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Modelling of Covid - 19 spread in a supermarket

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Declaration

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Abstract

For the past 2 and half years, Covid -19 has been menacing to human society and has claimed numerous lives. Its impacts are not just limited to physical health but also the economy of society. Scientists, researchers, and governments have invested a lot of time and money to explore the determinant factors of transmission of Covid-19 to find strategies, and protocols to contain it. Geometric modelling of epidemic spread can help to mimic Covid-19 spread and analyse mitigation protocols to restrict it. In this paper, modelling of epidemic spread is done in a supermarket using 2 models, first an agent-based model for the customer to simulate realistic behaviour, and second, a virus transmission model to mimic covid -19 spread in the supermarket. The store layout, customer, and virus model simulation are all done using python libraries pyglet and networkx. A recommender system was created based on Machine learning. The recommender system would predict each customer's path for the nth day based on his/her historic data. To make it realistic, each customer has a stationary time in each aisle they visit based on exponential distribution, simulating a customer spending some time to think whether to buy a particular item or not. To make sure customer entry into the supermarket is not disorganised. Gamma distribution was used. Once the initial setup was done, all mitigation protocols were implemented. To avoid any transmission of covid-19 through air particles, masks were introduced to block covid 19 droplets both in infected users' mouths as well as susceptible users' mouths. There is still a chance of transmission if 2 users are very close to each other, and thus social distancing was implemented. It is evident that the population following these protocols is important, hence both of these strategies were implemented as mandatory and non-mandatory. In the longer run, human beings need natural immunity against covid, and thus various vaccinations were made. In this simulation, users were provided either with 1st of dose or both doses. These protocols do help reduce transmission for each user but do not disinfect the surfaces around which gives the possibility of transmission from surfaces to hand and then later to mouth. Thus proper sanitization is as important as any other strategy. Alcohol and non-alcohol-based hand sanitizers were used by customers to sanitise their hands to protect themselves from covid-19. The results from these simulations are analysed and presented to help understand the effectiveness of each protocol against virus spread.

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Nomenclature

A	Repulsion force between customers
B	Relaxation distance between customers
R	Social radius
d	Euclidean distance between customers
k	number of events in the Poisson distribution
m	efficiency of masks in trapping virus particles
p	percentage of population wearing masks
$\bar{c}$	Average contact number
c_x	relative velocity in x dimension
c_y	relative velocity in y dimension
R_0	Basic reproduction rate
v_{xi}	Velocity in x dimension for ith customer
v_{yi}	Velocity in y dimension for ith customer
x_i	x coordinate of customer 1
x_j	x coordinate of customer 2
y_i	y coordinate of customer 1
y_j	y coordinate of customer 2
λ	probability of events in Poisson distribution
θ	parameter to control horizontal and vertical stretch in gamma distribution
τ	Transmissibility

1 Introduction

The Coronavirus Disease 2019 (Covid -19) pandemic could easily be one of the biggest contenders to have such a big impact on human civilization in the 20th century. Its impact varied from the death of loved ones to the environment. However, its impact has reduced a bit in the year 2022 because of various reasons. One of the most important is the awareness of what measures to take to counter covid-19 was more evident and effective this year. But this was not the case initially, even after various measures, governments and organisations had no clue of how to restrict covid - 19 spread. In the initial days, even proper treatment and cure were a mystery. A lot of governments decided to implement a lockdown to reduce virus spread, but it was not that effective. A big reason behind that was that people still had to go to the supermarket for basic needs. Food being a primary necessity in everybody's life, became one of the most vital sectors which can adversely have a huge negative impact on human society as it can contribute to a large-scale transmission (3) of covid - 19. This is because supermarkets are a major source of all kinds of groceries in one place, they provide a lot of variety or options for a single product granting users to pick the best available product in terms of quality, quantity, and price. Because of this a lot of people between 20-40 (4) preferred going to a supermarket. Supermarkets are commonplace with a lot of people shopping indoors in close quarters accessing the same things like shelves, stairs, walls, etc. Thus, it signifies the importance of proper mitigation strategies to be implemented in a supermarket to provide safety to all the people buying from it. This can be done in various ways both in terms of structural layout as well as norms and protocols advised to the customers to follow inside the supermarket. Some of them could be like regulating the number of customers allowed inside the supermarket at a time. Having several till counters and opening only the alternate ones with shorter queues. Reducing waiting time in all areas like entry to the supermarket, waiting in line for billing, etc. Encouraging customers to not spend more than n minutes of each stop or to go to only those places where they feel important to create customer-oriented pathways. Customers can also be asked to wear masks and maintain social distance or use hand sanitizers before entering the supermarket. Customers can also have immunity through vaccination. With these many strategies, proper scenarios should be set up and tested to find the best possible outcome. Simulation can be used to mimic the exact behaviour of customers, virus spread, and all environment-related elements to find the best possible strategies which can be implemented to restrict the spread of the virus among customers without putting real-life customers at risk. This research aims to simulate a day to day activity of customers inside a supermarket with various mitigation protocols to analyse answers to a bigger question of how to make supermarkets safe. The code can be found **here**.

The Coronavirus Disease 2019 is an infectious disease caused by a novel virus, which is commonly known as Severe Acute Respiratory Syndrome Coronavirus (SARS-COV-2). It starts affecting the respiratory system and then may lead to multiorgan dysfunction and eventually death (5). In December 2019, covid-19's first case was detected. It is a contagious disease, it quickly spread throughout the world. Resulting in a global pandemic which was later declared by the World Health Organisation in March 2020. Covid symptoms can be changeable from person to person, but the most common symptoms were fever, cough, headache, loss of smell, fatigue, loss of taste, and difficulties in breathing after walking. It was found that only two-thirds of people infected showed any signs of these symptoms while others acted as unknown carriers. Most 81% of the ones who had these symptoms had a mild episode of covid -19. Few others, which is close to 14%, unfortunately, developed severe symptoms which had a major impact on their bodies. Lastly, 5% of patients had severe effects which lead to organ failures and death. Once a person is infected with Covid -19, it nearly takes 2-3 days for a person to show above mentioned symptoms. This is referred to as the incubation period for a person. During the incubation period phase, less likely is the infected person capable of transmitting the virus to someone else. After 7-10 days, either the person would recover or would start showing severe effects due to which they could be hospitalised. It is advised that an infected person should be quarantined for 14 days to prevent transmission of covid - 19 to others. Another issue is that there might be a good chance that an infected person does not show any of the above symptoms which may be unrevealed and undetected and contribute to the transmission of the virus to others.

1.1 Motivation

Covid -19 transmission takes place in either of the two ways, first by physical contact between individuals and second if particles are airborne (6). The primary source of transmission is the respiratory droplets which are created and transmitted while talking to other people, coughing, and sneezing. If anybody comes into contact with these particles or inhales air infected by these droplets, they will get infected. Even if these particles are residing on a surface, they can be traversed into the respiratory organs by travelling from a person's hand to their mouths, nose, or eyes. From research, it was found that these particles can stay up to 20 min in air and close to 2 hours on surfaces (6). The impact of Covid-19 is huge when viewed in terms of all sectors of the world. From reports, 6.4 million people have lost their lives between December 2019 and Aug 2022 (7), but it is estimated that nearly 18 million people have died due to covid-19.

