion, rsource use changes, and policy analysis. *Agricultural Economics*, *25*(2–3), 245–260. https://doi.org/10.1111/j.1574-0862.2001.tb00205.x.

Berger, T., & Troost, C. (2012). Agent-based Modelling in the Agricultural Economics Tradition of Recursive Farm Modelling and Adaptive Micro-Systems. In *Managing Resources of a Limited Planet, Sixth Biennial Meeting*. Leipzig, Germany. Retrieved from http://www.iemss.org/society/index.php/iemss-2012-proceedings.

Berlo, D. K., Lemert, J. B., & Mertz, R. J. (1969). American Association for Public Opinion Research Public Support for American Presidents : A Cyclical Model Author (s): James A . Stimson Published by : Oxford University Press on behalf of the American Association for Public Opinion Research Stable URL. *American Association for Public OPinion Research*, 563–576.

Berman, M., Nicolson, C., Kofinas, G., Tetlichi, J., & Martin, S. (2004). Adaptation and sustainability in a small arctic community: Results of an agent-based simulation model. *Arctic*, *57*(4), 401–414. https://doi.org/10.2307/40512643.

BHP Billiton. (2008). *Resourcing the future: Sustaiability report 2008*.

Black, L. D. (2013). The social licence as a framework for managing cumulative impacts: a case study of the upper hunter mining dialogue. In *Proceedings of the International Association of Impact Assessment Annual Conference*. Calgary.

Bonabeau, E. (2002). Agent-based modeling: methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences, 99*(suppl. 3), 7280–7287. https://doi.org/10.1073/pnas.082080899.

Booch, G., Rumbaugh, J., & Jacobson, I. (1998). *The Unified Modeling Language User Guide*. New York.: Addison-Wesley.

Bounova, G., & de Weck, O. (2012). Overview of Metrics and their Correlation Patterns for Multiple-Metric Topology Analysis on Heterogenous Graph Ensembles. *Physical Review E, 85*(1).

Boutilier, R. (2011). *A Stakeholder Approach to Issues Management. Business Expert*. LLC, New York, USA.

Boyle, A. (2010). Some Forecasts of the Diffusion of E-assessment Using a Model. *The Innovation Journal: The Public Sector Innovation Journal*, *15*(2), 1–30.

Brass, D. J., Butterfield, K. D., & Skaggs, B. C. (1998). Relationships and Unethical: A Social Network Perspective. *The Academy of Management Review*, *23*(1), 14–31.

Bridge, G. (2004). CONTESTED TERRAIN: Mining and the Environment. *Annual Review of Environment & Resources*, *29*(1), 205–259. https://doi.org/10.1146/annurev.energy.28.011503.163434.

Brock, W. A., & Durlauf, S. N. (2001). Discrete Choice with Social Interactions. *A Review of Economic Studies*, *68*, 235–260.

Brown, D. G., Page, S. E., Riolo, R., & Rand, W. (2004). Agent-based and analytical modeling to evaluate the effectiveness of greenbelts. *Environmental Modelling and Software*, *19*(12), 1097–1109. https://doi.org/10.1016/j.envsoft.2003.11.012.

Browne, A. L., Stehlik, D., & Buckley, A. (2011). Social licences to operate: for better not for worse; for richer not for poorer? The impacts of unplanned mining closure for “fence line” residential communities. *Local Environment*, *16*(7), 707–725.

Brundtland. (1987). World Commission on Environmental and Development (WCED), 43.

Bryson, J. (1995). *Strategic Planning for Public and Nonprofit Organizations*. San Francisco CA: Jossey- Bass.

Bullnheimer, B., Dawid, H., & Zeller, R. (1998). Learning from own and foreign experience: technological adaptation by imitating firms. *Computational & Mathematical Organization Theory*, *4*(3), 267–282. https://doi.org/10.1023/A:1009680612160.

Bunn, D. W., & Oliveira, F. S. (2008). Modeling the Impact of Market Interventions on the Strategic Evolution of Electricity Markets. *Operations Research*, *56*(February 2015), 1116–1130. https://doi.org/10.1287/opre.1080.0565.

Burton, R. (1927). *The Anatomy of Melancholy*. New York: Farrar and Rinehart.

Buskens, V., & Yamaguchi, K. (1999). A New Model for Information Diffusion in Heterogeneous Social Networks. *American Sociological Association*, *29*, 281–325.

Buttle, F. . (1998). Word of mouth: understanding and managing referral marketing. *Journal of Strategic Marketing*, *6*, 241–254.

Caldart, A. A., & Ricart, J. E. (2007). Corporate strategy: An agent-based approach. *European Management Review*, *4*(2), 107–120. https://doi.org/doi:10.1057/palgrave.emr.1500077.

Calvó-Armengol, A., & Jackson, M. O. (2004). The Effects of Social Networks on Employment and Inequality. *The American Economic Review*, *94*(3), 426–454.

Campbell, K. E., Marsden, P. V., & Hurlbert, J. S. (1986). Social Resources and Socioeconomic Status. *Social Networks*, *8*, 97–117.

Chen, S. H. (2012). Varieties of agents in agent-based computational economics: A historical and an interdisciplinary perspective. *Journal of Economic Dynamics and Control*, *36*(1), 1–25. https://doi.org/10.1016/j.jedc.2011.09.003.

Cheney, G., & Christensen, L. T. (2001). *Organisational communication: linkages between internal and external communication. In The New Handbook of Organisational Communication: Advances in Theory, Research, and Methods*. Thousands Oaks, CA: Sage.

Chindo, M. I. (2011). Understanding Community Characteristics in Resource Development Development: A Case Study of the Nigerian Oil Sands. *The Social Sciences*, *6*(4), 283–290.

