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

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By

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Declaration of Co-Authorship

I. Co-Authorship

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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I certify that, with the above qualification, this thesis, and the research to which it refers, is the product of my own work.

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Abstract

The spread of Coronavirus, widely known as COVID-19, has posed detrimental effects worldwide, affecting almost every primary sector. Due to its asymptomatic behavior and non-early diagnosis, government and health organizations implemented interventions such as physical distancing, lockdown, and quarantine, to mitigate the spread of the virus. Studies have shown that a connection exists between social isolation and health risks experienced by individuals. Thus, this research proposes an agent-based model to address the impact of varying interventions in our society. For simulation purposes, the SEIR model is followed, and agents are categorized into two classes based on their pace of movement, low and high mobility agents. These are further classified into four different states: susceptible, infected, recovered, and dead depending upon their changing health status. Their corresponding probabilities are determined, and the algorithm proceeds accordingly. Simulations of different scenarios before and during the COVID-19 are performed using multi-agents. Resulting outcomes are evaluated and analyzed, where agents may follow one or more interventions at a time. Various parameters are used in this research to imitate real-time physical situations while formulating the simulation environment. Some of these include the hospitals count, hospital capacity, transmission rate, and recovery time for agents in different states. Our model defines certain metrics based on the number of contacts an agent has with the other agents and the distance between the agents and its neighbors. Considering these multiple parameters and metrics enable the model to simulate varying conditions. For validation purposes, the simulation environment is made similar to the real-world society. Our model may benefit in deciding the mitigating factors in times of a similar pandemic or epidemic situations in the long term. Policymakers, health professionals, or researchers may extend this model and simulate the dissemination of ailments identical to this one.

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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Table of Contents

List of Figures

Chapter 1

Introduction

This section provides a brief introduction to the subject matter. It gives background information regarding social isolation both in general and in the pandemic and about agents and multi-agent systems. Apart from this, motivation for solving the problem at hand, description of the given problem, research objectives, and contributions followed by a brief outline of thesis documentation is presented.

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].

1.2 Social Isolation in Pandemic

Coronavirus, popularly known as COVID-19, has led to the separation of various individuals from their family members and friends due to the health authorities and government organizations' interventions, like lockdown and social distancing. In this thesis, social distancing and physical distancing are used interchangeably. 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 approximately 29% increased occurrences of heart disease and 32% rise in chances of heart stroke along with 50% increased risk of developing dementia [16]. On the other hand, according to a Canadian survey, around 38% of the citizens felt lonely and socially isolated as a result of COVID-19 pandemic [17]. 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. Another survey by the Statistics Canada [18] exhibits that 13% fewer citizens reported good mental health during the COVID-19 pandemic as compared to the time before pandemic. The National Child Mortality database reported an increase in suicide rates among children during the pandemic in the UK [19]. Also, female students specifically suffered a decline in their mental health in Switzerland due to the lack of interactions and emotional support [20]. Preliminary surveys conducted in the United States of America indicated a 20-30% increase in loneliness while there is a threefold increase in emotional troubles in the time of pandemic [15]. Other problems related to isolation were mass panic and anxiety [21].

1.3 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 [22]. 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, etcetera. Some of the challenges faced by the agents in these systems include coordination, security, and learning [23]. 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, etcetera [22]. 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 [24].

1.3.1 Agents

Agents can be defined as independently acting or functioning entities that make decisions based on a set of regulations to achieve their goals [25–29]. 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 [28]. 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 as 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 [28]. 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

[26–28]. It blends the elemental units of multi-agent systems, game theory, evolutionary programming, complex systems, emergence, and computational sociology [30]. 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 and hence, Agent-based modeling is preferred over other modeling techniques [31]. Some of its benefits are that it captures the emergent phenomenon, that is, 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 too [26].

1.4 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 [25], handles uncertainties, and saves time [32]. Agent-based modeling has its applications in various fields, businesses, social sciences, technology, etcetera. 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 [22].

During the COVID-19 pandemic, apart from coronavirus, various other mental health issues gained attention, such as feelings of stress, loneliness, depression, isolation [33]. Due to the increasing number of confirmed cases and deaths, these mental disorders became more popular [34]. 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,to the best of our knowledge, there is no study 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 during 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 during it. This model will focus on different scenarios based on interventions.

1.5 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.

1.5.1 Modeling the spread of the disease

To simulate the human interactions based on the spread of the disease among individuals according to different situations like lockdown, social distancing, an outbreak in a nursing home/long-term care home, etcetera, 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 depending 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.

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

1.5.2 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, in Figure 1.1, 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 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, P1. 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 in our model.

Similarly, the distance from these contacts is measured. Following the previous example, 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 with respect to our model.