Many people have had long-term effects of Covid - 19 on their health. The impact is not just physical, the whole world was forced into lockdown for months to stop the transmission of covid-19 viruses which lead to mental strain and stress on families, and friends living together. On the contrary, 24% of the population ended up feeling lonely because of staying away from family and friends. With all classes and education moving online nearly 1.4 billion children got affected and had to improvise for their education and exams. The world economy also took a hit with a lot of sectors gaining no money at all. Tourism, Airlines, Restaurants, bars, etc. all had major financial losses in the past 2 years. It is estimated that nearly a quarter million people will be pushed into poverty by the year 2030. A lot of countries had to spend millions of dollars to provide and facilitate health amenities and infrastructures for the safety of their people which also pushed countries' economic goals further. Many green initiatives to save the environment also took a hit, as a lot of governments did not have the money and time to plan and initiate schemes to protect the environment. In the initial stages, no vaccines or medical treatments were there to save people's lives. It nearly took 3-4 months to find a cure to save people to some extent. But even today, it is difficult to save everyone. Instead, it was found that non-pharmaceutical protocols were quite effective in curbing the spread of disease. These protocols helped in various ways, like masks and social distancing can help in the prevention of transmission of covid -19 droplets. hand sanitizers can be used to clean hands to make sure that there is no possibility of transmission (8)(1)(9)(10)(2). Voluntary isolation when not feeling well can also have a good impact on transmission. Ultimately after implementing all these strategies, the rampage around the world has come to a minimum, and countless lives have been saved throughout the world.

2 Background

For the simulation, a lot of initial setups are required to make the simulation realistic. First of all, supermarkets are stores where a lot of groceries are present. Taking things like these into consideration, various elements were considered. And once the setup was done, customers' mobility model was simulated based on the history of products they bought in the store. The virus transmission model was set for the transmission of the virus among customers based on various factors. Transmission of the virus was dependent on numerous elements and mitigation protocols. Each protocol has a lot of elements or prerequisites, which have to be installed or informed to the customer. Like for masks, governments have to let people know that the policies are mandatory and should be followed at all times. In the real world, a person's actions are based on his/her own will. But in simulation, based on the stats found in existing research, some percentage of people were made to follow these protocols to make it realistic. For example, it was found that when masks were not mandatory, only 41% of the population wore masks (11)(12). Similarly, when it was mandatory, 95% of the population wore masks (12).

2.1 Supermarket layout

Supermarkets are one of the most important settings, which was needed to facilitate customers. The layout was built with n number of aisles and m number of shelves in each aisle mimicking the food section aisle etc. in a supermarket. This was a basic setup and hence had only one entrance to the store and one exit from the store. The biggest problem was that the superstore had only 1 checkout counter. Note that tills are a very important element of a supermarket, as every customer who buys any stuff had to go through that. For future work, the design of the supermarket can be changed as the layout of the supermarket is critical for limiting virus transmission in a supermarket. Each customer would enter only through the entrance, traverse their path through these aisles and shelves buying stuff, and then traversing to the till counter before leaving through the exit. The history of each customer was saved in a database stating what aisle, and what shelf a customer went to in their previous runs.

2.2 Agent based Customer mobility model

To understand real-life situations or scenarios where various factors affect the behaviour of the subject population, agent-based modelling gives a better understanding as compared to equation-based models (13). In this modelling, the population whose behaviour is analysed are called agents. And the factors affecting them and their behaviour are the environmental variables (13). The main reason agent-based models are better is because by using machine learning models and artificial intelligence they can predict the behaviour of the agent. This makes the attributes and properties of each agent similar to their real-life counterparts. Then from the simulation, the interaction between agents can be analysed by the observers. The results of the simulation can be used for many other predictive, exploratory, and explanatory purposes. Similarly, supermarkets here are used as the environment for an agent based model. Where each customer is the agent, whose mobility model is predicted by the recommender system mimicking real-life customer path. Factors affecting these agents are the shelf and aisle of the supermarket, entrance, till counter, and exit section of the supermarket. The main factor affecting the simulation is the virus transmission model which tells how the virus spreads through the customers from the infected customer to all susceptible customers for a given period. The results can be analysed and where mitigation protocols can also be tested to verify whether these strategies are effective against virus transmission or not. This simulation is effective, safer, and cost-effective as real-life people are not affected by this simulation.

2.3 Virus Transmission model

To simulate the spread of the virus in a supermarket, a model was set up to mimic real-life transmission. The transmission of the virus should not be as obvious as affecting customers passing by. The chances of getting affected by covid-19 virus depend on various factors such as the duration of infectiousness (14), average rate of contact between the infected person and the susceptible person, transmissibility, and basic reproduction number of the virus.

2.3.1 Basic reproduction number

Which is also known as the basic reproductive number, basic reproductive ratio, or basic reproductive rate. It is denoted by R0. The basic reproductive ratio of any virus tells how many people would get infected if there is 1 infected person in the population and all individuals are susceptible candidates with equal probabilities. The biggest application of the basic reproduction number is to find out how quickly a virus would spread in a given population and what section of the population should be treated as quickly to eradicate the virus. Treatment of the population is done by vaccination (15). If the rate is >1 then the virus will spread to other individuals in the population. Thus larger the value of the basic reproduction number, the larger will be the difficulty to contain it. The basic reproductive rate depends on several factors such as the infectivity of infected individuals (which is basically how quickly transmission happens for these individuals), the infectiousness of the virus, and the number of susceptible individuals. From (15), it was found that the basic reproduction number of covid-19 was close to 3.39 with a range of 1.9 to 6.49. Which tells how quickly transmission of the virus is possible and how difficult it is to contain it. To control it the basic and most effective way is to limit the number of susceptible individuals in the population.

2.3.2 Duration of Infectiousness

The main purpose of calculating the duration of infectiousness will tell how effective is the transmission of the virus from the infected customer based on his/her immunity and the number of days they were affected from. From (16)(17), it was found the infectiousness of an infected customer is the highest when it's between 2-4 days. The range of infectiousness can go up to 14 days, and thus for the delta variant, 14 days of isolation is mandatory to minimise the infectiousness. From this, the main aim is to minimise this exposure time for the susceptible customers. In the simulation, this is based on customer stationary aisle waiting time. If two customers are on the same shelf of an aisle, out of which one is an infected individual whereas the other is a potential susceptible customer, then the infectious day for the infected customer will play a crucial role in infecting the susceptible customer.

2.3.3 Average rate of contact

It is the mean range of contact for the susceptible customers and the infected customer to meet in any aisle of the supermarket. The longer the path of the infected customers, the higher will be the chance of the rate of contact. Similarly, the rate of contact can also be higher for a customer if they happen to be at one spot for a very long period. Thus from (18), a reasonable estimate between 1-3 was taken with the range going up to an extent of 9.

2.3.4 Transmissibility after mitigation protocols

Once the transmissibility was calculated based on the terms mentioned above, it is compared with the transmissibility of each mitigation protocol implemented. Based on the difference between the two, that would give the chance of getting affected by the virus. For example, let's say transmissibility between an infected customer and a susceptible customer is 100% and the transmission with mitigation protocol is 50% effective, then it can be said that there is a 50% chance that the customer will get infected.

