

A Framework to Study the Impact of Interventions on Social Isolation during Pandemics using Multi-Agent Simulation

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Simranpreet Kaur

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by

Simranpreet Kaur

APPROVED BY:

K. Pfaff

Faculty of Nursing

S. Samet

School of Computer Science

P. Moradianzadeh, Advisor

School of Computer Science

15 May 2021

Declaration of Co-Authorship/Previous Publication

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I hereby declare that this dissertation incorporates material resulting out of the research conducted under Dr. Pooya Moradian Zadeh (My Supervisor). Under all circumstances, the fundamental ideas, essential contributions, experimental model, study of data and perception were implemented and tested by the author whereas the co-authors' support and contribution was essentially by means of proofreading the published documents. Dr. Pfaff and Dr. Samet contributed in sharing the suggestions related to the project.

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Abstract

Here is an abstract, it's very short and very nice.

Dedication

To my family who supported me through every thick and thin:

Father: S. Darshan Singh Gulati

Mother: Manjit Kaur Gulati

Brothers: S. Harmanpreet Singh Gulati and S. Parampreet Singh Gulati

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Chapter 1

Introduction

1.1 Background



1.1.1 Social Isolation

The importance of social relations has a considerable impact on an individual's mental and psychological well-being, as observed by various practitioners and policymakers. There are higher feelings of loneliness and a lower number of social networks among those who use or are linked to mental health services [1]. Social Isolation can be defined as the state of a person not being interested or unable to have any contact with other members of a society and who prefers to be alone [2–6]. Loneliness, on the other hand, is related to personal feelings and avoiding to have communications with others [6, 7]. Scientists and researchers normally use these terms interchangeably; however, the major difference between them is that social isolation refers to objective separation from other community members, while loneliness is more subjective and related to a person's feelings [7].

There are various factors associated with social isolation and some of them are stated here; however, they are not limited to just the ones discussed. Social isolation tends to affect the population of senior citizens more when compared to the group of younger generations [8, 9]. On the other side, the health status of individuals also plays a considerable role in affecting the state of social isolation. For instance, physical activities such as Running, Sports, Yoga, or Exercises performed outside may lower levels of feelings of social isolation, stress, and

depression [9, 10]. Also, Past events, especially the traumatic ones in an individual's life, may also affect the mindset of individuals in forming social relations [11]. The state of relationships such as being single, married, or any other kinds of relationships in which the individual is present may also affect and lead to the feelings of social isolation and loneliness [9, 12]. In addition, the affluence and type of locality influence the social relationships of an individual, thus ultimately affecting the behavioral tendencies of undergoing social isolation and loneliness [12]. People in urban areas feel more isolated in comparison to rural areas [10]. Various health disorders have been found to be directly or indirectly connected to the feelings of loneliness and social isolation. Some of them include depression, suicidal thoughts and behavior, personality issues, increasing level of delusions and deficiency in perception. [1]. Another health-related problem linked to social isolation is the increased risk of premature mortality [13].

1.1.2 Social Isolation in Pandemic



The effect of COVID-19 has spread to almost every part of the world and has affected millions of people around the globe. Due to the widespread nature of the virus, many events such as social, business, indoor and outdoor activities have been suspended for a long time [14]. Some of the researchers have named both the COVID-19 and social isolation conditions as double pandemic situations. The double pandemic name came from the fact that during COVID-19, the restrictions imposed on the people in terms of social distancing, quarantine, lockdowns and isolation, people were confined to their own houses, some of them alone and some with their family, thus, affecting their social life and leading to increasing numbers in social isolation levels [15]. According to an American study, Social Isolation links with approx. 29% increased occurrences of heart disease and 32% rise in chances of heart stroke along with 50% increased risk of developing dementia [16]. Problems related to social isolation have increased during COVID-19. The increasing number of restrictions on social gatherings and quarantine and isolation has led to the people feeling more socially isolated and lonely. 28% of the Americans live alone, thereby, no social contact and communication for a long period of time during COVID-19 [15]. Some of the sources indicate various health issues among groups of younger generations during the worldwide pandemic. The National Child Mortality database reported an increase in suicide rates among children

during the pandemic in the UK. [17]. Also, female students specifically suffered a decline in their mental health in Switzerland due to the lack of interactions and emotional support [18]. Preliminary surveys conducted in the United States of America indicated a 20-30% increase in loneliness while there is a three-fold increase in emotional troubles in the time of pandemic [15]. Other problems related to isolation were mass panic and anxiety. [19]

1.1.3 Agents



Agents can be defined as independently acting or functioning entities that make decisions based on a set of regulations to achieve their goals [20–24]. They learn and evolve from their environments to modify themselves to reach their goals. It is an entity that responds autonomously to a situation by taking into consideration some simple rules, goals, and capabilities [23]. Some of an agent’s features are that it is identifiable, situated, goal-directed, autonomous, and flexible. An agent is described as identifiable because it is an individual entity that is governed by a set of properties and traits guiding it’s behaviors and actions. It is named a situated agent when it exists in a specific world where it interacts with other agents. Goal-directed agents are when an agent possesses a need or a purpose to complete a task or fulfill a goal. An agent is described as autonomous because it is itself an entity that is capable of learning and acting independently. Flexible agents have the ability to modify it’s behaviors according to the situation, and it’s past experiences. However, these modifications in behavior might be governed by certain rules [23]. An agent-based model depicts the system of agents and the connections between them. These models simulate real-world phenomena and extract some important and useful information about these systems [21–23]. It blends the elemental units of multi-agent systems, game theory, evolutionary programming, complex systems, emergence, and computational sociology [25]. Advanced level of agent-based models may also incorporate evolutionary designs, neural networks or other research procedures supporting the learning and adaptation in real-world systems [26]. Agent-based modeling procedure is preferred over other modeling techniques. Some of its benefits are that it captures the emergent phenomenon, i.e., a situation about to happen or exist. Another is that it states a natural depiction of a system. This basically means that it depicts the system more clearly and accurately when compared with that of real systems. Agents are known to be flexible. The flexibility of ABM can be observed

along various dimensions. Also, the agents can be increased or decreased by any number. Their complex features such as behavior, logical extent, learning and evolving abilities and rules of interactions can be modified. [21].