Cho, Y., Wang, J., & Lee, D. (2012). Identification of effective opinion leaders in the diffusion of technological innovation: A social network approach. *Technological Forecasting and Social Change*, *79*, 97–106. https://doi.org/10.1016/j.techfore.2011.06.003.

Cioppa, T. M., Lucas, T. W., & Sanchez, S. M. (2004). Military Applications of Agent-Based Simulations. In *Proceedings of the 36th Conference on Winter Simulation* (pp. 171–180). https://doi.org/http://doi.org/10.1109/WSC.2004.1371314.

Coleman, J., Menzel, H., & Katz, E. (1966). *Medical Innovations: A Diffusion Study*. Bobbs Merrill.

Corman, S. R., Trethewey, A., & Goodall, B. (2007). *A 21st Century Model for Communication in the Global War of Ideas From Simplistic Influence to Pragmatic Complexity*. Arizona State University. Retrieved from http://csc.asu.edu/wp-content/uploads/pdf/114.pdf.

Coupechoux, E., & Lelarge, M. (2014). How Clustering Affects Epidemics in Random Networks. *Advances in Applied Probability*, *46*(4), 985–1008. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=bsu&AN=100052853&site=ehost-live.

Crooks, A. T. (2010). Constructing and Implementing an Agent-Based Model of Residential Segregation through Vector GIS. *International Journal of Geographical Information Science*, *24*(5), 661–675. https://doi.org/10.1080/13658810903569572.

Cumming, J. F. (2001). Engaging stakeholders in corporate accountability programmes: A cross-sectoral analysis of UK and transnational experience. *Business Ethics: A European Review*, *10*(1), 45–52. https://doi.org/Article.

D'Andreta, D. (2011). *Urban cohesion and resident social networks: An analysis of spatial, structural and ideational forms of interaction and consequences for deprived*. A Thesis Submitted to the University of Manchester.

Daganzo, C. (1979). *Multinomial Probit: The Theory and Its Application to Demand Forecasting*. New York: Academic Press.

Dale, A. P., Chapman, P., & McDonald, M. L. (1997). Social Impact Assessment in Queensland: Why Practice Lags Behind Legislative Opportunity. *Impact Assessment*, *15*(2), 159–179. https://doi.org/10.1080/07349165.1997.9726130.

Davis, R., & Franks, D. M. D. (2011). The costs of conflict with local communities in the extractive industry. *First International Seminar on Social Responsibility in Mining*, 19–21. Retrieved from https://www.csrm.uq.edu.au/Portals/0/11srm_cap06_p88.pdf.

Dawid, H. (2006). Agent-based models of innovation and technological change. *Handbook of Computational Economics*, *2*, 1235–1272.

Debenham, J., & Wilkinson, I. (2006). Exploitation versus exploration in market competition. *Industry and Innovation*, *13*(3), 263–289.

Deroian, F. (2002). Formation of social networks and diffusion of innovations. *Research Policy, 31*(5), 835–846. https://doi.org/Doi: 10.1016/s0048-7333(01)00147-0.

Dia, H. (2002). An agent-based approach to modelling driver route choice behaviour under the influence of real-time information. *Transportation Research: Part C*, *10*, 331–349. https://doi.org/10.1016/S0968-090X(02)00025-6.

Dimitropoulos, A., & Kontoleon, A. (2009). Assessing the determinants of local acceptability of wind-farm investment: A choice experiment in the Greek Aegean Islands. *Energy Policy*, *37*(5), 1842–1854. https://doi.org/10.1016/j.enpol.2009.01.002.

Dodds, W. (1973). An Application of the Bass Model in Long-Term New Product Forecasting. *Journal of Marketing Research*, *10*(3), 308–311. https://doi.org/10.2307/3149700.

Dover, Y. (2011). *Network Traces on Penetration: Uncovering Degree Distribution from Adoption Data*. *Thesis Submitted for the degree of Doctor of Philosophy*. The Senate of the Hebrew University of Jerusalem.

Dudka, S., & Adriano, D. C. (1997). Environmental Impacts of Metals Ore Mining and Processing: A Review. *J. ENVIRON. QUAL.*, *26*.

Earthworks and Oxfam America. (2004). *Dirty Metals: Mining , Communities and the Environment.*

Easley, D., & Kleinberg, J. (2010). *Networks, Crowds, and Markets: Reasoning about a Highly Connected World*. Cambridge University Press.

Elkington John. (1998). *Cannibals with Forks: The triple Bottom Line of 21st Century Business*. Gabriola Island, BC: New Society.

EPA. (1998). *Principles of Environmental Impact Assessment*.

Epstein, J. M. (1999). Agent-based computational models and generative social science. *Complexity*, *4*(5), 41–60. https://doi.org/10.1002/(SICI)1099-0526(199905/06)4:5<41::AID-CPLX9>3.3.CO;2-6.

Evans, R., & Kemp, D. (2011). Community issues. *SME Mining Engineering Handbook*, 1767–1777. Retrieved from http://espace.library.uq.edu.au/view/UQ:254065.

Evans, T. P., & Kelley, H. (2004). Multi-scale analysis of a household level agent-based model of landcover change. *Journal of Environmental Management*, *72*, 57–72. https://doi.org/10.1016/j.jenvman.2004.02.008.

Festinger, L. (1957). *A Theory of Cognitive Dissonance*. Stanford, California: Stanford University Press.

Fiksel, J. (2003). Designing resilient, sustainable systems. *Environ. Sci. Technol*, *37*(23), 5330–5339.

Filatova, T., Verburg, P. H., Parker, D. C., & Stannard, C. A. (2013). Spatial agent-based models for socio-ecological systems: Challenges and prospects. *Environmental Modelling and Software*, *45*, 1–7. https://doi.org/10.1016/j.envsoft.2013.03.017.