2.4 Customer Path Recommendation model

To facilitate both a customer's personal as well as behaviour choice, a hierarchical representation model is used to predict all customer's nth day shopping paths based on their history transactions and profile data (19). To bridge between the two behaviours, Matrix Factorization matrix and Markov chains methods can be used to create a dynamic model based on the sequential behaviour of users. Neural networks are always a reliable model to predict any customer behaviour of what they will buy next based on their history of items bought (20).

2.4.1 Recurrent Neural Network

In Artificial Neural networks, in each flow, there is a relationship established between the sequential nodes forming a directed or undirected graph. A recurrent neural network is a part of this artificial neural network that creates relations between nodes, or the items a customer would buy the next time they visit sequentially (21). Recurrent neural networks acquired properties from feedforward neural networks and they can process any hierarchical erratic programs based on any sequence of inputs by using their internal memory. This way, RNN can be used to dynamically find a customer's path based on their behaviours in a correct sequence(21).

2.4.2 Gradient Boosting algorithm

Boosting algorithms are used to reduce any biased behaviour of a model. Making gradient boosting the most efficient algorithm in machine learning. Gradient boosting algorithms can be used both as a regressor (for predicting continuous target variables) and as a classifier (for predicting categorical target variables). Its cost function changes accordingly, it is a mean square error when GBM is used as a regressor, and the cost function is log loss when GBM is used as a classifier making GBM favorable.

2.5 Customer Initial infected people

At the start of the simulation, few people are initially infected, for virus transmission models to trigger and spread among the customers in the supermarket. Concerning Dublin in Ireland, it was estimated that with peak transmission rate (22), 1236/100000 can be estimated as the initial infection rate.

2.6 Customer Entry to the Supermarket

To make sure that the entry of customers is not disorganized, a queuing system is introduced all around the world at all times. During covid, the flow of customers inside the supermarket was even more crucial, as if a lot of people are inside the supermarket then the susceptible population will be high, making virus transmission at its peak. Thus proper management of customers is important. Gamma distribution was used to design the queuing system for the customers. At every tick, the probability of a customer being added to the queue will be based on the distribution. And with every tick, a customer in the queue will be allowed to go inside the supermarket. Bimodal gamma distribution perfectly designs the flow of customers because of its symmetrical distribution.

2.7 Customer Stationary aisle waiting time

To mimic real-life scenarios, each customer was assigned a stationary aisle waiting time. Whenever a customer visits a supermarket, he/she often spends some time on each shelf of an aisle to decide whether to buy the product or not. Similarly, in the simulation, each customer was assigned stationary time based on Poisson distribution, which will give independent time intervals based on the probability of the customer visiting that particular aisle. This will ensure that each customer spends some time in the supermarket as in real life.

2.8 Masks

The first non-pharmaceutical intervention implemented in this project is the use of different masks by the customers. Masks are always reliable in acting as a mitigation strategy against virus spread because they block virus droplets from the infected customers, which is known as the outward efficacy of masks (23). Similarly, masks also block virus droplets from entering the mouth which is known as the inward efficacy of masks (23). Both these are important properties of masks that define a mask's effectiveness. From the data it was found even if a larger percentage of customers were even wearing a less effective mask, it had a meaningful effect on reducing virus transmission in the supermarket. Masks are also effective for asymptomatic customers, as it prevents any outward transmission from them. For the simulation, the 3 most common masks used are N95, surgical, and cloth masks. Each of these masks has different inward and outward efficacies but it is assumed that the overall efficacy of the mask has a linear relationship with the inward and outward efficacy of the masks (24).

2.8.1 N95 Masks

N95 masks or respirators were initially made for industrial and health care settings. They are basically designed to fit stiffly around the face and mouth in order to make sure that none of the small contaminated airborne particles go in. These are approved by NIOSH(National Institute of Occupational Safety and Health) and are reusable masks that can be disposed of after multiple uses. N95 masks had a higher efficacy both in terms of inward and outward efficacy with 98-99% for inward and >95% for outward efficacy (23). Thus N95 masks were widely used once they were mass produced throughout the world.

2.8.2 Surgical Masks

A surgical mask as the name suggests is a medical face mask that is used by health care personnel and blocks airborne particles like pathogens, and respiratory droplets from the patients. Surgical masks like N95 also have a higher efficacy but they are not as effective as N95, it was found that surgical masks had 72-85% inward efficacy and 70-90% outward efficacy (25). Surgical masks were readily available and had higher effectiveness, also surgical masks were cheaper which made them a popular choice in terms of both reusability and disposable.

2.8.3 Cloth Masks

Cloth or homemade masks are one of the widely used masks because they can be made with normal day-to-day clothes like handkerchiefs, bandanas, tea cloth, etc. Easily washable and reusable made them favourite during the initial days, but the biggest flaw of these masks was their efficacy. Mask both inward and outward efficacy depended upon the materials used for making the masks, and how tight were the masks. They could be equally effective and ineffective at the same time and had their inward efficacy between 20-80%, whereas outward efficacy remained moderate at >50% (25). A lot of people started using cloth masks in the beginning but later realised the importance of other effective masks.

2.9 Social Distancing

It was found that even after wearing masks the risks of getting affected were not obsolete. Even when people were wearing high efficient masks. There could be many reasons behind it, a few of those could be, that not a lot of people were wearing masks. Even if people were wearing masks, they were not tightly fitted. Or the most important reason could be that people were still very close to each other. From the research it was found, that masks are efficient but there is still a chance that virus droplets may pass through the mask and affect others. Thus it was advised that people should start maintaining social distance from each other. Social distance is a protocol where every customer tries to make sure that they are 1.8m apart from every other customer (26). It was found that the large respiratory particles from any infected person can reach up to 1.5m (27) in an indoor environment and would evaporate before falling 2m away. Thus concerning the velocity of each customer, it was advised that every person should try to maintain social distance between each other. It is very important when standing in a line or standing in an aisle while buying stuff. It's natural for any person to maintain a social radius around them, even when they are not maintaining social distance. Based on the following formula 6 and 7, the social distance was calculated between 2 customers based on their position, velocity, euclidean distance, and social radius.

2.10 Mandatory vs Non-Mandatory

All the protocols mentioned above are only effective when people follow them. For example, if only one customer is wearing a mask, and no other customer is wearing one, the chances of getting affected by the only customer wearing a mask are still very high. Similarly, even if a majority of people are wearing masks, even if the masks are not that effective, the chances of transmission will significantly be lower than none of the people wearing masks, and the transmission will depend on exposure time for each customer. Rules have always been a part of society since ancient civilization. But not all people always follow them, and because of this, the government has to make laws to bind people with these rules. Similarly, when these mitigation protocols were introduced, people were asked to wear them, and it was found (12) that only a few people followed them initially. This could be because of many reasons like people at that time did not know about the effects of covid - 19, and some people did not even know about these non-pharmaceutical interventions. And there were some, who knew, but still did not care to follow them. Or it could be even simpler like, they did not like it or were not comfortable wearing it. From (12), it was found that only 41% of the population wore masks when it was not mandatory, which signifies that the population of the society was reluctant to wear masks every day everywhere. And from the research (11), it is evident that if only 41% of people are wearing masks, the effectiveness of masks will not matter a lot, and virus transmission could be still high. Social distancing is a tough protocol to follow, as it is always subjected to everyone else. Similarly like before it will always depend on each customer to maintain social distance from each other. Thus, whether these policies were mandatory or not, made a lot of difference in the transmission of the virus in the supermarket.