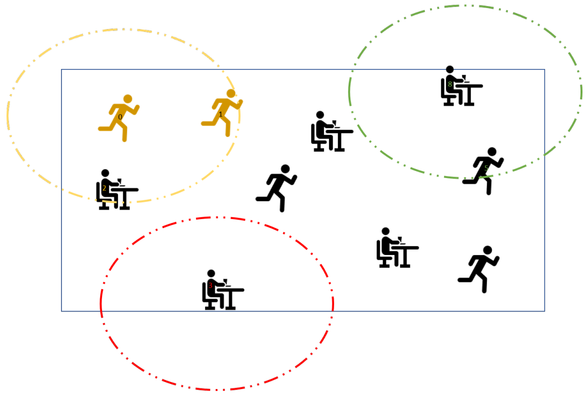

FIGURE 1.1: An example demonstrating the concept of neighbors and contacts

1.6 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 human interactions during pandemic based on different situations such as lockdowns, social distancing.
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 [35]. The interventions play a huge role in the state of an individual.

1.7 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, all 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 the 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, and also can be extended or modified to various interventions possible. Moreover, policymakers and other organizations may design their policies considering the group of affected people.

1.8 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 given in chapter 4 followed by conclusion, and future works in chapter 5.

Chapter 2

Related Work

This section provides a brief review of the existing techniques aimed at identifying, mitigating, or just monitoring the spread of social isolation during the pandemic and before its existence. It also presents the research work done using agent-based modeling and its use in social isolation and similar health disorders.

2.1 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 is [36] in which the researchers 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. In [37], the researchers aimed at studying the impact of the COVID-19 pandemic on Twitter users in terms of social isolation. They conducted a combined analysis on multiple datasets including tweets from the dataset they collected themselves, Google real-time mobility trends among the individuals during this pandemic, extensive amount of COVID-19 and social isolation related hashtags dataset and WHO dataset signifying the number of confirmed cases and number of deaths occurring during the pandemic. As a result, meaningful patterns were obtained and analyzed using Sentiment Analysis, IBM analytics services such as Watson analyzer, and personality insights. Visualization of these patterns was done both at an individual level and collective level. A strong correlation was observed among mobility trends and usage of social isolation-related hashtags in tweets along with WHO data. They highlighted the importance of the research in identifying the status of different health disorders and policymakers in designing different policies related to the health of the individuals.

On the other hand, in [38], the researchers 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 work, [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 [39], 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 [40] 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 [41] 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 [42], 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 [43] in which the authors 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 [44], 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.

2.2 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 [22, 45–48] , manufacturing [49–52], disaster management [53–56], personalized recommendations [57–59], telecom services [60] and engineering [61–64] 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 [22], the researchers 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 [65], 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 [66] 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. In [67], the researchers 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. 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 [68] 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 [69] 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. The 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 [70] 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 [71] 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 [72], 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 [73] 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.

2.3 Agent Based System and the Pandemic

The authors in [74] 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. In [75], the researchers 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 in [76] 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.

In [77], the researchers 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. The 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. Similarly, the researchers in [78] 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. The authors in [79] 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. In [80], 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 was investigated. Based on the demographic data, ABM produced more than 24 million software agents representing an anonymous individual.

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 using computational models. 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 create and simulate 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

This section provides a detailed description of the proposed methodology used in this research. Metrics used and different scenarios focused are also discussed.

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 Figure 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:

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

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(event). The

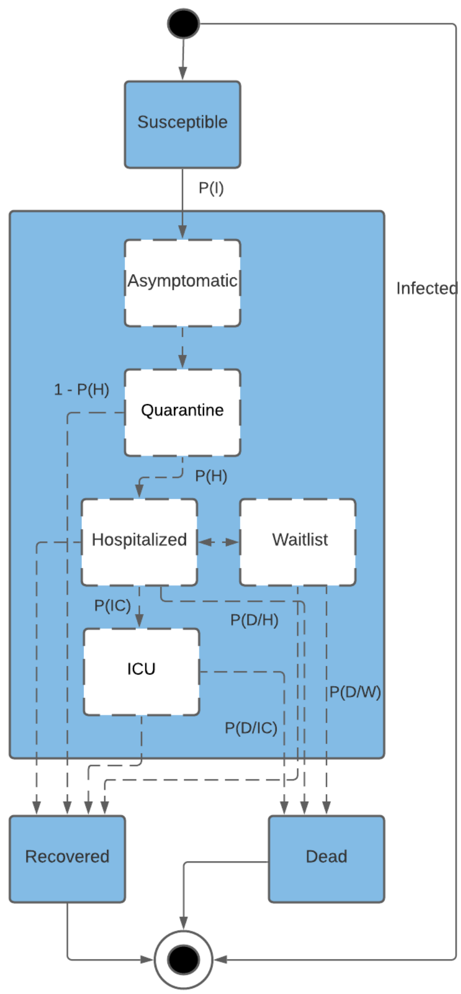

FIGURE 3.1: Disease Spread Model(based on SEIR model)