Folcik, V. A., An, G. C., & Orosz, C. G. (2007). The Basic Immune Simulator: an agent-based model to study the interactions between innate and adaptive immunity. *Theoretical Biology & Medical Modelling*, *4*, 39. https://doi.org/10.1186/1742-4682-4-39.

Franks, D. ., Cohen, T., McLellan, B., & Brereton, D. (2010). *Technology Futures Discussion Paper: Technology Assessment and the CSIRO Minerals Down Under National Research Flagship. Prepared for CSIRO Minerals Down Under Flagship, Minerals Futures Cluster Collaboration*. Brisbane.

Freeman, R. (1984). *Strategic Management: A Stakeholer Perspective*. Englewoods Cliffs, New Jersey: Prentice Hall.

Freeman, R. E., & Gilbert, D. R. (1998). *Corporate Strategy and the Search for Ethics*. Prentice Hall, Englewood Cliffs, NJ.

Friedman, A. L., & Miles, S. (2001). Socially Responsible Investment and Corporate Social and Environmental Reporting in the UK: An Exploratory Study. *The British Accounting Review*, *33*(4), 523–548. https://doi.org/10.1006/bare.2001.0172.

Friedman, R. (2015). *Jewish Wisdom for Growing Older: Finding Your Grit & Grace Beyond Midlife*. Jewish Lights Publishing, Woodstock, Vermont.

Fujiono, H. (2011). *The Diffusion of Innovation in the Mining Industry: Agent-Based Modeling and Simulation*. Colorado School of Mines.

Gao, L., & Hailu, A. (2012). Ranking management strategies with complex outcomes: An AHP-fuzzy evaluation of recreational fishing using an integrated agent-based model of a coral reef ecosystem. *Environmental Modelling and Software*, *31*, 3–18. https://doi.org/10.1016/j.envsoft.2011.12.002.

Gao, S., & Zhang, J. (2006). Stakeholder engagement, social auditing and corporate sustainability. *Business Process Management Journal*, *12*(6), 722–740. https://doi.org/10.1108/14637150610710891.

Garcia, R. (2005). Uses of Agent-Based Modeling in Innovation/New Product Development Research. *Journal of Product Innovation Management*, *22*(617), 380–398. https://doi.org/10.1111/j.1540-5885.2005.00136.x.

Gilbert, N. (2008). *Agent-Based Models*. Sage Publications Inc.

Goldstone, R. L., & Janssen, M. A. (2005). Computational models of collective behavior. *Trends in Cognitive Sciences*, *9*(9), 424–430. https://doi.org/10.1016/j.tics.2005.07.009.

Goodwin, N. R. (2003). *Five Kinds of Capital : Useful Concepts for Sustainable Development*. *Global Development And Environment Institute Working Paper* (Vol. 3).

Gramming, J., Hujer, R., & Scheidler, M. (2005). Discrete Choice Modelling in Airline Network Management. *Journal of Applied Econometrics*, *20*, 467–486.

Granovetter, M. (1973). The Strength of Weak Ties. *The Journal of Sociology*, *78*(6), 1360–1380.

Grimm, V., U., Berger, F. Bastiansen, S. Eliassen, V. G., J. Giske, J. Goss-Custard, T. Grand, S. K. H. and, & G. Huse. (2006). A Standard Protocol for Describing Individual-Based and Agent-Based Models. *Ecological Modelling*, *198*, 115–126.

Gunningham, N., Kagan, Robert, A., & Thornton, D. (2004). Social License and Environmental Protection: Why Businesses Go beyond Compliance. *29 Law & Soc. Inquiry*, *307*.

Gunningham, N., Kagan, R., & Thornton D. (2003). *Shades of Green: Business, Regulation and Environment.* Stanford, CA: Stanford University Press.

Günther, M., Stummer, C., Wakolbinger, L. M., & Wildpaner, M. (2011). An agent-based simulation approach for the new product diffusion of a novel biomass fuel An agent-based simulation approach. *Journal of the Operational Research Society*, *62*(1), 12–20. https://doi.org/10.1057/jors.2009.170.

Hagerstrand, T. (1967). *Innovation Diffusion as a Spatial Process*. Chicago: University of Chicago Press.

Hajkowicz, S. A., Heyenga, S., & Moffat, K. (2011). The relationship between mining and socio-economic well being in Australia's regions. *Resources Policy*, *36*(1), 30–38. https://doi.org/10.1016/j.resourpol.2010.08.007.

Halog, A., & Manik, Y. (2011). Advancing integrated systems modelling framework for life cycle sustainability assessment. *Sustainability*, *3*(2), 469–499. https://doi.org/10.3390/su3020469.

Hanneman, R. a., & Riddle, M. (2005). *Introduction to Social Network Methods*. Riverside, CA: University of California, Riverside. Retrieved from http://www.faculty.ucr.edu/~hanneman/nettext/

Hart, R. (2012). *Introduction to the Legal Framework for Mining in Canada*. Retrieved from http://miningwatch.ca/publications/2012/7/18/introduction-legal-framework-mining-canada.

Hausman, J., & Wise, D. (1978). A conditional probit model for qual- itative choice: Discrete decisions recognizing interdependence and heterogeneous preferences. *Econometrica*, *48*, 403–429.

Hill, R. ., & Dunbar, R. . (2002). Social network size in humans. *Hum. Nat*, *14*(1), 53–72.

Hipp, J. ., & Perrin, A. . (2009). The simultaneous effect of social distance and physical distance on the formation of neighborhood ties. *City & Community*, *8*(1).