2.11 Hand sanitizers

Another form of non-pharmaceutical intervention is the use of hand sanitizers. Masks and social distancing make sure that no airborne virus particles or droplets affect other customers. But there is still a major chance that customers will get affected by the virus from surfaces.

There is a good chance that an infected person happens to be in aisle 22 for some time and another customer enters aisle 22 for shopping and could get infected from the virus droplets on the shelves of the aisle. It was found that virus droplets can stay on top of surfaces from 10 seconds to 2 hours depending on the temperature and humidity of the environment. Then a person can touch the surface and then later their mouth or nose and thus get infected from the virus. Proper and regular sanitization is as important as the mitigation strategies mentioned above because it makes sure that the environment is always clean and safe for customers. hand sanitizers are usually available in a dispenser at the entrance of the supermarket. But during the initial days, hand sanitizers were expensive and scarce. Many people did not even have a habit of sanitizing their hands regularly and especially after visiting a commonplace. Because of all these reasons, hand sanitizers were not widely used in the early days. However, even after using hand sanitizers, their effectiveness against covid-19 was crucial and it was found that non-alcohol-based hand sanitizers protected covid-19 virus for only 2 mins (10) which is significantly less when compared to the time a customer would spend time inside the supermarket. From the research (10)(2), it was found that alcohol-based sanitizer had a great impact on the covid-19 virus because of its properties. It protected virus transmission from the hands of each customer for 10 min (10). It was significantly more effective than the normal non-alcohol ones. In this simulation, it is assumed that the sanitizer was only available at the entrance of the supermarket.

2.11.1 Non-alcohol based hand sanitizers

Non-alcohol-based hand sanitizers mostly contain active ingredients like quaternary ammonium and benzalkonium chloride (28) which are common in disinfectant hand sanitizers. But they were not that effective for a longer period. There is also a chance that hand sanitizers do not provide any efficacy which can prove bad for the customers and may lead to the transmission of any virus.

2.11.2 Alcohol based hand sanitizers

Alcohol-based hand sanitizers are a bit more expensive than non-alcohol-based ones and can cause various problems like irritation, and slight burn if not prepared in appropriate amounts. Alcohol-based hand sanitizers majorly contain ethanol, isopropyl alcohol, n-propanol, or an amalgam of these (28). Alcohol-based hand sanitizers can cause dizziness if people drink them. Even after these cons, alcohol-based hand sanitizers are effective against virus transmission as they quickly eradicate any viruses or virus particles available on the surface, from (10) it was found that they can provide the effectiveness of >95% for 10 min, which is better than the non-alcohol based hand sanitizers.

2.12 Vaccines

Sometimes after all these measures, there is a good chance that customers will get affected by the covid-19 virus. The human body immunity system is one of the best ways to counter virus transmission in the longer run, as it will make sure that the customers are not critically affected by the virus. Many organisations and governments spent a lot of money on developing various vaccines to make sure that people are safe once they are vaccinated. Vaccination does not guarantee 100% immunity. But it ensures that the chance of transmission is reduced for a vaccinated person as compared to the person who is not. Also, vaccination helps make sure that the affected customer is not critically ill because of the virus. Vaccination can be effective only on a few variants of the virus and can be completely ineffective against a newer variant of the virus. In this simulation, 3 kinds of most commonly used vaccines against the delta covid-19 virus were implemented.

2.12.1 1st dose vs fully vaccinated

The effectiveness of vaccines can vary based on the number of doses a person is vaccinated with. It was found that efficacy after 1 dose was relatively lower for people against the delta variant. It was similar for all vaccines (29). After both doses, all vaccines showed notably higher effectiveness against covid -19. In this simulation, booster doses were not implemented.

2.12.2 AstraZeneca

AstraZeneca, a British-Swedish company along with Oxford university developed a vaccine named covishield or vaxzervia. A vaccine that was approved by the British government first showed remarkable results from the very beginning showing 81% efficacy against the alpha variant of covid-19. Covishield showed similar results against the delta variant, its effectiveness was 67% after 2 doses against the delta variant (29). AstraZeneca vaccine was found to be stable in colder temperatures making it easily transportable and with good safety. Most importantly, there was a very rare case of the negative impact of the vaccine making it safe for customers all over the world.

2.12.3 Pfizer

The Pfizer vaccine was created by the German company BioNTech. Which was also called Comirnaty. Pfizer had a similar trait to AstraZeneca and showed remarkable effectiveness against covid - 19 with potential efficacy of 88% which was higher than the covishield (29) (30). Pfizer had more popularity because of various reasons, first, it was available for different age groups in many countries. Second, it was tested on a larger set of people during the clinical trial displaying robustness. Pfizer had very few side effects which would go away in a few days.

2.12.4 Other Vaccines

There were plenty more vaccines all around the world developed by companies in cooperation with the government. One of them was Johnson and Johnson vaccine, this category was taken as an average of all these vaccines and it was found that efficacy for these vaccines against the covid-19 delta variant was 74.5% (30).

3 Related Work

With Covid -19 affecting so many lives all over the world, many governments, scientists, and companies have invested a lot in finding appropriate effective, and reliable mitigation protocols to contain it. And thus a lot of research has been done to simulate covid-19 spread in an indoor environment and explore the effectiveness of mitigation strategies. A lot of work was effective in their approach but was not close enough to real-life scenarios. The type of model used is essential while simulating a real-life scenario. A lot of different models were created at different stages and scales with several different populations and groups. Some of them were modelled on indoor settings like airports, supermarkets, and hospitals. And few of them were on large-scale models based on a whole country.

3.1 Models

Each of the models can differ in several ways. First, models can differ in the type of variations in mathematical distributions used to define the flow of covid-19 virus in the environment. For example, different types of distributions and models can be made based on different variants of covid - 19, similarly, different models can be made based on different stages of covid 19, like when it's increasing or is at its peak, or when the population already has been affected from it have gained herd immunity (31). Second, models can differ in terms of the category of the model, it can be an agent-based model or an equation-based model. Some models vary based on the different environment variables which play an important role in the simulation(32). Some have different acquisition processes or the hypothesis of the model is different (31).

3.1.1 Graph Based Models

A graph model can also be used to connect the customers infected and the transmission of the virus can be modelled (33). In this model, the mitigation protocols that can be implemented were social distancing, geographical and demographic properties affecting transmission based on different locations, and the time duration of contact between the infected customer and susceptible customers. But it was found that factors may lead to very complex models, which might work at a stage for a location but would not predict easily because there are many other factors affecting them like the economy of the country, social and demographic lifestyle of the country and majorly the population density in that area (31) (33).