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 and 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 measures 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:

$$N(a_i) = P_i * \sum_{T=0}^{t} |N(a_i, T)|_e \tag{3.2}$$

where, P_i is the probability of an Agent, i to Interact with their neighbors.
Average number of contacts an agent has can be defined with μ_N given by:

$$\mu_N = \frac{\sum_{a_i \in \{A\}} N(a_i)}{n} \tag{3.3}$$

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

$$\{\forall a_i \in A | Z(N(a_i) < -1, a_i \in IS_N\} \tag{3.4}$$

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:

$$Z = \frac{N(a_i) - \mu_N}{\sigma_N} \tag{3.5}$$

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

$$ND(a_i) = \sum_{T=0}^{t} \frac{\sum_{j \in \{N(a_i,T)\}} dist(a_i, a_j)_e}{P_i * |N(a_i, T)|_e} \tag{3.6}$$

where, ND(a_i) is the 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:

$$\mu_{ND} = \frac{\sum_{a_i \in \{A\}} ND(a_i)}{n} \tag{3.7}$$

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:

$$\{\forall a_i \in A | Z(ND(a_i) > 1, a_i \in IS_N D\} \tag{3.8}$$

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 are imposed, such as 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 can be anything like wearing double masks, lockdown, social distancing, etcetera but for simplicity we have used two interventions only, i.e., social distancing and lockdown. 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. For instance, if 50% lockdown and 50% social distancing is followed, it means 50% of the total population follows lockdown and 50% of the remaining population follows social distancing.

Scenario 4: This scenario is different from the others since it considers the agents living in a nursing home. In this case, adults are viewed as Low-mobility agents and healthcare workers are considered to provide vacant hospital beds for care. 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 healthcare workers 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.

Table 3.1 and table 3.2 shows the different parameters used whereas table 3.3 and table 3.4 shows the different settings used in this research for scenario 1, 2 and 3 and scenario 4, respectively.

Fixed Parameters	***Value***
Space	$850 \times 850\ m^2$
Initial Infected agents	27
Total ticks	480
Total days	60
Number of hospitals	2
Hospital Capacity	30
Mobility	1000-8000 m
Latent Period(λ)	5 days
Quarantine Period(λ_Q)	9 days
Total Recovery Period for Quarantine Agents(λ_R)	14 days
Total Recovery Period for Hospitalized Agents(λ_H)	19 days
Total Recovery Period for ICU Agents(λ_{IC})	26 days
Transmission Rate(P(I))	80%
Hospitalization Rate(P(H))	12%
Critical cases Rate(P(IC))	2.5%
Death Rate for hospitalized agents(P(D|H))	2.3%
Death Rate for critical agents(P(D|IC))	30%

Table 3.1: Parameters(Fixed) used in the Simulation for Scenario 1, 2 and 3

Fixed Parameters	***Value***
Space	$75 \times 75\ m^2$
Total ticks	480
Total days	60
Mobility	0-1000 m
Latent Period(λ)	5 days
Quarantine Period(λ_Q)	9 days
Total Recovery Period for Quarantine Agents(λ_R)	14 days
Total Recovery Period for Hospitalized Agents(λ_H)	19 days
Total Recovery Period for critical Agents(λ_{IC})	26 days
Hospitalization Rate(P(H))	12%
Critical cases Rate(P(IC))	2.5%
Death Rate for hospitalized agents(P(D|H))	2.3%
Death Rate for critical agents(P(D|IC))	30%

Table 3.2: Parameters(Fixed) used in the Simulation for Scenario 4

Setting	***Initial Total Agents (Susceptible agents)(S1,S2,S3)***	***Proportion (High-mobility(A_H):Low-mobility(A_L))***
1	5000	70:30
2	5000	50:50
3	10000	70:30
4	10000	50:50

Table 3.3: Settings used in the Simulation for Scenario 1, 2 and 3

Setting	***Initial Total Agents (Susceptible agents)(S4)***	***Infection Rate***
1	105(100 Adults + 5 Healthcare Workers)	10
2	105(100 Adults + 5 Healthcare Workers)	50
3	107(100 Adults + 7 Healthcare Workers)	10
4	107(100 Adults + 7 Healthcare Workers)	50
5	110(100 Adults + 10 Healthcare Workers)	10
6	110(100 Adults + 10 Healthcare Workers)	50

Table 3.4: Settings used in the Simulation for Scenario 4

Chapter 4

Evaluation

This section provides a detailed description of the simulation experiment conducted in this research. It begins with an explanation of experimental setup followed by results and analysis. It highlights the resulting outcomes and certain inferences drawn from the experiment in this research.