1.1.4 Multi-Agent Systems

Multi-Agent Systems consist of self-governing entities known as agents. Because of their autonomous nature of implicit learning and making decisions, these agents provide more flexibility when compared to that of Distributed Problem Solving computing entities. [27]. The interactions of agents with their neighboring agents make them adaptive to new situations and this flexible nature of MAS makes it a useful mechanism in diverse areas such as marketing, anthropology, healthcare, engineering, etc. Some of the challenges faced by the agents in these systems include coordination, security, and learning [28]. The roles of agents differ based on the environment they are in. MAS proves to be useful in environments that have attributes, for instance, variations in population size, intricate interactions, and behaviors. These systems are adequate for dealing with large amounts of data, broken down into different components allocated to each agent. Experts can benefit from MAS in simulation and monitoring the behavior of dynamic networks in determining the solution for any given problem occurring in the society. One of the primary applications of MAS in research is to model healthcare systems. Because of the large amount of data and paradigms required for finding solutions to the problem, these systems focus on different areas such as management of data, security in distributed systems, gathering and collecting different resources, decision-making systems, simulation systems, platform for care and nursing, alarming and monitoring systems. Actors in a healthcare model may be classified into patients, doctors, nurses, relatives of patients, etc. [27]. Some of the scenarios in modeling are focused which happen everyday in hospitals, such as, treatment method of patients, visits to wards, interactions between healthcare providers and visitors. The results obtained from simulation indicate the efficiency of the model in modeling the dynamic status of everyday activities, like medical procedures disturbed or affected by hospital visitors [29].

1.2 Research Motivation

The use of multi-agent systems in modeling and simulation is widely known. The simulation of real-world systems helps in finding solutions to problems occurring in real life. Some of the benefits of simulating are that it reduces the cost of performing experiments, dangers of negative consequences, provides a safe environment, speed up hospital preparedness, knowledge, and awareness [20], handles uncertainties, and saves time [30]. Agent-based modeling has its applications in various fields, businesses, social sciences, technology, etc. The interaction of agents in multi-agent systems: Various healthcare experts have used agent-based modeling to determine solutions to different problems faced in the real world. Some of them determine the hospital capacity, palliative care given to patients and their responses, optimization of emergency departments.

During the COVID-19 pandemic, apart from coronavirus, various other mental health issues gained attention, such as feelings of stress, loneliness, depression, isolation. Due to the increasing number of confirmed cases and deaths, these mental disorders became more popular. It is crucial to monitor these issues to mitigate their spread and recover those already suffering from them. Various research works focus on identifying the extent of social isolation among older generations and other age groups before this situation of coronavirus emerged. However, there are few studies that focused on modeling its impact and extent during this time of the pandemic. We believe that there might be a lot of changes in the results obtained before and after the given time period. These changes may help practitioners and other officials to decide policies, methods, and other alternatives keeping in mind their condition.

Thus, it became necessary to determine the comparison of effects on people before the pandemic situation and after it. This model will focus on different scenarios based on interventions.

1.3 Problem Statement

To model and study Social Isolation in a widespread pandemic, we propose a novel Agent-Based framework. An individual in the population can be categorized as a Low-mobility individual or a High-mobility individual such that population of agents, $A = A_L \vee A_H$, where A_L consists of low mobility agents and A_H consists of high-mobility agents. As described before, the problem of Social Isolation can be divided into two sub-problems.

1.3.1 Modeling the spread of the disease

To simulate the spread of the disease among individuals based on different situations like Lockdown, social distancing, an outbreak in a nursing home, etc., a disease spread model based on the SEIR model is used. In this model, an agent can belong to one of the four classes, which are defined as, Susceptible (S), Infected (I), Recovered (R), and Dead(D). The infected class is further divided into Asymptomatic (AS), Quarantined (Q), Hospitalized (H), ICU (IC), and Wait-list (W). The infected agent can be in any of these states depends on its disease progression. Furthermore, classes are dynamic; therefore, an agent migrates from one state to another with time according to their health status. For this purpose, each agent is assigned a color.

To give an example, Assume an agent0 belongs to a high-mobility susceptible class, so it is given the color pink. If this agent gets infected and is asymptomatic, he is changed to the color Brown. Furthermore, this agent will go to the quarantine state, and its color would be yellow. After that, let's say it got recovered, so its color changed to Turquoise. Table 1.1 demonstrates different classes along with the colors used.

1.3.2 Measuring the impact of Social Isolation in different Scenarios

The concept of social isolation in this model may be referred to as detecting those agents who do not interact much with the other agents or those distant from other agents.

For example, ten agents understudy out of which five are low mobility agents, five are high mobility agents, and the total time to study them is four. Any agent's neighborhood is represented by an area surrounding this person up to a certain extent. The agents located

Class	Color
Susceptible(S)	Pink White
Infected(I):	
Asymptomatic(AS)	Brown
Quarantine(Q)	Yellow
Hospitalized(H)	Magenta
ICU(IC)	Sky
Waitlist(W)	Lime
Recovered(R)	Turquoise
Dead(D)	xxxxxxxxxxx

TABLE 1.1: Classes representation with colors

in this area are termed as neighbors of that agent. However, they interact with a few and are termed as **Contacts**.