3.1.2 SIR(D) models

Many essential factors need to be considered while modelling complex different hierarchical scenarios. And models can be divided into multiple classifications like machine learning models, statistical models, or mathematical-mechanistic state space models Equation-based SIR(D) is one of these models, it is designed to calculate the effect of lockdowns on the transmission of virus spread. Since there is a huge amount of data in regards to the covid-19, customers, and policies, an approach based on the computational efficiency of quantum mechanics is used to handle the complexities of space and time related to the data (34). It was found that once travel restrictions were implemented, the curve flattened (34).

3.1.3 Agent or Equation Based models

The most common models for virus spread are Agent-based models and Equation based models. Both models have their pros and cons over each other. Agent-based models are more realistic and permit the creation of several heterogeneous customers or agents, which can have their own behaviour and characteristics which can have an impact on others as well, and similarly, they can get infected based on their own conditions and likelihood. The behaviour of each agent is based on their own decision, which makes the simulation more realistic than their real-life counterparts. This gives an edge to the agent-based models over the equation-based models because they are based on fixed variables and factors which are designed for a similar kind of population or group or simply homogeneous population. With each increase in variables and factors the equation would keep on getting more complex making them slower and a bit inefficient. When the model is homogenous, the probability of a person getting infected will also be based on the equation and will be similar for all the customers as they will have an equal probability of getting infected, which is not at all similar to real life (35). Hence Agent-based models can be effectively used to simulate real-life scenarios where customers will follow the path predicted by the recommender system based on their history of transactions and the products they have bought in their previous visits.

A lot of studies have worked on the simulation using Python, but have failed to create a shop with detailed inner structures. The objective of this project and the previous ones are similar, but the main aim is to make the simulation similar to real-life scenarios. In previous studies (36), customers moved in a random haphazard manner based on a matrix that provides a correlation between various sections of the supermarket they would visit. This project improves on this gap, and a Machine learning-based recommendation system is used to predict the customer mobility model.

3.2 Environment variables

Environment variables can be key, various public health protocols can have a significant impact on the prediction of the virus spread, and it was found that limiting travel restrictions of customers or implementing lockdowns can significantly reduce virus spread. Hence, it was found that when restrictions are already in place, the virus transmission model can get significantly affected as it will directly affect the basic reproduction rate of the virus and will not give a conclusive result of a real-life simulation. Thus, strategies used have to be selected with extreme caution as they can act as clear deviations from the epidemiological input variables. In this project, none of these factors were added to make sure that input epidemiological parameters are the results of well-informed decisions.

3.3 Recommender System

The simulation is divided into 2 models - the agent-based customer mobility model and the virus transmission model (37). Customers in different supermarkets have different shopping behaviours, and the aim is to mimic them as efficiently as possible using a Machine learning-based recommender system to predict customers' nth shopping behaviour based on their previous visit. The customer behaviour model can be based on 2 methods, first is at an individual level, when a customer simply follows the path which they majorly followed in the previous visit. Second, is the segment-level (38) which defines the behaviour of a group of customers based on their age, gender, etc. With the combination of both these methods, the customer's nth-day shopping path will be predicted.

To facilitate both a customer's personal as well as behaviour choice, a hierarchical representation model is used to predict all customer's nth day shopping paths based on their history transactions and profile data (19). To bridge between the two behaviours, Matrix Factorization matrix and Markov chains methods can be used to create a dynamic model based on the sequential behaviour of users (39). Neural networks are always a reliable model to predict any customer behaviour of what they will buy next based on their history of items bought (20). RNN can be used to dynamically find a customer's path based on their behaviours in a correct sequence (21). Previous work (38), used various machine learning models to predict movement: decision trees, support vector machines, random forests, logistic regression, and neural networks. But it could not predict the hierarchical setup of the customer mobility model. Since in this simulation, the main focus is the prediction of customer movement based on historical data and model virus transmission on these customers in the supermarket, recurrent neural networks and gradient boosting algorithms were used (40).

3.4 Mitigation protocols

In recent years, a lot of research has been done to contain covid-19 because of its high negative impact. But the protocols used are not all new. Masks and social distancing have been part of various sectors of society. With covid-19, the efficiency of these protocols against the SARS virus was analysed. It was found most of the protocols were efficient in limiting the spread of covid-19 virus spread.

3.4.1 Masks

It was found that the use of masks decreased the transmission of the virus in a linear relationship with the efficiency of the mask used, like the higher the efficiency of the mask, the lower will be the transmission rate (23). It was also found that even if some fraction of the population wore a relatively ineffective mask, even then the transmission rate of the covid-19 virus was less. Thus it suggested that the use of masks is effective as it always blocks a fraction of virus droplets both from the infected person and all susceptible customers. In the last decade, various types of masks have been tested against all kinds of viruses like tuberculosis, etc. it was found that masks were effective for hospital staff, as they had high inward and outward efficacies for the hospital staff (6). All masks were effective and had their pros and cons, some were cheaper, some were effective, some were reusable, and some were comfortable.

From (25), it was found that the N95 mask had high efficiency because of the materials used and its tight fitting. N95 masks had inward efficiency of nearly >95% if they were used properly by the customers. Similarly, N95 had outward efficiency of 98-99% against the covid-19 virus, making them reliable. But N95 masks are a bit costlier, and were not readily available at the beginning of the pandemic in various parts of the world, as it was earlier used by medical staff or for industrial purposes.

Surgical masks were the next best option, they were readily available as they were often used by the medical staff. They were cheaper, easily reusable, washable, and could easily be disposed of, making them useful. Surgical masks also had a higher efficacy, not as high as N95 masks, they had an inward efficacy of 70-90% depending on the duration of exposure to the infected person. Surgical masks also had an outward efficacy of 72-85% making them effective in not-so-crowded places (25).

During the initial stages of the pandemic, when masks were not readily available, many people out of comfort started using a cloth or homemade masks. These masks were easily available, can be reused many times, and disposed of when ineffective. But the efficiency of masks depends on various factors like how good the fitting of the mask was, how well they were made, and most importantly the kind of materials used. Cloth masks had an inward and outward efficacy of 20-80% based on the factors mentioned above making them not so reliable in all situations (25). But in all these situations, the effectiveness of masks was tested against viruses, but none of the time was simulated in a supermarket where the population is high in close quarters. And the transmission can take place between 1 to many people as well as many to 1. Thus in this simulation, this gap is filled and scenarios are tried out.

3.4.2 Social distancing

It was discovered that the dangers of contracting an illness persisted even when masks were worn. even when wearing highly effective masks. There may be various causes for it, but a few of them include the possibility that few people were wearing masks. From (26) it was found that the impact of social distancing is high against the covid-19 virus. Also, social distancing does not depend on the layout of the store, the economy of the society, or any other major factors. Social distancing only depends on the discretion of the customers themselves. In the earlier research, a social distancing between any two customers was based on various elements of distance. First, the distance between two customers is based on the tendency of either of the customers. Here tendency was based on the desired velocity of both customers based on their own will and physiological reasons (26). Second, was the actual distance between the two customers based on their social radius, the euclidean distance between them, and their relative velocity. Third, was the distance a customer might travel in randomness if they are very close to the other customer (26). Lastly, distance is calculated around the corners or any obstacles in the supermarket (26). Once all these distances were calculated between the customer, the susceptible customer will be vulnerable to the virus if the distance between them and the infected customer is less than the threshold. But the main question is, are all those social distances important, if taken from a point of view of a customer, these distances are random and are solely dependent on the customer, which can vary from customer to customer making the simulation of social distancing very difficult. Thus in this simulation, only the actual distance (the second one) was used, which actually calculated the distance between the customers based on their relative velocity, euclidean distance, and social radius.