4.1 Setup

We used NetLogo for performing our agent-based simulation and to examine the interactions occurring among the agents. Besides being a programming language, NetLogo serves as an integrated development environment applicable to perform simulation and agent-based modeling experiments. Programming in Netlogo involves agents which are addressed with different names such as turtles, links, patches, and the observer. As far as experimental setup and requirements are concerned, this experiment is performed on Windows 10 (10.0.19042 Build 19042), 64-bit Acer (System Model: Aspire A315-54K) with Intel(R) Core(TM) i5-6300U CPU @ 2.40GHz, 2496 Mhz, 2 Core(s), 4 Logical Processor(s), 256 GB ROM and 8 GB RAM. NetLogo 6.1.1 [81] is used for performing the agent-based simulations throughout the experiment whereas Tableau 2020.3 [82] is used for visualizations.

Agents are classified into two classes: high mobility agents and low mobility agents depending on their pace of movement (mobility). As the name suggests, the agents with high mobility can cover longer distances when compared to those of low mobility agents.

Based on the changing health status, agents perform different procedures. For instance, if an agent's health status is Asymptomatic, then the procedure corresponding to it is performed. For the setup, a grid is initialized, and the agents are assigned to random locations which serve as home to them, to which most of them may return by the end of the day. Hospitals are assigned a location, too, represented by its X and Y coordinates. There is a limit on the number of vacant beds that a hospital can possess. Furthermore, few agents are labeled as infected while the rest of them are labeled susceptible.

Following the initialization process, agents undergo various procedures conforming to their health status. This status may be labeled as any of the following: Susceptible, Infect, Asymptomatic, Quarantine, Hospitalize, ICU, Recovered, Dead. When an agent is labeled as dead, it becomes static in the simulation, and therefore it loses its existence in the simulation.

Our simulation assumes that a distance of 1 unit = 1 meter and a day is divided into 8 ticks. Also, the maximum distance that an agent can have to become a contact of another agent is 20m. The total number of days considered in each simulation considering each scenario is 60 days with 480 ticks. The total population of agents in the initial phases of the experiment is 5000 and 10000 with infected agents as 27. For Scenario 4, total population can be 105,107 and 110 where Low-mobility agents are 100. The distribution of these agents with high mobility and low mobility are considered in a ratio of 70-30 and 50-50 and all the scenarios along with different settings are simulated 3 times each to achieve more accuracy in results. The area of accommodation taken for performing the simulation is 850×850 m^2. Every day, count of contacts met by an agent and the magnitude of their distance from the agent are recorded. To gather more understanding and with analysis point of view, the data is visualized using Tableau. Graphs are made to analyze the levels of Social Isolation in different Scenarios.

4.2 Results and Analysis

As we mentioned earlier, to analyze the change in Social Isolation, this model simulates different Scenarios with different settings and parameters. For this purpose, Scenario 1 is taken as the baseline for identifying the change in the levels of social isolation when the virus is present. Metric-based comparison is performed to determine the distinguishing factors that differentiate these scenarios from one another. As far as metric 1 is concerned, social isolation levels increased in all the scenarios compared to baseline. The population of agents is taken in the form of proportions, for instance, 70:30 depicts 70% of total agents possess high mobility while the rest of them have lower mobility. With an increase in the percentages of low mobility agents, the levels of social isolation increased although in small amounts in all the scenarios except for Scenario 2 with 10,000 agents with respect to the distance metric, i.e., these levels tend to be more when the agents are in an equal proportion as compared to the 70:30 proportion of agents as shown in Table 4.1-4.8. Hence, it can be inferred that there are higher chances of social isolation to affect the agents with low mobility in comparison to the agents possessing high mobility.