Hodge, R. A. (2014). Mining company performance and community conflict: Moving beyond a seeming paradox. *Journal of Cleaner Production*, *84*(1), 27–33. https://doi.org/10.1016/j.jclepro.2014.09.007.

Holm, S., Lemm, R., Thees, O., & Hilty, L. M. (2016). Enhancing Agent-Based Models with Discrete Choice Experiments. *Journal of Artificial Societies and Social Simulation*, *19*(3), 3. https://doi.org/10.18564/jasss.3121.

Howard, T. (2015). Olivebranches and idiot's guides: frameworks for community engagement in Australian wind farm development. *Energy Policy*, *78*, 137–147.

Hunt, L. M., Kushneriuk, R., & Lester, N. (2007). Linking agent-based and choice models to study outdoor recreation behaviours: a case of the Landscape Fisheries Model in northern Ontario, Canada. *Forest Snow and Landscape Research*, *81*(1/2), 163–174.

Ibarra, H. (1995). Race , Opportunity , and Diversity of Social Circles in Managerial Networks. *Academy of Management Journal*, *38*(3), 673–703.

ICMM (International Council on Mining & Metals). (2012a). *"Trends in the Mining and Metals Industry: Mining's Contribution to Sustainable Development."* Retrieved from http://www.icmm.com/document/4441.

ICMM (International Council on Mining and Metals). (2008). *Planning for integrated mine closure : Toolkit*.

ICMM (International Council on Mining and Metals). (2009). *Human rights in the mining & metals inductry: Handling and resolving local level concerns & grievances*. Retrieved from www.icmm.com.

ICMM (International Council on Mining and Metals). (2010a). *Good practice guide: Indigenous peoples and mining*. Retrieved from www.icmm.com/library/indigenouspeoplesguide.

ICMM (International Council on Mining and Metals). (2010b). *Good practice guide: Indigenous peoples and mining*.

ICMM (International Council on Mining and Metals). (2012b). *Community development toolkit*. Retrieved from www.icmm.com.

IFC (International Finance Corporation). (2014). *A Strategic Approach to Early Stakeholder Engagement: A Good Handbook for Junior Companies in the Extractive Industries.*

IFC (International Finance Corporation). (1998). *Doing better business through effective public consultation and disclosure*. Washington DC.

IFC (International Finance Corporation). (2007). *Stakeholder engagement : A good practice handbook for companies doing business in emerging markets*. Washington DC.

IFC (International Financial Corporation). (2007). *Stakeholder engagement : A good practice handbook for companies*. Washington DC.

IFC (International Financial Corporation). (2009). *Good practice note: Addressing grievances from project-affected communities*. Washington DC.

Ivanova, G., & Rolfe, J. (2011). Assessing development options in mining communities using stated preference techniques. *Resources Policy*, *36*(3), 255–264. https://doi.org/10.1016/j.resourpol.2011.03.001.

Ivanova, G., Rolfe, J., Lockie, S., & Timmer, V. (2007). Assessing social and economic impacts associated with changes in the coal mining industry in the Bowen Basin , Queensland , Australia, *18*(2), 211–228. https://doi.org/10.1108/14777830710725867.

Jackson, M. O. (2008). *Social and Economic Networks*. Princeton, New Jersey: Pinceton University Press.

Jenkins, H., & Yakovleva, N. (2006). Corporate social responsibility in the mining industry: Exploring trends in social and environmental disclosure. *Journal of Cleaner Production*, *14*(3–4), 271–284. https://doi.org/10.1016/j.jclepro.2004.10.004.

Joyce, S. & Macfarlane, M. (2001). Social Impact Assessment in the Mining Industry: Current Situation and Future Directions. *Mining, Minerals, and Sustainable Development*, (46), 28. Retrieved from http://pubs.iied.org/pdfs/G01023.pdf.

Joyce, S., & Thomson, I. (2000). Earning a social licence to operate: Social acceptability and resource development in Latin America. *Canadian Mining and Metallurgical Bulletin*, *93*(1037), 49–53.

Kadushin, C. (2004). Introduction to Social Network Theory: Some Basic Network Concepts and Propositions. *(DRAFT)*.

Keenan, K., de Echave, J., & Traynor, K. (2003). Mining and Communities: Poverty Amidst Wealth. In *International Conference on Natural Assets*. Tagaytay City: Political Economy Research Institute and Center for Science and the Environment.

Kempe, J. O. (1983). Review of Water Pollution Problems and Control Strategies in the South African Mining Industry. *Water Science and Technology*, *15*(2), 27–58.

Kesler, S. (2007). Mineral supply and demand into the 21st century. In *Proceedings, Workshop on Deposit Modeling, Mineral Resource Assessment, and Sustainable Development* (pp. 55–62). Retrieved from http://pubs.usgs.gov/circ/2007/1294/reports/paper9.pdf.

Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: A review. *Central European Journal of Operations Research*, *20*(2), 183–230. https://doi.org/10.1007/s10100-011-0210-y.

Klugl, F., & Bazzan, A. L. (2012). Agent-based modeling and simulation. *AI Magazine*, *33*(3), 29–40.

Kollman, K., Miller, J. H., & Page, S. E. (1992). Adaptive parties in spatial elections. *The American Political Science Review*, *86*(4), 929–937.

Kong, D. Y., & Bi, X. H. (2014). Impact of social network and business model on innovation diffusion of electric vehicles in China. *Mathematical Problems in Engineering*. https://doi.org/10.1155/2014/230765.

Kossinets, G., & Watts, Duncan, J. (2006). Empirical Analysis of an Evolving Social Network. *American Association for the Advancement of Science*, *311*(5757), 88–90.

Kwiecien, R., Kopp-Schneider, A., & Blettner, M. (2011). Concordance Analysis: Part 16 of a Serieis on Evaluation of Scientific Publications. *Dtsch Arztebl Int*, *108*(30), 515–521. https://doi.org/10.3238/arztebl.2011.0515.