3.4.3 Mandatory vs non-mandatory

Both the above protocols depend a lot on the population following them. And thus, in earlier papers, the population following it was based on the average for that particular location. Also in one of the research, when policies were non- mandatory it was assumed that <5% will wear masks (11). But these were not in proportion with the policies by the government and the population who are following these policies. In this simulation, when the policies are mandatory, from (11) research it was found that a lot of people were wearing masks. And only a few of the people did not. Whereas, when the policies were non-mandatory, nearly half the population wore masks before and after the peak of covid-19 (12). This data is set based on the delta variant. Since the infection rate is all set based on the delta variant of covid-19.

3.4.4 Vaccination

In earlier papers, vaccine effectiveness can vary depending on how many doses are administered. Efficacy after 1 dose was relatively lower for people against the delta variant. All vaccines showed similar results. All vaccines showed a significant increase in effectiveness against covid -19 after both doses. Booster doses were not included in this simulation (29). In this simulation, the work of previous studies is extended.

3.4.5 Sanitizers

To prevent airborne virus particles and droplets from infecting other customers, masks and social distancing are used. Customers are still likely to get infected by the virus from surfaces. The importance of proper and regular sanitization is just as important as the mitigation strategies mentioned above since it ensures that the environment is always clean and safe for customers. In previous studies (10)(2), the effectiveness of sanitizers is compared between alcohol and non-alcohol-based sanitizers. But in neither of the situations, their efficiency is considered in an indoor environment where the availability of hand sanitizers is not readily available. In this simulation, it is assumed that there is only one hand sanitizer dispenser at the entrance of the supermarket. And the customers who use it have immunity in their hands for some time. If they happen to touch their faces any time after the mark, they would be vulnerable to transmission of covid-19.

3.5 Research Question

Can these scenarios be implemented in real-life situations like a supermarket where customers follow an agent-based model where their path for a particular day is based on their previous trips to the supermarket? Are there any impacts of these mitigation protocols to reduce the impact of covid-19?

Table 3.1: Summary of some related work till date

Research Paper	Context	Approach
C. I. Siettos.(32); Xiang, Y, et al (31)	Categories of modelling	Complexities and factors in statistical, mathematical machine-learning based models.
Alguliyev, R.(33); Xiang, Y, et al (31)	Graph based model	Covid-19 spread based on graph and relation between transaction history of a customer.
E. Hunter.(35)	Agent vs Equation based models	Comparing pros and cons of agent based models and equation based models.
F. Ying, N. O'Cl.(37)	Modelling of covid-19 in a supermarket.	Two separate models: agent based customer mobility model and virus transmission model.
Rendle, Steffen.(39) F. Yu, Q. Liu,(21) S. Peke(38)	Path Recommender system	Predicting Customer shopping behaviour on nth day based on their history.
Alguliyev, R.(33); Xiang, Y, et al (31)	Virus Transmission	Covid-19 spread based on graph and relation between transaction history of a customer.
Howard, J, et al.(11); Arp, N, et al (12)	Impact of people wearing masks when its mandatory vs non - mandatory	Transmission rate depends on 2 factors – masks efficacy level and % of population wearing it.
Eikenberry, S, et al.(23)	Modelling the potential of different face masks	Efficiencies of different masks when both the transmitter and the receiver are wearing same masks.
Antczak, T, et al (41); Tsukanov, A (26)	Social distance - check out design	Mandatory distance in queues, distance calculated between 2 customers in same node at the same time. Multiple checkout designs (not implemented in this project)
Golin, A, Dexter C, and Aziz G. (2)	Hand sanitizers with and without alcohol	Customer with sanitizer have 99% virus reduction.
Bernal, J, et al. (29); Rosenberg, E, et al. (30)	Effectiveness of various vaccines against covid-19	Efficacies of various vaccines after one/two dose.
M. D'Zmura.(1) C. G. McAllen. (18) C. Cheng. (16)	Parameter value for Virus transmission model	Basic reproduction rate, duration of infectiousness, average contact

4 Methodology

In this simulation, the modelling of covid-19 epidemic spread in a supermarket is done in 2 parts: First is the agent-based customer mobility model. And second is the virus transmission model. For the agent-based customer mobility model, a path recommender system is created to predict every customer's next-day shopping behaviour based on their previously bought items. Once the path is predicted, the customer will traverse the path in a day's simulation in the supermarket until they leave. Meanwhile, the virus transmission model will formulate the virus transmission between the initial infected customers and all other susceptible customers.

4.1 Experiment Design

In this section, the simulation design is explained through a flowchart (4.1). During the initial start of the simulation, a lot of preliminary enrichment processes take place. Those processes can be seen on the very left side in Figure 4.1. First, a customer pool is created, these will be the customers who will be allowed inside the supermarket if designed time allows. Out of all the customers, only a few will be infected based on the initial infection rate (22) set based on the peak infection rate, and the duration of their infectiousness which is the number of days they are affected with covid-19. A machine learning recommender system is used to predict the shopping behaviour of these customers based on their previously bought items using the Instacart dataset (42). A vector of position nodes depicting probabilities of shelf number in the aisle a customer will likely visit. For all those visiting nodes a stationary aisle waiting time will be generated based on Poisson distribution. Once these enrichment processes are done, the simulation for the day will start and will run for the allotted time. Each customer will be added to the queuing system after every tick, and then based on bimodal gamma distribution, customers in front of the queue will be allowed inside the supermarket and then for the rest of the simulation this will continue. Once customers are inside the supermarket, they will keep on moving inside the supermarket based on their predicted path and will wait for a decided stationary time on a designated shelf in the aisle based on the vector generated earlier. The predicted vector will be stored for future use.