In figure 1.1, Agent0 has its neighbors as Agent1 and Agent2; however, he has a contact with Agent1 with some probability, P_1 . If the total number of contacts Agent0 has for the whole time frame is less than one standard deviation below the mean of the population, he is said to be socially isolated.

Similarly, the distance from these contacts is measured. Following the previous example,

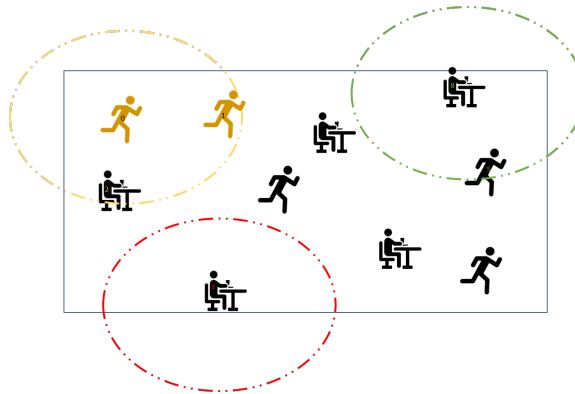


FIGURE 1.1: An example demonstrating the concept of neighbors and contacts

the distance between Agent0 and Agent1 is considered. For this, if the total distance Agent0 has from these particular contacts for the whole time frame is greater than one standard deviation above the mean of the population, then it is said to be socially isolated.

1.4 Research Objectives

We propose a novel Agent-Based framework to model and study Social Isolation in a widespread pandemic. The main objectives of this research are to solve two sub-problems related to social isolation.

1. Simulate the spread of the virus among individuals based on different situations such as lockdowns, closure of public spaces.
2. Measure the impact of interventions on social isolation.

The SEIR (Susceptible Exposed Infected Recovered) model is one of the popular models based on different conditions of individuals in pandemics such as being susceptible and exposed to the virus, getting infected, and recovering from the disease [31]. The interventions play a huge role in the state of an individual.

1.5 Research Contributions

A novel agent-based model for modeling and studying Social Isolation in a widespread pandemic is proposed in this research work. Various research works focus on modeling social isolation using agent-based modeling; however, most of them were done before the pandemic situation emerged. To the best of our knowledge, there has been no work done based on the combination of categorized social isolation during the pandemic and creating agent-based models in different scenarios. These scenarios are mostly related to the interventions imposed by Government and health officials during that time. Thus, the impact of these interventions is also studied in this research.

The outcomes of this project can assist various decision-makers in deciding such interventions aimed at mitigating the extent of social isolation. Since the proposed model is flexible, therefore, with a certain amount of information, it can be applied or can simulate different parts, regions or areas of the country. Moreover, policymakers and other organizations may design their policies considering the group of affected people.

1.6 Thesis Outline

The remaining part of the thesis is categorized into chapters starting with review of some of the existing techniques and models in the field of social isolation, multi agent systems and agent based modeling in the time of pandemic in chapter 2. The proposed methodology for fulfilling the objectives of this research is given in chapter 3. Experimental setup, results and analysis are covered in chapter 4 followed by conclusion, discussion and future works in chapter 5.

Chapter 2

Related Work

2.0.1 Social Isolation

There have been various researches conducted on determining the extent of social isolation in different sections of people and in different time periods. Some of the studies focused their attention on socially isolated senior citizens. One of them [32] explored the contributions of different types of robots and their everyday tasks in the lives of older people. Besides highlighting the pros of carebots in augmenting movement and hence, easing self-support, they underlined the cons of neglecting the senior groups and letting them with robots for longer time. They also explained the factors that can hinder their possibility to have social contact. Finally, some guidelines were suggested that can be helpful for the well-being of the elderly. Another research [12] demonstrated a predictive model to deduce the social isolation levels among older adults. For this purpose, social networking sites and ambient intelligence were examined to find the appropriate attributes using evaluation methods. These attributes are then utilized to select a single predictive model by evaluating with respect to the accuracy, sensitivity, specificity, and predictive values. To further validate the chosen model, a questionnaire was used that helped to identify social isolation in eight Older Adults. As a result, an accuracy of 87% and a type 2 error rate of 15% were obtained by their selected ABS model. In [33], the researchers exploited the benefits of Natural Language Processing by collecting data from medical-related documents to identify the individuals facing Social Isolation. For this purpose, Prostate Cancer Patients' dataset was

extracted and divided into two parts, with one part consisting of three-fourth of the data for training purposes, and the remaining was used to test the system's efficiency. In order to measure the system performance, the algorithm was evaluated by three measures, that were, precision, f-measure, and recall, accompanied by manual reviewing of the test dataset. The results showed that the proposed algorithm provides high accuracy in detecting social isolation among individuals. The authors in [34] had made an effort to validate the elements and levels of social isolation and loneliness, theoretically and practically, by developing a social isolation scale specifically for Indian society. Their research demonstrated the use of existing literature to produce the items required and further examining them using various factors. A ten-item scale was evaluated for social isolation by contriving the dataset of 128 people. Using this scale, they have concluded greater reliability, criterion validity, and convergent validity by exhibiting no issues for internal as well as external quality to assist further research related to Social Isolation.