Total Agents	***Proportion(A_H:A_L)***	SI_N***(Average in %)***	SI_{ND}***(Average in %)***	SI_N***(Std in %)***	SI_{ND}***(Std in %)***
5000	70:30	14.92	13.04	0.27	0.05
5000	50:50	15.26	13.76	0.49	0.59
10000	70:30	15.83	13.23	0.85	0.48
10000	50:50	16.44	13.32	0.39	0.46

Table 4.1: Percentage of Socially Isolated Agents in Scenario 1

Total Agents	***Proportion(A_H:A_L)***	SI_N***(Average in %)***	SI_{ND}***(Average in %)***	SI_N***(Std in %)***	SI_{ND}***(Std in %)***
5000	70:30	19.89	14.34	0.28	0.39
5000	50:50	20.01	14.15	0.11	1.05
10000	70:30	19.7	14.48	0.4	1.1
10000	50:50	20.04	13.23	0.93	0.45

Table 4.2: Percentage of Socially Isolated Agents in Scenario 2

Total Agents	***Proportion(A_H:A_L)***	SI_N***(Average in %)***	SI_{ND}***(Average in %)***	SI_N***(Std in %)***	SI_{ND}***(Std in %)***
5000	70:30	15.63	16.32	0.28	0.22
5000	50:50	15.85	16.94	0.13	2.07
10000	70:30	16.98	16	0.13	0.9
10000	50:50	17.38	16.11	0.79	0.28

Table 4.3: Percentage of Socially Isolated Agents in Scenario 3 with 0% Lockdown and 50% Social Distancing

As compared to scenario 1, social isolation levels increased by a considerable amount (nearly 5 %) in scenario 2 when metric 1 is taken under consideration. One of the interesting facts to note about this observation is that the interventions were not yet imposed on the population of agents; still, the levels of social isolation grew. The basis for this observation can rest upon the hypothesis that the absence of interventions leads to high chances of infection transmission among individuals. Hence, many agents will be infected, eventually leading to a greater number of deaths among the agents. These increasing numbers of

Total Agents	***Proportion(A_H:A_L)***	SI_N***(Average in %)***	SI_{ND}***(Average in %)***	SI_N***(Std in %)***	SI_{ND}***(Std in %)***
5000	70:30	16.84	14.58	0.61	0.68
5000	50:50	17.05	17.51	0.1	0.79
10000	70:30	18.09	11.04	0.52	1.02
10000	50:50	18.27	11.14	0.31	0.34

Table 4.4: Percentage of Socially Isolated Agents in Scenario 3 with 0% Lockdown and 80% Social Distancing

Total Agents	***Proportion(A_H:A_L)***	SI_N***(Average in %)***	SI_{ND}***(Average in %)***	SI_N***(Std in %)***	SI_{ND}***(Std in %)***
5000	70:30	17.9	14.02	0.81	0.19
5000	50:50	18.2	14.52	0.69	0.12
10000	70:30	19.5	13.8	0.14	0.57
10000	50:50	20.35	14.65	0.87	0.26

Table 4.5: Percentage of Socially Isolated Agents in Scenario 3 with 50% Lockdown and 80% Social Distancing

deaths will reduce the overall count of agents in the simulation, thereby increasing social isolation with respect to metric 1. Due to the scarcity of agents, the distance among them decreases thus, scenario 1 and 2 becomes equivalent with regard to metric 2. It is observed that the range of values of dispersion lies below 1 in case of baseline, contrary to scenario 2, where these are spread over a comparatively wider range.

On observing scenario 3, diverse amounts of changes are observed in situations where social distancing is practised alone without the lockdown. In this experiment, varying percentages of social distancing are taken into account. It is noted that the extent of social isolation increased by 1 to 2% while examining metric 1. On comparing scenario 3(0% Lockdown and 50% Social Distancing) with baseline in terms of metric 2, increasing the percentage of social distancing to 50 results in an increase of 3% in the amount of social isolation. However, when this percentage is increased to 80, the levels of social isolation become similar to the baseline. When the population of agents equals 10000, the measure of social isolation values declined. This may have occurred because the majority of agents are following the imposed intervention, in this case, social distancing. Hence, the problem might still be present, however, the cumulative average of socially isolated agents becomes lower, thus making its effect almost unnoticeable.

As long as standard deviation is concerned, various trends were observed in the levels of social isolation. When both the interventions (lockdown and social distancing) are imposed equally, a significant increase was observed in the magnitude of social isolation. Similar to 0:50 scenario, the increase in the population of agents was followed by a decline in the levels of social isolation in regard to metric 2 because the distance among agents reduces. Relying

Total Agents	***Proportion(A_H:A_L)***	SI_N***(Average in %)***	SI_{ND}***(Average in %)***	SI_N***(Std in %)***	SI_{ND}***(Std in %)***
5000	70:30	19.16	13.88	0.11	0.2
5000	50:50	19.3	13.86	0.33	0.14
10000	70:30	20.11	14.12	0.43	0.09
10000	50:50	20.14	14.65	0.67	0.31

Table 4.6: Percentage of Socially Isolated Agents in Scenario 3 with 50% Lockdown and 50% Social Distancing