Simulation is run for the allotted time for n number of ticks in a day. Customers will keep on

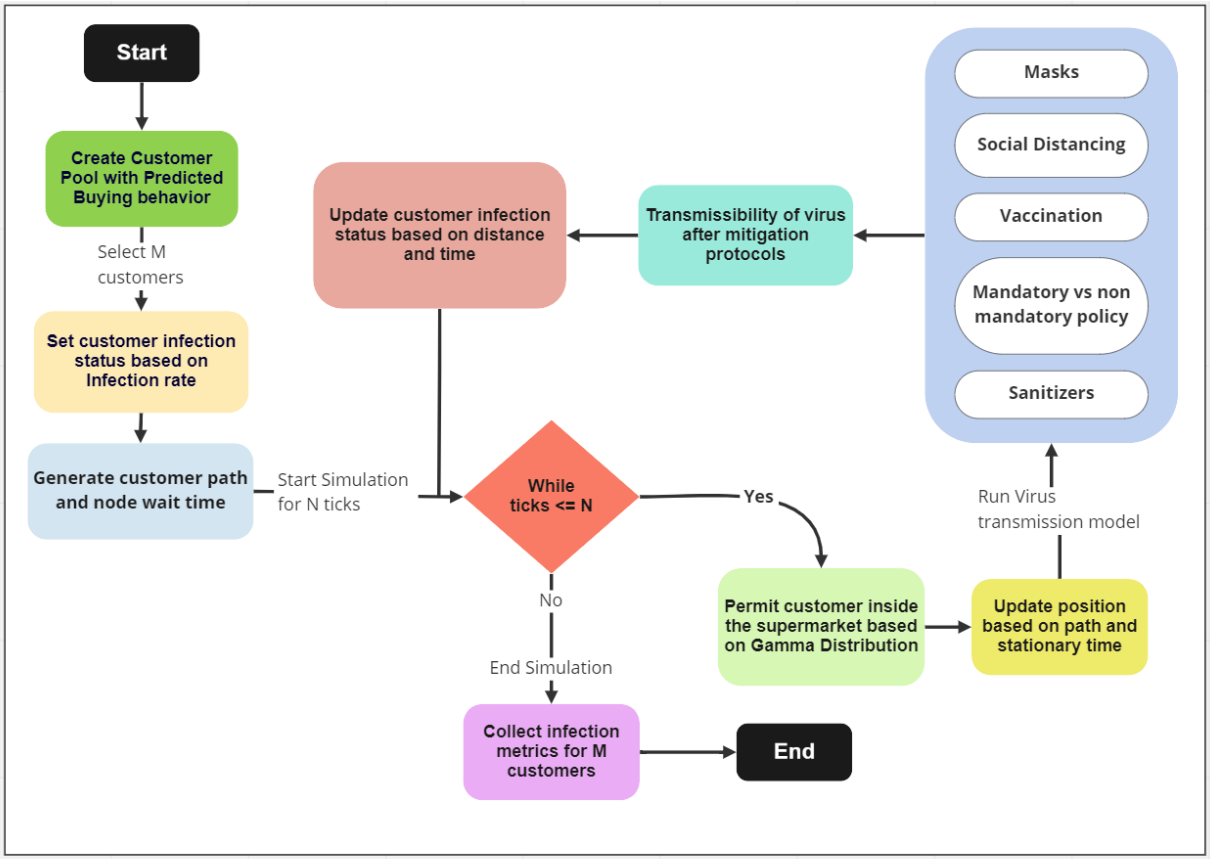

Figure 4.1: Flowchart representing the simulation process flow

coming into the supermarket for their shopping and will then head towards the till counter and then later exit. During these times, the virus transmission model will decide the transmission rate between customers based on contact between the infected customer and the susceptible customers, exposure time, the infectiousness of the infected customer, and any mitigation protocols implemented in the supermarket. If transmissibility is high, a large number of customers would be vulnerable to the virus. Newly infected customers and all other results will be stored for further analysis.

4.1.1 Customer Shopping Behaviour Prediction

As in real life, each customer usually has their items list ready they plan to buy every time they visit the supermarket. And these items list change marginally from visit to a visit. And these items decide the customer's path in the supermarket. This mobility model makes simulation more realistic and similar to real-life counterparts. Since this prediction is based on the customer's data, it can be applied to every other supermarket with their customer data making the system scalable. When each supermarket has its prediction system, it can make mitigation policies and strategies based on their customer paths and flow and effectively reduce covid-19 transmission. In this simulation, the recommendation system is based on the instacart dataset(42) to predict the customer behaviour model.

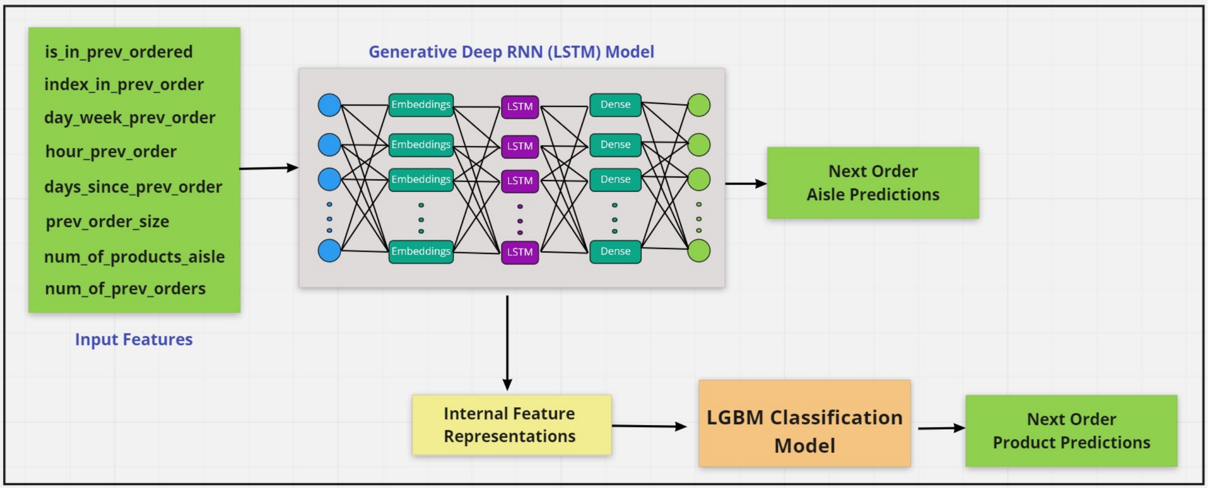

Figure 4.2: Recommender System Design: LGBM stacked on top of deep RNN(LSTM)

A publicly available dataset from instacart.com contains more than 200,000 records of online grocery shopping transactions. Time and date are recorded in the order_products table along with a customer's purchase sequence. Products are grouped by aisles and departments in the products table of the dataset, which contains almost all the items found in most supermarkets. Depending on the user, the dataset contains between 4 and 100 orders with the product sequence for each order. The order also indicates what week and hour was placed, as well as how long had passed since the previous order. It serves as the basis for training the recommendation system to determine the next order a customer should place based on his or her past purchasing patterns.

As seen in Figure 4.2, the recommender system will decide and predict if a certain product will be in the customer's next shopping order. Factors affecting this decision are any product, whether that customer has bought this product or not, and when was the last time this customer bought this product. Models are stacked to build the recommender system. A deep recurrent neural network (DRNN) was first used to fit part of the data. In the second level model, the internal representation of the DRNN model was used as a feature. The second level model used the features from the first model to predict whether a user will buy a specific product in their next order using Light Gradient Boosting (LGB). The product predictions were mapped to aisle levels to get recommendations at an aisle level, i.e. to predict whether a customer will visit an aisle in their next purchase.

Test data containing 5819 customers was used to run the model. Customer mobility inside the supermarket was modelled using these aisle level prediction data.

4.1.2 Customer Mobility Model

This section discusses how to design customer mobility across a custom supermarket floor plan. A customer mobility model was created from the output from the previous customer behaviour prediction model. Each customer's buying behaviour was used to sample independent shopping paths within a customised supermarket.