Additionally, the authors in [35] proposed a novel technique to detect the effects of social isolation and loneliness by associating individuals with health plans to medical expenditures and a survey. They anticipated health-related expenditures using multivariable regression with the help of dependent variables as objective isolation and loneliness. As a result, individual suffering from objective isolation tends to have higher expenses as compared to the one with loneliness depicting the former with the high risk of disease. In [11], the authors emphasized the four minority groups of Chihuahua and Aguascalientes to apprehend the concept of social isolation. To demonstrate the causes and effects of high levels of Social Isolation, Firework Algorithm was used. This study was performed using a questionnaire that described four categories, out of which two were related to Social Isolation. Finally, they pointed out 4 out of 9 students that were facing social isolation by utilizing nine factors.

In [36], the authors claimed to overcome the drawbacks of the existing work of clustering networks by proposing a novel algorithm, SCAN (Structural Clustering Algorithm for Networks). In addition to detecting communities within the network, their algorithm was able to see the nodes that act as a common link between the communities (hubs) and the nodes with little or no participation in the network (outliers). Moreover, both the structure and

the adjoining nodes of the vertex were considered in order to replicate the characteristics of real networks. To evaluate the performance of their algorithm, it was applied to real-world networks and compared with fast modularity-based algorithms with respect to performance and efficacy. As a result, SCAN depicts better efficiency than the other algorithm.

Considering the drawbacks of SCAN algorithm in identifying clusters, hubs, and outliers by evaluating the density of all the vertices in the neighborhood, SCAN++ was introduced in [37] that used a new data structure named directly two-hop-away reachable node-set (DTAR). It is the collection of only those nodes that are away from the current node by a length of 2. The algorithm utilized two methods for making it efficient. Initially, it analyzes only the nodes in DTARs for computation, thereby lowering the number of density evaluations. Secondly, a part of the evaluations of the DTARs were reused, thus boosting its performance. The authors claimed that using SCAN++, the same results were obtained but cutting the computational costs. Another effort to spot the outliers was demonstrated in [38], in which novel outlier edge detection algorithms were presented. It determined the isolated nodes by using two random graph generation models. For this purpose, the relationship between two nodes and among their neighboring nodes demonstrated by the four different schemes was integrated with the above-mentioned models. To evaluate the proposed algorithm, it was studied on real-world networks, and as a result, it was claimed that their algorithms successfully detect the noisy edges. Furthermore, they compared the proposed algorithm with the existing outlier edge detection metrics for measuring the performance, and it came out to be more efficient than the others. Nonetheless, it was observed that discarding these edges leads to greater distance between the nodes and high clustering coefficient. Finally, three applications were discussed that anticipated its potential.

One of the research works of an agent-based simulation model by [39] focused on proposing a mathematical model and design aimed at detecting the socially isolated individuals in a community, taking the structural features of the network under consideration. Firstly, mapping a community to a weighted directed social network graph is done. The nodes with their social connected index are at least one standard deviation less than the average of society. The isolated nodes are detected using the information propagation approach. Hence, the results obtained depict the ability of the proposed model in identifying the socially

isolated nodes. As their future work, they may take the combination of the individuals' behavior and features while detecting the socially isolated nodes.

2.0.2 Multi-Agent Systems

Researchers deploy the use of agent-based systems in various modeling and simulation activities for so many years. The field of healthcare [27, 40–43], manufacturing [44–47], disaster management [48–51], personalized recommendations [52–54], telecom services [55] and engineering [56–59] are some of the domains in which the multi agent systems are used either in terms of modeling, simulation or any other model based application.

In the Healthcare field, there are various areas in which these multi-agent systems find use, for instance, in [27] formulated an optimization problem in palliative care network and proposed a multi-agent model bringing together both the patient and care provider in a social network aimed at benefiting the older population in maintaining an active lifestyle. This social network assists the patients in searching for a team of care providers who are more appropriate depending on their condition. In addition to that, they also developed an algorithm for the message transfer approach transferring requests from patients to agents with the help of some common links such as friends. Another goal focused by the researchers was to test the efficiency of their approach, keeping in mind the requirements, ability and individual inclination. The evaluation of the proposed system's efficiency and functionality was done using real and non-real palliative networks. The results showed a decline in the operational expenses and up-gradation in the quality of the service. When compared to other existing models in both static and dynamic environment, their proposed methodology obtained greater level of satisfaction in a comparatively lesser amount of time.

Another application in [60], with an objective to interpret the structuring of the social networks, the authors developed an agent-based model in a single scale network with no initial connections, but with every following step, two agents were chosen randomly to form an acquaintance. However, the friendship built up with preferential selection was based on two criteria: contact with the same person and mutual interest. In order to add new friends to the contact list, previous connections need to be removed. The experiment conducted on 84 schools of USA and 90118 questionnaires has concluded that their static model is accurate in terms of clustering coefficient, degree distributions, and friendship distributions. For

fitness-based applications, the authors in [61] conducted a research on the in-depth design of conversational agents. These agents are built to provide counseling related to wellness (such as motivating to exercise and telling real-time stories of individuals who suffered from the same problem and their ways of dealing with them) of older individuals who are undergoing the problem of isolation and cater to their needs at a social level for a continuous time period. They formulated three hypotheses by examining 12 affected individuals and observed that the efficiency of coping up with loneliness is more significant when the interaction of the affected section of adults is initiated through an agent in comparison to initiation from the side of individuals. Another claim made by the authors is that conversational agents have a greater potential in mitigating the initial losses when illness, death, and independence in the elderly population are concerned. The interaction of the agent with the affected section of adults in real-time may assist in controlling varying mood trends and treatment for ailments linked to the problem of isolation. R Jayaraman proposed a novel Agent-based model for emulating social networks that makes use of ‘Positive Social Influence’ applied by the specialists to aid in decision-making for individual specialization [62]. This paper also uses cultural algorithms, allowing them to evolve their capabilities by finding appropriate producer agents. The author concluded that the described framework had helped optimize the results with lower distance cost and operational cost compared with genetic algorithm, exhaustive search, and random search; nonetheless, it improved the system’s efficiency.