Lacey, J., Parsons, R., & Moffat, K. (2012). *Exploring the concept of a Social Licence to Operate in the Australian minerals industry: Results from interviews with industry representatives*. Brisbane.

Laciana, C. E., Rovere, S. L., & Podestá, G. P. (2013). Exploring associations between micro-level models of innovation diffusion and emerging macro-level adoption patterns. *Physica A: Statistical Mechanics and Its Applications*, *392*(8), 1873–1884. https://doi.org/10.1016/j.physa.2012.12.023.

Law, A. M., & Kelton, D. (2000). *Simulation modeling and analysis* (3rd ed.). New York: McGraw-Hill.

Lee, T., Yao, R., & Coker, P. (2014). An analysis of UK policies for domestic energy reduction using an agent based tool. *Energy Policy*, *66*, 267–279. https://doi.org/10.1016/j.enpol.2013.11.004.

Li, X., & Liu, X. (2008). Embedding sustainable development strategies in agent-based models for use as a planning tool. *International Journal of Geographical Information Science*, *22*(February), 21–45. https://doi.org/10.1080/13658810701228686.

Ligmann-Zielinska, A., & Sun, L. (2010). Applying time-dependent variance-based global sensitivity analysis to represent the dynamics of an agent-based model of land use change. *International Journal of Geographical Information Science*, *24*(12), 1829–1850. https://doi.org/10.1080/13658816.2010.490533.

Lilien, G. ., Rangaswamy, A., & De Bruyn, A. (2007). *The bass model: marketing engineering technical note. In: Lilien, G.L., Rangaswamy, A., De Bruyn, A. (Eds.), Principles of Marketing Engineering*.

Lockie, S., Franettovich, M., Petkova-Timmer, V., Rolfe, J., & Ivanova, G. (2009). Coal mining and the resource community cycle: A longitudinal assessment of the social impacts of the Coppabella coal mine. *Environmental Impact Assessment Review*, *29*(5), 330–339. https://doi.org/10.1016/j.eiar.2009.01.008.

Ma, H., Yang, H., Lyu, M. M. R., & King, I. (2008). Mining social networks using heat diffusion processes for marketing candidates selection. In *Proceedings of the 17th ACM conference* (pp. 233–242). https://doi.org/10.1145/1458082.1458115.

Macal, C. M., & North, M. J. (2006). Tutorial on agent-based modeling and simulation part 2: How to model with agents. *Proceedings - Winter Simulation Conference*, (October 2016), 73–83. https://doi.org/10.1109/WSC.2006.323040.

Macal, C., & North, M. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, *4*(3), 151–162. https://doi.org/10.1057/jos.2010.3

Mahajan, V., Muller, E., & Bass, F. M. (1990). New Product Diffusion Models in Marketing: A Review and Directions for Research. *Journal of Marketing*, *54*(1), 1–26.

Marschak, J. (1959). *Binary choice contraints on random utility indications.* Mathematical Methods in the Social Sciences, Stanford Univeristy Press.

Martens, P. N., & Rattmann, L. (2001). Mining and Society : No Mining , No Future. In *17 International Mining Conference and Exhibition of Turkey*.

Mason, R., & Mitroff, I. (1981). *Challenging strategic planning assumptions*. New York: John Wiley & Sons.

Mathews, M. R. (1997). Twenty-Five Years of Social and Environmental Accounting Research: Is There a Silver Jubilee to Celebrate. *Acounting, Auditing & Accountability Journal*, *10*(4), 481–531.

Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., & Gotts, N. M. (2007). Agent-based land-use models: A review of applications. *Landscape Ecology*, *22*(10), 1447–1459. https://doi.org/10.1007/s10980-007-9135-1.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics*, *1*(2), 105–142. https://doi.org/10.1108/eb028592.

McFadden, D. (1974). *Conditional Logit Analysis of Qualitative Choice Behavior*. New York: Frontiers in Econometrics.

Mcfadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Joural of Applied Econometrics*, *15*(5), 447–470.

Mchugh, M, L. (2009). “The odds ratio: Calculation, Usage and Interpretation.” *The Journal of Croatian Society of Medical Biochemistry and Laboratory Medicine*. Retrieved from http://www.biochemia-medica.com/content/odds-ratio-calculation-usage-and-interpretation.

MCMPR (Ministerial Council on Mineral and Petroleum Resources). (2005). *Principles for Engagement with communities and stakeholders*.

McPherson, M., Smith-lovin, L., & Cook, J. M. (2001). B IRDS OF A F EATHER : Homophily in Social Networks. *Annual Review of Sociology*, *27*, 415–444. https://doi.org/10.1146/annurev.soc.27.1.415.

Meade, N., & Islam, T. (2006). Modelling and Forecasting the Diffusion of Innovation—A 25-Year Review. *International Journal of Forecasting*, *22*(3), 519–545.

Midgley, D. F. (1976). A Simple Mathematical Theory of Innovative Behavior. *Journal of Consumer Research*, *3*(1), 31–41. https://doi.org/10.1086/208648.

Miller, J., & Page, S. (2009). *Complex Adaptive Systems: An Introduction to Computational Models of Social Life*. Princeton University Press.

Miranda, M., Chambers, D., & Coumans, C. (2005). *Framework for Responsible Mining: A Guide to Evolving Standards*.

Moffat, K., & Zhang, A. (2014). The paths to social licence to operate: An integrative model explaining community acceptance of mining. *Resources Policy*, *39*(1), 61–70. https://doi.org/10.1016/j.resourpol.2013.11.003.