Total Agents	***Proportion(A_H:A_L)***	SI_N***(Average in %)***	SI_{ND}***(Average in %)***	SI_N***(Std in %)***	SI_{ND}***(Std in %)***
5000	70:30	18.48	13.34	0.63	0.38
5000	50:50	18.81	13.98	0.21	0.67
10000	70:30	19.59	14.05	0.27	0.06
10000	50:50	19.96	14.31	1.13	0.13

Table 4.7: Percentage of Socially Isolated Agents in Scenario 3 with 80% Lockdown and 50% Social Distancing

on the previous observations, the existence of social isolation is confirmed, however, because of agents' population and distance constraints, it is not as evident as one would normally expect. Similar findings are observed in 80:50 and 80:80 scenarios. The correlation found between baseline and remaining scenarios with changing amount of interventions depicted that there was an increase observed in the levels of social isolation in respect of metric 1. On the whole, the maximum divergence values of social isolation are observed in a scenario where 50% of agents follow social distancing at a population size of 5000 and the proportion of the agents being equivalent to 50:50.
For our simulation, another scenario taken under consideration was monitoring the spread of the infection in nursing homes. In this case, the infection rates are varied, and observations are recorded accordingly. With the increase in the number of Healthcare workers/Volunteers in the nursing homes, Social isolation levels tend to decrease concerning both interaction metric and distance metric where the rate of infection equals 10% as shown in Table 4.9.

Similarly, when the infection rate is 50% as observed from Table 4.10, same trend is followed; however, the decreasing rate is less as compared to with the infection rate of 10%. The supporting evidence to prove the above finding is the increasing number of deaths due to higher infection rates. Comparing the level of social isolation at 50% rate of infection, social isolation may decrease since more deaths may have occurred.
On completing the simulation, it is examined that with number of healthcare workers going up, the number of fatalities declines. This highlights the importance of these healthcare workers in controlling the spread of infection.
The magnitude of social isolation in different scenarios with respect to various factors is

Total Agents	***Proportion(A_H:A_L)***	SI_N***(Average in %)***	SI_{ND}***(Average in %)***	SI_N***(Std in %)***	SI_{ND}***(Std in %)***
5000	70:30	18.28	13	0.46	0.7
5000	50:50	18.52	13.48	0.15	0.48
10000	70:30	19.31	14.13	0.75	0.04
10000	50,50	20.86	14.15	0.99	0.71

Table 4.8: Percentage of Socially Isolated Agents in Scenario 3 with 80% Lockdown and 80% Social Distancing

Total Agents	SI_N***(Average in %)***	SI_{ND}***(Average in %)***	SI_N***(Std in %)***	SI_{ND}***(Std in %)***
105	23.75	16.74	1.33	1.97
107	20.14	10.65	1.78	7.53
110	17.37	10.25	1.28	3.29

Table 4.9: Percentage of Socially Isolated Agents in Scenario 4 with 10% Infection rate

represented using bar graphs too for more understanding. These factors include different ratios of interventions imposed, rates of infection, varying population of agents depending upon the scenario under observation and many more.

Comparison of three different scenarios is made to detect social isolation as shown in Figure 4.1. Metric 1 is considered to be the basis for this comparison. The bar chart indicates that the level of social isolation is lowest in scenario 1 among all the distribution of agents. The highest levels of social isolation are obtained in scenario 3 in a total population of 10000 agents consisting of equally divided high mobility and low mobility agents, i.e., 50:50. The ratio of interventions equals 80:80, representing lockdown to social distancing, which is the highest parameter used for this research. When no lockdown is imposed, and agents only follow social distancing, the social isolation is observed to be below 20%, while in the rest of the Scenarios except for the baseline, the social isolation levels reach 20% or more. Social

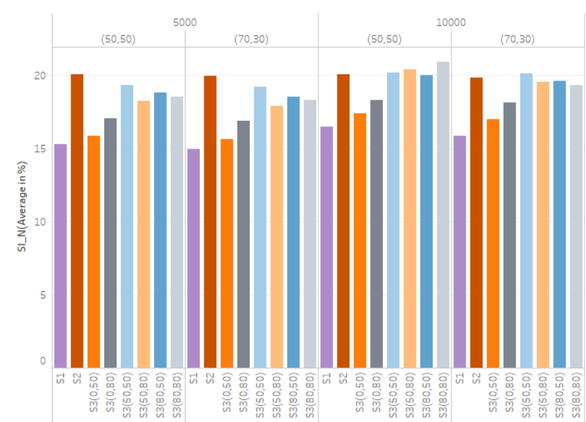

Figure 4.1: Average Socially Isolated Agents with respect to Metric 1 for Scenario 1, 2 and 3