To study the evolution of social relationships of the students with time, the authors in [63] proposed a novel Agent-Based Simulator, ABS-SOCI, which takes as input the initial sociogram that can be loaded or be given manually category-wise. This model illustrated the psychological description of the students temporally based on numerous factors like group size, empathy between students of different categories. To evaluate the righteousness of this simulator, four different scenarios were considered with three different phases where each phase was divided into two datasets, that is, training and test dataset. As a result, using binomial testing, the sociograms obtained through ABS SOCI and the real relationships were alike. Furthermore, this research was also found to be acceptable as per sensitivity and cross-validation. The authors in [64] aimed at modeling the spread and ubiquity of epilepsy disease in India through an agent-based model denoted by IndiaSim. Based on the

proposed model, agents involved in their approach were either free of epilepsy or according to the health status of treatment (with or without seizures). They analyzed three schemes adopted by Government-funded epilepsy programs. Benefits in terms of health and economy with respect to epilepsy are monitored. Some of the measures include considering the affected individuals who remain untreated, the personal expenditure involved, and insurance benefits. Thus, they concluded that just publicly funding the first line of antiepilepsy drugs will not be enough for most of the individuals belonging to lower sections of society. Hence, providing costs for both first and second-line epilepsy and therapeutic costs may help prevent extra financial costs usually faced by patients in India, which ultimately results in the country's improved health status.

The Agent-based model developed in [65] assisted in depicting the approach of the engagement of patients within the complex psychological care ecosystem. In addition to monitoring the modifications and the reasoning of the treatment plans and their delivery, it also aids in examining the overall dynamics and efficiency of the system by predicting the effects of care coordination technologies. To validate the claims put forward, the authors presented the challenges as well as the initial results of this simulation manifest the importance of their model. To handle and manage the caregiver routing problem with numerous constraints in the home health care system, an agent-based simulator is presented in [66] that simulated the behavior of caregivers in a dynamic environment. For this purpose, caregivers were provided with four decision rules to help them in making decisions with respect to their level of autonomy and the local context. The results were evaluated for their performances based on five metrics using a multi-agent platform using two real-world examples.

In [67], the authors developed a network-oriented Multi-Agent System that assists in providing home-care to the patients by keeping in mind the HC knowledge and guidelines representation. One of the main characteristic considered in their proposed system is the Care Plan personalization which is designed using clinical guidelines which are further customized according to the patients' requirements, especially for those with more than one chronic disease. The authors developed a three-layer architecture consisting of a knowledge layer, data abstraction layer, and agent-based layer, making it reusable, adaptable

and flexible. The authors in [68] aimed at constructing and implementing an agent-based framework based on cultural evolution. The main objective of their research was to explore the learning capabilities of an artifact in the absence of former insights related to the artifact. Both cultural and genetic algorithms were integrated to form a new model. The secondary objective included the comparison of social learning and distance learning of the potential of the artifact. Upon experimentation, it was observed that social learning tends to be more preferable than individual learning, making it clear that cultural learning can be best used to learn the complex nature of the artifacts, and observational learning works better in the case of simpler artifacts. Also, it is highlighted that agents should have the ability to emulate the noticeable attributes of the artifact.

2.0.3 Agent Based System and the Pandemic

[69] stated that most of the researchers used SIRS and one of its improved versions that is, SEIR model. They further stated that social distancing and hospital capacity are some of the important factors that help controlling the spread of the disease. They created an agent based simulation focused on modeling different scenarios to simulate an epidemic that is a consequent of an infectious disease and recommended some measures that could be taken in order to reduce its effects. As a result, they found that social isolation activation delay has been proven to be useful in reducing the impact of the disease. Hence, the authors claimed that along with predicting the outputs of various intricate situations to a certain extent, this model can modify infection parameters, like incubation period, infection rate, and other recovery factors. They also claimed that it could model and analyze actual data with respect to lockdown activation delay, the capacity of the hospital, and the total lockdown period for a catastrophe of any region. [70] proposed a contemporary model aimed at simulating the COVID-19 epidemic by employing a population of agents. They conducted the simulation based on seven scenarios considering the interventions some of which include lockdowns, isolation levels (vertical, partial), face masks and social isolation. The simulation encourages the importance of lockdowns in limiting the number of infected individuals and deaths. They also stated that economical level remedies have to be implemented by the Government to cover the financial losses incurred because of the halt of the working of workplaces, possibility of large scale unemployment, recession and other negative financial

ramifications. They further found out that vertical level isolation is not much effective. The best scenario according to their simulation results came out to be the combination of partial isolation with the use of masks and also proved to be more realistic as compared to others both in terms of its implementation and social cooperation.

Another agent based model by [71] presented a model to evaluate the transmission risks in different facilities during the COVID-19 pandemic. They simulated the transmission process in temporal space where the decisions are made by the simulated agents based on the rules that were usually designed from the spatial patterns and infectious conditions that may be possible during the interaction of agents. The agents also have their individual profiles showing their social states, health status and conditions that were employed during their interaction with other agents. Various theoretical scenarios have been examined to evaluate the performance of the proposed model. The results have shown that new strategies may be implemented aimed at bringing down the COVID-19 risks of transmission within different facilities and prepare informed decisions accordingly.