Morrison, E. W. (2002). The role of social network ties during socialization. *Academy of Management Journal*, *45*(6), 1149–1160. https://doi.org/10.2307/3069430.

Munashinge, M., & Shearer, W. (1995). *Defining and Managing Sustainability*. The Work Bank, Washington.

Nakagawa, M., Bahr, K., & Levy, D. (2013). Scientific understanding of stakeholders' behavior in mining community. *Environment, Development and Sustainability*, *15*(2), 497–510. https://doi.org/10.1007/s10668-012-9389-x.

National Center for Health Statistics. (2014). *Utah Department of Health Data Resources; advanced users dataset queries.(IBIS‑PH Indicator‑Based Information)*. Retrieved from http://ibis.health.utah.gov/query/ Index.html%22.

National Mining Association. (2016). *The Economic Contributions of U.S. Mining (2015 Update)*.

Nelsen, J., & Scoble, M. (2006). Social Licence to Operate Mines: Issues of Situational Analysis and Process: *Department of Mining Engineering, University of British Columbia, Vancouver*.

Newman, M. . (2003a). The structure and foundation of complex networks. *SIAM Rev.*, *45*(2), 167–256.

Newman, M. E. (2003b). Properties of highly clustered networks. *Phys Rev E Stat Nonlin Soft Matter Phys*, *68*(2 Pt 2), 26121. https://doi.org/10.1103/PhysRevE.68.026121.

North, M. J. (2001). Multi-Agent Social and Organizational Modeling of Electric Power and Natural Gas Markets. *Computational & Mathematical Organization Theory*, *7*, 331–337. https://doi.org/10.1023/A:1013406317362.

North, M., & Macal, C. (2007). *Managing Business Complexity*. New York: Oxford University Press.

North M. J, & Macal, C. M. (2007). Tutorial on Agent-Based Modeling and Simulation. In *75th Military Operations Research Society Symposium (MORSS)*.

O'Faircheallaigh, C. (2012). Community development agreements in the mining industry: an emerging global phenomenon. *Community Development*, 222–238. Retrieved from http://dx.doi.org/10.1080/15575330.2012.705872.

Ostroff, C., & Kozlowski, S. (1992). Organizational Socialization As a Learning Process: the Role of Information Acquisition. *Personnel Psychology*, *45*(4), 849–874. https://doi.org/10.1111/j.1744-6570.1992.tb00971.x.

Owen, J. R., & Kemp, D. (2013). Social licence and mining: A critical perspective. *Resources Policy*, *38*(1). https://doi.org/10.1016/j.resourpol.2012.06.016.

Peres, R. (2014). The impact of network characteristics on the diffusion of innovations. *Physica A: Statistical Mechanics and Its Applications*, *402*, 330–343. https://doi.org/10.1016/j.physa.2014.02.003.

Petkova, V., Lockie, S., Rolfe, J., & Ivanova, G. (2009). Mining developments and social impacts on communities: Bowen basin case studies. *Rural Society*, *19*(3), 211–228. https://doi.org/10.5172/rsj.19.3.211.

Porter, M. E., & Kramer, M. R. (2011). Creating Shared Value. *Harvard Business Review*, *89*, 63–77. https://doi.org/https://doi.org/10.1108/09600039410055963.

Potts, J., Cunningham, S., Hartley, J., & Ormerod, P. (2008). Social Network Markets: A New Definition of the Creative Industries. *Journal of Cultural Economics*, *32*(3), 167–185.

Premo, L. S. (2006). Agent-based models as behavioral laboratories for evolutionary anthropological research. *Arizona Anthropologist*, *17*, 91–113.

Prno, J. (2013). An analysis of factors leading to the establishment of a social licence to operate in the mining industry. *Resources Policy*, *38*(4). https://doi.org/10.1016/j.resourpol.2013.09.010.

Prno, J., & Scott Slocombe, D. (2012). Exploring the origins of “social license to operate” in the mining sector: Perspectives from governance and sustainability theories. *Resources Policy*, *37*(3), 346–357. https://doi.org/10.1016/j.resourpol.2012.04.002.

Que, S. (2015). *Describing local community acceptance with discrete choice theory for enhanced community engagement*. Doctoral Dissertations. Paper 2416. Missouri University of Science and Technology.

Que, S., & Awuah-Offei, K. (2014). Framework for mining community consultation based on discrete choice theory. *International Journal of Mining and Mineral Engineering*, *5*(1), 59–74. https://doi.org/10.1504/IJMME.2014.058919.

Que, S., Awuah-Offei, K., & Samaranayake, V. A. (2015). Classifying critical factors that influence community acceptance of mining projects for discrete choice experiments in the United States. *Journal of Cleaner Production*, *87*(1), 489–500. https://doi.org/10.1016/j.jclepro.2014.09.084.

Rand, W., Herrmann, J., Schein, B., & Vodopivec, N. (2015). An Agent-Based Model of Urgent Diffusion in Social Media. *Journal of Artificial Societies and Social Simulation*, *18*(2), 1. Retrieved from http://jasss.soc.surrey.ac.uk/18/2/1.html.

Ratna, N. N., Dray, A., Perez, P., Grafton, R. Q., & Kompas, T. (2008). Innovation diffusion among heterogeneous agents: Exploring complexity with agent-based modelling (ABM). *In Applications of Complex Adaptive Systems (*, 113–141. IGI Global.

Reed, M. S., Graves, A., Dandy, N., Posthumus, H., Hubacek, K., Morris, J., … Stringer, L. C. (2009). Who's in and why? A typology of stakeholder analysis methods for natural resource management. *Journal of Environmental Management*, *90*(5), 1933–1949. https://doi.org/10.1016/j.jenvman.2009.01.001.