Total Agents	SI_N ***(Average in %)***	SI_{ND} ***(Average in %)***	SI_N ***(Std in %)***	SI_{ND} ***(Std in %)***
105	21	14.73	2.84	2.7
107	18.91	12.29	0.85	2.41
110	18.65	13.11	0.84	1.39

TABLE 4.10: Percentage of Socially Isolated Agents in Scenario 4 with 50% Infection rate

isolation tends to be the highest when only social distancing is followed, and no lockdown is imposed with respect to Metric 2 as shown in the Figure 4.2. As described already, when social distancing is imposed, the distance between the agents' increases, which thereby leads to more number of socially isolated agents for Metric 2. The two maximum values of social isolation are found in cases where 80% of agents follow social distancing without any lockdown being the highest, and the scenario with 0% Lockdown and 50% Social distancing followed gives the second-highest value. The total population considered is 5000, and the agent population is 50:50. In contrast, the minimum value for social isolation was found in cases where lockdown intervention is imposed on 80% of agents among a total population of 10000. Also, it is observed that there is a change in the levels, however, not that extreme in other scenarios. Figure 4.3 shows the bar graph for values of social isolation in scenario

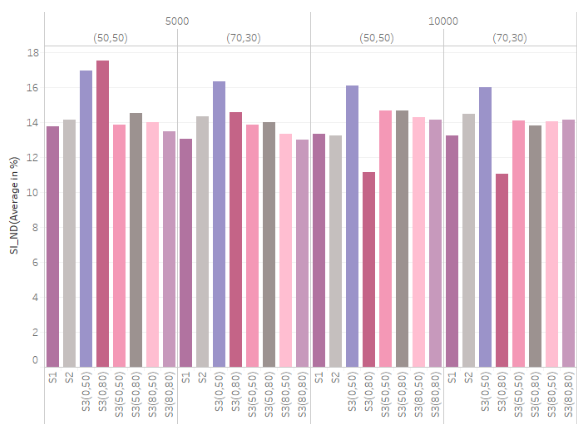

FIGURE 4.2: Average Socially Isolated Agents with respect to Metric 2 for Scenario 1, 2 and 3

4, taking into consideration the interactions taking place among the agents. Comparison of two kinds of infection rates (10% and 50%) is done. Interestingly, in cases with 5 and 7 Healthcare workers, Social Isolation was higher in the Scenario with 10% Infection, whereas in the case with 10 Healthcare workers, the opposite trend is detected, that is, Social Isolation was higher in the Scenario with 50% infection. The justification for this trend was discussed earlier about the number of deaths being higher when the infection rate is higher.

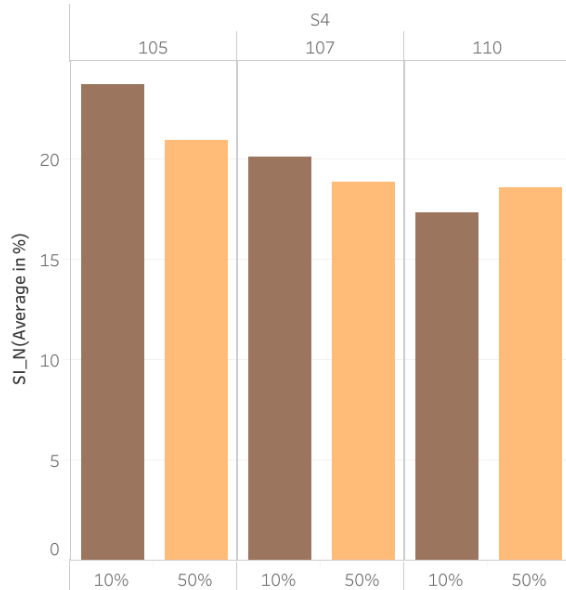

FIGURE 4.3: Average Socially Isolated Agents with respect to Metric 1 for Scenario 4

Figure 4.4 illustrates the percentage of social isolation values in a bar graph for the population of agents taking two different infection rates in scenario 4 with respect to Metric 2. In Scenario 4, the number of Low mobility Agents, which are Adults is constant initially in all the settings. When 105 agents are present, the difference in social isolation levels between the case with 10% infection rate and 50% infection rate was around -2%. In contrast, in the setting with 107 agents, an increase of 1% in the social isolation rates is observed between the scenario of 10% infection rate and 50% infection rate.

On the other hand, in settings with 110 agents, social isolation increased by around 2.5%, which was highest among the agents in Scenario 4 with respect to the distance metric.