[72] expressed their attention towards the stress imposed on the public health systems by the COVID-19 pandemic. Major countries at risk during that time were Italy and Spain. Since, the effectiveness of implementing lockdowns and partial confinement measures are unknown therefore, they created a modified partition based model from the original SEIR model where undiagnosed individuals and population of isolated individuals at different levels were considered prone to infection. Benefits of the model include the adjustments made to the model proved to be accurate and did not show much differences in the other existing complex models. They further claimed that based on their observations, interventions of labor for around three weeks could lead to larger decline in contact among different people and ultimately result in reducing the spread of the pandemic and also help in saving lives of various people. [73] simulated the spread of COVID-19 through an agent based model. Their model is based on the SEIR model where fear acts as a motivation for the agents leading to isolating themselves and help contain the spread of the pandemic. The advantage of their model is it being able to generate numerous waves of infections which is essential in studying the dynamics of COVID-19 epidemic. They further employed the two constraints as applied by the government that were testing and contact restriction and travel constraints. The results of the experiment showed that implementation of both of these approaches may assist in reducing the curve of the number of infected individuals in a day throughout the

course of the pandemic. They further stressed the importance of testing in combination with contact tracing and not just alone.

[74] proposed an agent-based model capable of simulating the spread of COVID-19 among the inmates of any city irrespective of its location. Agents are made susceptible to the disease so that infection can occur among them. Validation of the proposed model was done based on the real data from Ford county, USA. For experimentation, efficacy of the digital herd immunity model is analyzed by exploring the effect of tracing the contact and search for different parameters that help in eliminating the epidemic within the city. The results indicate that it is feasible to gain immunity and reduce the number of infections in digital herd sooner. [75] investigated the significance of real time genome sequencing of SARS-CoV-2 in a section of infected patients during the first ten weeks of COVID-19 containment in Australia. Based on the demographic data, ABM produced more than 24 million software agents representing an anonymous individual.

2.1 Conclusion



A review of some of the existing and leading techniques and arithmetic models to identify social isolation among different sections of people over diverse periods is given in a nutshell. We further provided an overview of the multi-agent systems both before and during the COVID-19 pandemic. It was observed that many models focused their attention on health care in general; however, not much attention was given to modeling or identifying social isolation during the pandemic. Also, multi-agent systems have been employed to study or determine the extent of various health problems; however, social isolation was not among them. In this research work, we created and simulated a model for identifying the degree of social isolation in four different scenarios with various settings, including both before and during the pandemic. To the best of our knowledge, there has been no research work done that combines both agent-based modeling and social isolation, especially during the pandemic situation. Therefore, our model is unique and efficient based on the observations of conducting this experiment.

Chapter 3

Proposed Model

3.1 The Disease Spread Model

As a solution for the first problem discussed in chapter 1 this section covers the detailed explanation of the Disease Spread Model which is based on SEIR model. It describes the states of the agents and the events that might happen during the course of pandemic. Agents can be categorized into four types of classes: Susceptible (S), Infected (I), Recovered(R) and Dead(D). Within the Infected class, an agent can belong to one of the five states which are Asymptomatic (AS), Quarantined (Q), Hospitalized (H), ICU (IC) and Waitlisted (W). Agents are dynamic and can migrate to any of these classes and/or states with time conforming to their health status as shown in Fig. 3.1

Most of the agents are susceptible (in S class) in the initial phases of the experiment. This means that these agents are healthy yet they may acquire infection from the agents who are in Asymptomatic(AS) state of Infected class. The agents in AS have already been exposed to the virus and are capable of infecting the susceptible agents at a certain distance from them. This distance is calculated based on the coordinates (x, y) in which they lie. This distance is known as Euclidean distance given by:

$$dist(a_i, a_j) = \sqrt{(y_i - y_j)^2 + (x_i - x_j)^2} \quad (3.1)$$

The risk of transmission tends to be higher when the distance between two agents a_i and a_j is less than or equal to two.

The possibility of events are calculated in terms of probabilities given by $P(\text{event})$. The

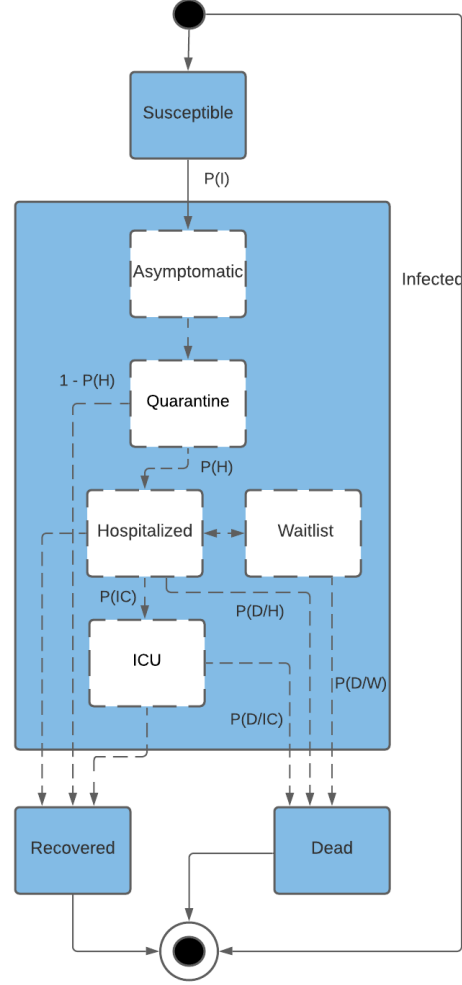


FIGURE 3.1: Disease Spread Model(based on SEIR model)

event can be anything from getting infected to recovered or dead. $P(I)$ refers to the probability of an infected agent transferring the infection to an agent who is susceptible to it. λ days is when the infected agent shows no symptoms, thus termed as asymptomatic (AS). Because of no prior knowledge of infection that has already been occurred, the infected agent may move carefree and thus infect other susceptible agents as well. When this time-period of λ days passes and symptoms become noticeable, the infected agent quarantines itself. When the quarantine period (λ_Q days) ends, one of the conditions may occur:

1. $1-P(H)$ is the likelihood when an infected agent continues to stay at home awaiting his recovery without the need to go to the hospital for λ_R days. Generally, it is anticipated that most of the agents recover from the infection in these many days. Here, $P(H)$ is the probability of getting hospitalized.
2. If the agent needs to be hospitalized with $P(H)$ due to symptoms getting worse, then one of the three conditions may occur:
 - (a) The agent gets hospitalized in a standard bed and stays in there for λ_H days, after which it may die or completely recover from the infection where the probability of dying becomes $P(D|H)$.
 - (b) The agent may be transferred to an ICU if conditions get critical where the probability will be $P(IC)$. When λ_{IC} days end, the agent may either recover or die with the probability, $P(D|IC)$.
 - (c) This model considers the hospital's capacity, thus leading to the notion of waitlist where an infected agent is placed when there are no vacant hospital beds. These agents on waitlist may still be quarantined at their homes. Hence, these agents may not recover or die from the infection because of inadequate health care where the probability becomes $P(D|W)$.

To emphasize the importance of hospital care, $P(D|W)=P(D|IC)>P(D|H)$ is considered even when the situation might not be critical at the time of admission. Also, recovery is only possible for infected agents that are not waitlisted.

As we follow the SEIR model, once an agent is recovered, it will be immune to the virus and can move freely.

3.2 Metrics for Social Isolation

The solution to the second sub-problem for our model aims at measuring the impact of social isolation in different situations. Two kinds of evaluation parameters are defined based on the level of interactions and distance between the agents. The level of interactions vary depending upon the contact an agent has with the other agents in its neighborhood.

Metric 1: The agents in the neighborhood represent the agents present in the area surrounding the agent upto a certain extent. There might be many neighbors in an agent's neighborhood, however it interacts with a few selected ones based on their own level of interactions and these few neighbors are called contacts. In other words, every agent has their own personality and intuition with which they interact with other agents.

Total number of contacts an agent has in the whole simulation is given by:

$$N(a_i) = P_i * \sum_{T=0}^t |N(a_i, T)|_e$$

where, P_i : Probability of an Agent to Interact with their neighbors.

Average number of contacts an agent has can be defined with μ_N given by:

$$\mu_N = \frac{\sum_{a_i \in \{A\}} N(a_i)}{n}$$

where, n : the number of alive agents. The socially isolated agents is identified using Z-score as follow:

$$\{\forall a_i \in A | Z(N(a_i)) < -1, a_i \in IS_N\}$$

which means an agent is said to be socially isolated with respect to the number of contacts, if the value of standard score (or z-score) is less than -1, where, z-score is given by:

$$Z = \frac{N(a_i) - \mu_N}{\sigma_N}$$

Metric 2: The second evaluation parameter is calculated in terms of distance between an agent and its contacts:

$$ND(a_i) = \sum_{T=0}^t \frac{\sum_{j \in \{N(a_i, T)\}} dist(a_i, a_j)_e}{P_i * |N(a_i, T)|_e}$$

where, $ND(a_i)$: Total distance an Agent has from its contacts during the whole simulation up to certain extent, e . and the average distance in the simulation is:

$$\mu_{ND} = \frac{\sum_{a_i \in \{A\}} ND(a_i)}{n}$$

Similar to the previous metric, socially isolated agents are calculated using z-score, however, they are said to be socially isolated if the z-score of its distance is greater than 1 given as:

$$\{\forall a_i \in A | Z(ND(a_i)) > 1, a_i \in IS_N D\}$$

3.3 Scenarios

In this research, two kinds of agents are considered: those who have high mobility and others with low mobility. Both the agents can move randomly, however, agents with high mobility tend to cover longer distances as compared to the agents with lower mobility.

For our model, we have considered 60 days in which each day is further divided into eight parts. Also, to relate to the real world, most of the agents return to their homes at the end of the day. Following scenarios are simulated and analyzed with various settings in each one of them:

Scenario 1: This scenario focuses on modeling the situation before the pandemic. Agents can roam about freely. There are no interventions imposed on them, such as a lockdown or social distancing. To focus on the spread of the disease and the deaths related to it, we have only considered the deaths related to the disease. There are no deaths involved due to coronavirus. Since no agent is infected in the whole simulation, the number of agents will remain the same at the end of the simulation, i.e., $dD=0$, where dD is the change in the number of deaths from start to the end of the simulation.

Scenario 2: This scenario evaluates a situation when COVID-19 is present, but no interventions were imposed, such as a lockdown or social distancing. Here, the movement of the agents is determined by their health status. Despite knowing its existence, only those agents who become aware of the infection quarantine or isolate themselves. Few agents are infected at the start and are considered as the basic reproductive number.

Scenario 3: Another situation assessed by our model is when the disease is present, and the interventions are imposed.

The interventions are imposed five days after the arrival of the virus when any of the agents are found to be infected; that is when an agent passes the Asymptomatic state. These interventions mainly include lockdown and social distancing. Various levels of these interventions are examined in combination to see the preferable percentages of both that may lead to less socially isolated individuals and also so that the spread of the virus is limited.

Scenario 4: This scenario is different from the others since it considers the agents living in a nursing home. In this case, nurses are viewed as High-mobility agents and the elderly as Low-mobility agents. We also assume that there are no infected agents initially in the nursing homes. However, the agents who go outside these facilities can bring the infection inside the nursing home with a certain probability.