Rezvani, M., Hamid, S., Hoseini, K., & Samadzadeh, M. M. (2012). Investigating the Role of Word of Mouth on Consumer Based Brand Equity Creation i n Iran ' s Cell - Phone Market. *Journal of Knowledge Management, Economics and Information Technology*, (8), 1–15.

Rizzo, A., & Porfiri, M. (2016). Innovation diffusion on time-varying activity driven networks. *European Physical Journal B*, *89*(20), 1–8. https://doi.org/10.1140/epjb/e2015-60933-3.

Rockwell, B. W. (2000). The Goldfield Mining District, Nevada: An Acid-Sufate Bonanza Gold Deposit. In Floyd F. Sabins (Ed.), *Fourteenth International Conference for Applied Geologic Remote Sensing*. Las Vegas, USA: in Guidebook for Field Trip to the Basin and Range.

Rogers, E. M. (1995). *Diffusion of Innovations*. New York: The Free Press.

Rogers, E. M. (2002). Diffusion of preventive innovations. *Addictive Behaviors*, *27*, 989–993. https://doi.org/10.1016/S0306-4603(02)00300-3.

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). New York: Free Press.

Rotheroe, N., Keenlyside, M., & Coates, L. (2003). Local agenda 21; Articulating the meaning of sustainable development at the level of the individual enterprise. *Journal of Cleaner Production*, *11*(5), 537–548. https://doi.org/10.1016/S0959-6526(02)00075-6.

Rowe, J., & Enticott, R. (1998). The role of local authorities in improving the environmental management of SMEs: some observations from partnership programmes in the west of England. *Journal of Eco-Management Auditing*, *5*(2), 75–87. https://doi.org/10.1002/(SICI)1099-0925(199807).

Russo, Michael, V. R. and, & Fouts, Paul, A. (1997). A Resource-Based Perspective On Corporate Environmental Performance And Profitability. *Academy of Management Journal*, *40*(3), 534–559. https://doi.org/10.2307/257052.

Ryan, B., & Gross, N. C. (1943). The Diffusion of Hybrid Seed Corn in Two Iowa Communities. *Rural Sociology*, *8*, 15–24.

Saltelli, A., & Annoni, P. (2010). How to avoid a perfunctory sensitivity analysis. *Environmental Modelling and Software*, *25*(12), 1508–1517. https://doi.org/10.1016/j.envsoft.2010.04.012.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S. (2008). *Global Sensitivity Analysis: The Primer*. John Wiley & Sons Ltd.

Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models* (Joint Rese). Ispra, Italy: John Wiley& Sons Ltd.

Schaefer, A. (2004). Corporate Sustainability-Integrating Environmental and Social Concerns? *Corporate Social Responsibility and Environmental Management*, *11*, 179–187. https://doi.org/10.1002/csr.070.

Schluter, M., Mcallister, R. ., Arlinghaus, R., Bunnefeld, N., Eisenack, K., Holker, F., Muller, B. (2012). New horizons for managing the environment: a review of coupled social-ecological systems modeling. *Nat. Resour. Model.*, *25*(1).

Scholl, H. (2001). Agent Based and System Dynamics Modeling: A Call for Cross Study and Joint Research. In *Proceedings of the 34th Annual Hawaii International Conference on System Sciences*.

Shrivastava, P. (1995). the Role of Corporations in Achieving Ecological Sustainability. *Academy of Management Review*. https://doi.org/10.5465/AMR.1995.9512280026.

Siero, F. W., & Doosje, B. J. (1993). Social Judgment Theory (Siro and Doosje 1993).pdf. *European Journal of Social Psychology, 23*, 541–554.

Sobkowicz, P. (2009). Modelling opinion formation with physics tools: Call for closer link with reality. *Jasss*, *12*(1).

Solley, W. B., Pierce, R. H., & Perlman, H. A. (1999). *Estimated Use of Water in the United States in 1995*. Denver, Colorado.

Soste, L., Wang, Q, Robertson, D., Chaffe, R., Handley, S., & Wei, Y. (2015). Engendering stakeholder ownership in scenario planning. *Technol. Forecast. Soc. Chang.* , *91*, 250–263.

Souder, W. E., & Palowitch, E. R. (1981). *Growth of longwall technologies in the United States: Longwall-shortwall mining: State of the art*. (R. V. Ramai, Ed.). The American Institute of Mining, Metallurgical, and Petroleum Engineers Inc.

Stave, K. A. (2003). A system dynamics model to facilitate public understanding of water management options in Las Vegas, Nevada. *Journal of Environmental Management*, *67*(4), 303–313. https://doi.org/10.1016/S0301-4797(02)00205-0.

Suo, S., & Chen, Y. (2008). The Dynamics of Public Opinion in Complex Networks. *Journal of Artificial Societies and Social Simulation*, *11*(4).

Szablowski, D. (2010). Operationalizing Free, Prior, and Informed Consent in the Extractive Industry Sector? Examining the Challenges of a Negotiated Model of Justice. *Canadian Journal of Development Studies*, *30*(1–2), 111–130.

ten Broeke, G., van Voorn, G., & Ligtenberg, A. (2016). Which Sensitivity Analysis Method Should I Use for My Agent-Based Model? *Journal of Artificial Societies and Social Simulation*, *19*(1), 1–35. https://doi.org/10.18564/jasss.2857.

Tesfatsion, L. (2002). Agent-Based Computational Economics Growing Economies from the Bottom Up Table of Contents : *Aritificial Life*, *8*(1), 55–82.

Thiele, J. C., Kurth, W., & Grimm, V. (2014). Facilitating Parameter Estimation and Sensitivity Analysis of Agent-Based Models : A Cookbook Using NetLogo and R. *Journal of Artificial Societies and Social Simulation*, *17*(3). https://doi.org/10.18564/jasss.2503.