Winding up the analysis of these results in different scenarios has led to the following observations. Until scenario 2, no interventions exist. Because of this, the number of deaths increased, ultimately raising the levels of social isolation. In scenario 3, interventions are imposed and are followed by agents in different proportions. Based on interactions and distance among the agents and its neighbors, two metrics are considered within varying sizes of populations of agents. Depending on the interaction metric, in a smaller population of agents (i.e., 5000), social isolation is observed to be highest where, 50% of agents follow lockdown and social distancing. In situations where the population size is more extensive (i.e., 10000), social isolation levels rose to their maximum when both these interventions are being followed in an 80:80 ratio. As far as the distance metric is concerned, social

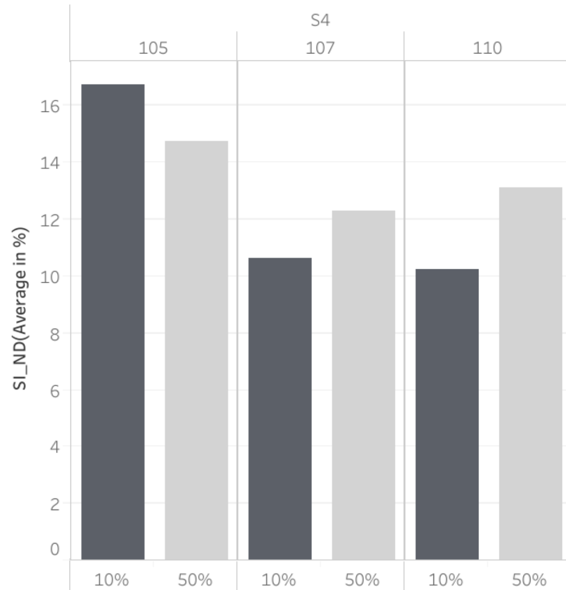

FIGURE 4.4: Average Socially Isolated Agents with respect to Metric 2 for Scenario 4

isolation is the highest in areas where there is no lockdown and 80% agents follow social distancing with a population size of 10000, and also where only 50% of the agents follow social distancing among less number of agents. When distance and interaction metrics are taken altogether with lockdown and social distancing in a ratio of 80:80, an increase of 5.25% in social isolation is found compared to the baseline with more agents. Similarly, an increase of 4.14% is observed in a smaller group of agents with an intervention ratio of 50:50. Another scenario considered in this research incorporates the concept of identifying social isolation in nursing homes. It emphasizes how healthcare workers may help control the spread of the virus and ultimately the occurrence of new deaths.

Chapter 5

Conclusion

The pandemic of COVID-19 has proven to be challenging both in identifying and limiting its spread. Interventions are thought to be effective and thus are imposed by the government and health officials however, it might lead to some feelings of loneliness, social isolation, and depression among the individuals. Hence, we proposed a multi-agent-based framework for modeling and simulating human interaction and how these interventions may have affected it. Our model focused on four distinguishable scenarios depicting the situation both before and during COVID-19. The agents are classified into two major classes, high mobility, and low mobility. We have also taken into account variations in parameters since it assists in studying every other possible factor that might be responsible for affecting the spread of the virus. These parameters involve the vacancy of hospital beds, the number of hospitals, different rates and probabilities for additional periods, and different states. Few metrics are defined to record the contact count that an agent has with its neighboring agents and the distance among the agents in different scenarios.

On observing the resulting outcomes, the number of socially isolated individuals has increased in number since the pandemic. Compared to the setting where the population consists of 70% high mobility agents and 30% low mobility agents, the extent of social isolation was a little higher in the setting when their population was equal. With the Lockdown to Social Distancing ratio of 80:80, an overall increase by 5.25%(Metric 1+Metric 2) in the levels of social isolation from the baseline is examined which is the highest in the population with high density. Whereas, when the population density is low, with a 50:50 intervention ratio, 4.14% more agents were affected with social isolation as compared to the baseline. Hence, it can be concluded that social isolation is found to increase in extreme cases. Moreover, by incorporating nursing homes in one of our scenarios, the importance of healthcare workers is highlighted in controlling the death count resulting from the epidemic. These findings support the hypothesis conducted by various studies and surveys that the pandemic situation has worsened the state of social isolation in different regions. Considering the availability of beds indicates their importance in the highly problematic real-world case.

5.1 Future Works

Our proposed model is not just limited to the interventions used or a single disease; and, it can be applied with any other intervention or during the spread of any identical disorder/illness. In the future, more experiments with different parameters and settings can be conducted to simulate different scenarios based on real-world data. One might incorporate extra parameters such as gender or age of agents that were not considered in this model and create a simulation environment depicting similar or dissimilar scenarios. In this model, we incorporated hospitals only; however, more infrastructural facilities and public spaces may be involved in the future that might be affecting the rate of spread of the disease in any manner.

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