Various factors have been considered for determining the spread of infection. Some of these include the rate of infection, the number of nurses in the nursing care facility, etcetera. These parameters help determine the factors that can help mitigate the spread of the infection as well as social isolation, and also the ways the infected agents could recover from the disease.

Algorithm 1 Algorithm for Proposed Model

Input: Parameters indicated in Table 1.**Output:** $S(t)$, $I(t)$, $R(t)$, $D(t)$, a list of Socially Isolated Nodes with respect to Metrics 1 and 2

```

for  $T \leftarrow 1$  to  $t$  do
  for  $i \leftarrow 0$  to  $n$  do
    if  $Disease = True$  then
      Call INFECT
      Call ASYMPTOMATIC
      Call QUARANTINE
      Call ICU
      Call HOSPITALIZE
      Call WAITLIST
    end if
    Call MOVE
    Call COUNT-NEIGHBOURS-AND-TOTAL-DISTANCE
  end for
end for

Compute  $\mu_N$  and  $\mu_{ND}$  using Equations 3, 6
Find the set of isolated agents using Equations 4,7

```

Procedure INFECT

Input: Susceptible Agents and Asymptomatic Agents**Output:** Asymptomatic Agents

```

if  $distance(a_i, other\_a_i) \leq 2$  and  $P(I)$  then
  Change Class from Susceptible to Infected
end if

```

Procedure ASYMPTOMATIC

Input: Asymptomatic Agents**Output:** Quarantine Agents

```

if agent.days_infected =  $\lambda$  then
    Change Class from Asymptomatic to Quarantine
    Move Quarantine Agent to house
end if

```

Procedure QUARANTINE

Input: Quarantine Agents**Output:** Hospitalized Agents, ICU Agents, Recovered Agents, Waitlist Agents

```

if  $\lambda_Q \leq agent.days\_infected < \lambda_R$  then
    if  $P(H)$  then
        if  $Vacant\_beds = 0$  then
            Change class from Quarantine to Waitlist
        else
            Change class from Quarantine to Hospitalize
        if  $P(IC)$  then
            Change class from Hospitalize to ICU
        end if
        Move to Hospital
    end if
else
    Change class from Quarantine to Recovered
end if
end if

```

Procedure HOSPITALIZE

Input: Hospitalize Agents**Output:** Dead Agents and Recovered Agents

```

if agent.days_infected >  $\lambda_H$  then
  if  $P(D|H)$  then
    Change Class from Hospitalize to Dead
  else
    Change Class from Hospitalize to Recovered
  end if
end if

```

Procedure ICU

Input: ICU Agents**Output:** Dead Agents and Recovered Agents

```

if agent.days_infected >  $\lambda_I C$  then
  if  $P(D|IC)$  then
    Change Class from ICU to Dead
  else
    Change Class from ICU to Recovered
  end if
end if

```

Procedure Waitlist

Input: Waitlist Agents**Output:** Hospitalize Agents and ICU Agents

```

if  $Vacant_{eds} > 0$  then
  if  $P(H)$  then
    Change Class from Waitlist to Hospitalize
  if  $P(IC)$  then
    Change class from Hospitalize to ICU
  end if
  Move to Hospital
end if
else if  $P(D|W)$  then
  Change Class from Waitlist to Dead
end if

```

Procedure MOVE

Input: Susceptible Agents, Asymptomatic Agents, Recovered Agents**Output:** None

```

if  $Lockdown = False$  and  $Social\_Distancing = False$  then
  Call SCENARIO 2
else if  $Lockdown = False$  then
  Call SCENARIO 3
end if

```

Procedure SCENARIO 2

Input: Susceptible Agents, Asymptomatic Agents, Recovered Agents**Output:** None

```

if  $a_i \in A_L$  then
  Move agent around randomly with conditions in Initialization
end if
if  $a_i \in A_H$  then
  Move agent around randomly with conditions in Initialization
end if

```

Procedure SCENARIO 3

Input: Susceptible Agents, Asymptomatic Agents, Recovered Agents**Output:** None

```

if Lockdown = True then
  if  $1 - P(L)$  then
    if  $P(SD)$  then
      if  $distance(a_i, other\_a_i) \leq 2$  then
         $distance(a_i, other\_a_i) + = 2$ 
      end if
    else
      if  $a_i \in A_L$  then
        Move agent around randomly with conditions in Initialization
      end if
      if  $a_i \in A_H$  then
        Move agent around randomly with conditions in Initialization
      end if
    end if
  else if Lockdown = False then
    if  $P(SD)$  then
      if  $distance(a_i, other\_a_i) \leq 2$  then
         $distance(a_i, other\_a_i) + = 2$ 
      end if
    else
      if  $a_i \in A_L$  then
        Move agent around randomly with conditions in Initialization
      end if
      if  $a_i \in A_H$  then
        Move agent around randomly with conditions in Initialization
      end if
    end if
  end if
end if

```

Procedure COUNT-NEIGHBOURS-AND-TOTAL-DISTANCE

Input: Susceptible Agents, Asymptomatic Agents, and Recovered Agents

Output: $N(a_i)$, $ND(a_i)$

 if $distance(a_i, other_a_i) \leq e$ **then**

 Compute $N(a_i)$ and $ND(a_i)$ using Equations 2, 5

 end if

Chapter 4

Evaluation

4.1 Experiment You Conducted

4.1.1 Result Stemming From This Experiment

Chapter 5

Conclusion

This is my conclusion. It ties together all I have talked about and provided insight into future directions and the contribution this work offers to science as a whole.

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Vita Auctoris

NAME: Simranpreet Kaur

PLACE OF BIRTH: India

YEAR OF BIRTH: 1996

EDUCATION: Your High School
Schooltown, ON, 2000