Thomson, I., & Boutilier, R. G. (2011). Social license to operate. *SME Mining Engineering Handbook*, 1779–1796.

Thurstone, L. (1927). A law of comparative judgement. *Psychological Review*, *34*, 273–286.

Tilton, J. E., & Landsberg, H. H. (1999). nnovation, productivity growth, and the survival of the US copper industry. *Productivity in Natural Resource Industries*, 109–39.

Torrens, P. M. (2010). Agent-based Models and the Spatial Sciences: Agent-based models and the spatial sciences. *Geography Compass*, *4*(5), 428–448. https://doi.org/10.1111/j.1749-8198.2009.00311.x.

Toth Jr, J. F., Brown, R. B., & Xu, X. (2002). Separate family and community realities? An urban-rural comparison of the association between family life satisfaction and community satisfaction. *Community, Work & Family*, *5*(2), 181–202. https://doi.org/10.1080/13668800220146364.

Train, K. (2002). *Discrete Choice Methods with Simulation*. Cambridge University.

Valbuena, D., Verburg, P. H., Bregt, A. K., & Ligtenberg, A. (2010). An agent-based approach to model land-use change at a regional scale. *Landscape Ecology*, *25*(2), 185–199. https://doi.org/10.1007/s10980-009-9380-6.

Valente, T. (1995). *Network Models of the Diffusion of Innovations.* Hampto Press.

Walt, G. (1994). *Can interest groups influence government policy? Health policy: an introduction to process and power*. London: Zed Publications.

Wang, L., Awuah-Offei, K., Que, S., & Yang, W. (2016). Eliciting drivers of community perceptions of mining projects through effective community engagement. *Sustainability (Switzerland)*, *8*(7). https://doi.org/10.3390/su8070658.

Williams, R., & Walton, A. (2013). The Social Licence to Operate and Coal Seam Gas Development. A literature review report to the Gas Industry Social and Environmental Research Alliance (GISERA). *CSIRO, Canberra*.

Windrum, P., Fagiolo, G., & Moneta, A. (2007). Empirical Validation of Agent - Based Models : Alternatives and Prospects. *Journal of Artificial Societies and Social Simulation*, *10*(2007), 1–21. https://doi.org/Article.

World Economic Forum. (2014). *Scoping Paper: Mining and Metals in a Sustainable World"* Retrieved from http://www3.weforum.org/docs/WEF_MM_MiningMetalSustainableWorld_ScopingPaper_2014.pdf.

Wu, M., Wang, L., & Li, M. (2015). An approach based on the Bass model for analyzing the effects of feature fatigue on customer equity. *Computational and Mathematical Organization Theory*, *21*(1), 69–89. https://doi.org/10.1007/s10588-014-9177-2.

Yates, B. ., & Horvath, C. . (2013). Social license to operate: how to get it, and how to keep it. In *Pacific Energy Summit*. Retrieved from http://www.nbr.org/downloads/pdfs/eta/PES_2013_summitpaper_Yates_Horvath.pdf.

Yuhara, N., & Tajima, J. (2006). Multi-driver agent-based traffic simulation systems for evaluating the effects of advanced driver assistance systems on road traffic accidents. *Cognition, Technology and Work*, *8*(4), 283–300. https://doi.org/10.1007/s10111-006-0045-9.

Zhang, T., Gensler, S., & Garcia, R. (2011). A study of the diffusion of alternative fuel vehicles: an agent-based modeling approach. *J. Prod. Innovat. Manag.*, *28*, 152–168. Retrieved from http://dx.doi.org/10.1111/j.1540-5885.2011.00789.x.

Zhang, T., & Nuttall, W. J. (2011). Evaluating Government ' s Policies on Promoting Smart Metering in Retail Electricity Markets via Agent Based Simulation. *Journal of Product Innovation Management*, *28*(2), 169–186.

Zhou, W. X., Sornette, D., Hill, R. ., & Dunbar, R. . (2005). Discrete hierarchical organization of social group sizes. *Proceedings of the Royal Society B*, *272*, 439–444. https://doi.org/10.1098/rspb.2004.2970.

VITA

Mark Kofi Boateng, was born in New Tafo-Akim, a town in the eastern part of Ghana. He received his PhD in Mining Engineering in July of 2017 from the Missouri University of Science and Technology. He received a BS in Mining Engineering in 2005 from the University of Mines and Technology (UMaT), formerly, KNUST-School of Mines, Tarkwa, Ghana. He has over five years of working experience from the mining industry both Open Pit and Underground operations.

From 2005 to 2006, he joined AngloGold Ashanti Limited, Tarkwa, Ghana as a mining engineer (National service). He later worked for Taywood Mining (Mining Contractor for AngloGold Ashanti), Tarkwa, Ghana, as an assistant mining engineer serving at both Load and Haul, and Drill and Blast sections from 2007 to 2008. From 2009 to 2011, he joined Aveng Moolmans- Ghana operation (Mining Contractor for AngloGold Ashanti), Tarkwa, Ghana as a mining engineer where he served in the capacities as a drill and blast engineer, and a production engineer. Prior to his PhD studies, from 2011 to 2012, he worked for Chirano Gold Mines Limited, Ghana, a subsidiary of Kinross Gold Corporation as a mine planning engineer.

Mark gained an admission into the Missouri University of Science and Technology in 2012 to pursue his PhD in Mining Engineering. During his PhD studies, he was appointed as a Teaching-Fellow from 2013 to 2014. Such an appointment afforded him the opportunity to visit Saudi Mining Polytechnic (SMP) in Arar, Saudi Arabia, as a Visiting Mining instructor. Mark worked under the supervision of his academic advisor, Dr. Kwame Awuah-Offei.