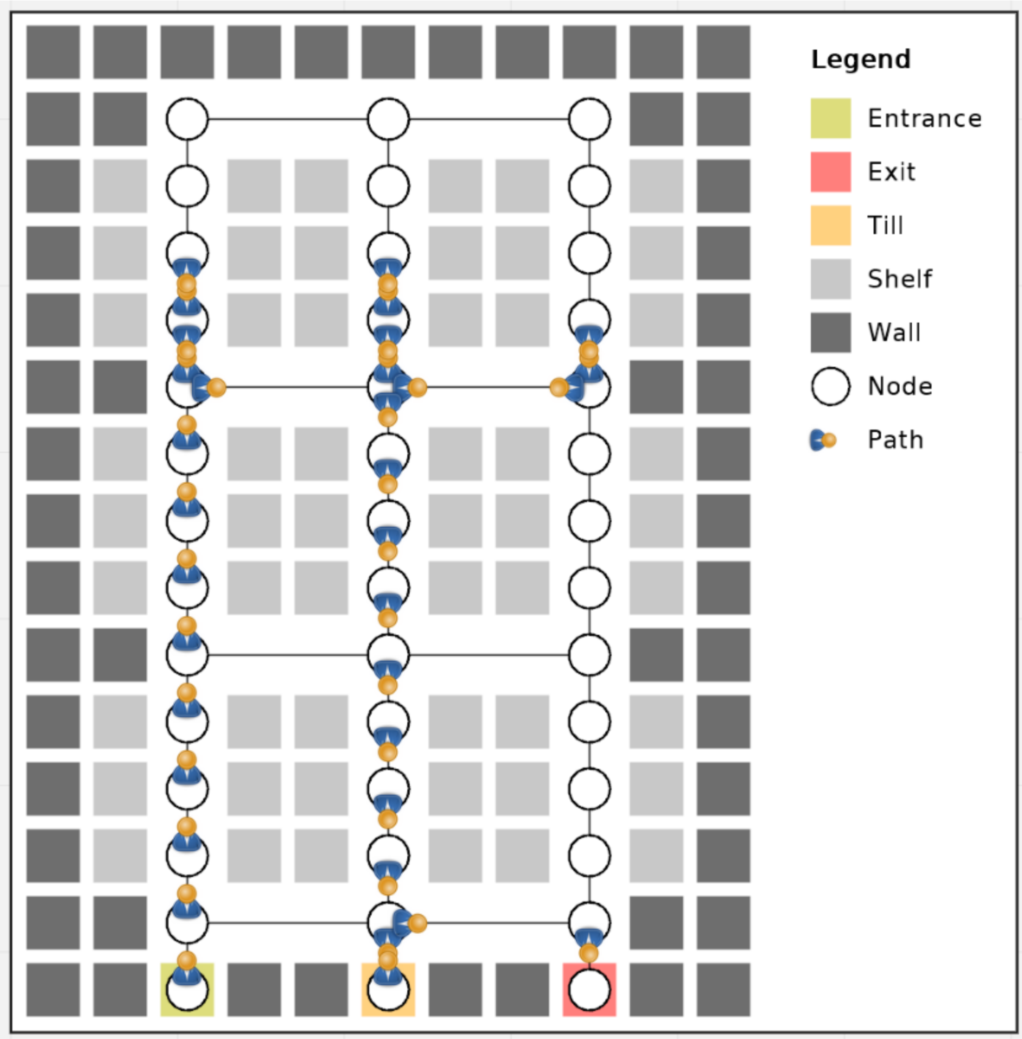

Figure 4.3: Customer Mobility Model: Path representation of a customer in the store

It is necessary to follow a path for customers to move from point A to point B within the store. During the simulation, a customer will be assigned several locations, or coordinates (shelf and aisle number), that they will visit during their journey. Basically, the path generator's job is to find a solution to the travelling salesman problem by finding the best path. Two methods were implemented to accomplish this. At first, a brute-force approach iterated through all permutations of the places a customer had to visit. Among these paths, the shortest one is selected.

Using the nearest neighbour method, the second method for generating paths was chosen. The customer initially chose this approach because it seemed more natural to them. Usually, people would try to find the closest next point to where they want to go rather than optimise their entire path. In addition, it is more efficient than a complete brute-force search. In this case, the customer's initial coordinates are used to determine which of the nodes they want to go to is currently closest to them. The next node is selected, and the process is repeated until all of the nodes have been visited. Figure 4.3 shows a sample path in our custom supermarket design. It can be seen from Figure 4.3 that a customer traverses to the till counter and then exits the supermarket.

4.1.3 Virus Transmission model

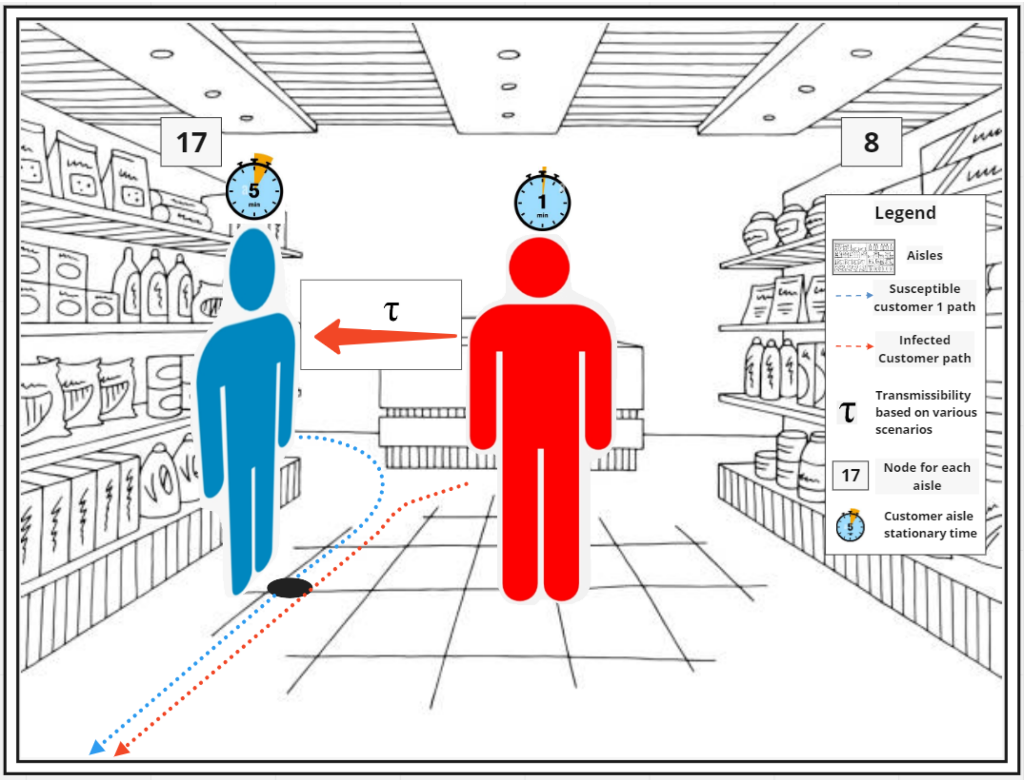

Figure 4.4: Virus Transmission: Susceptible customers might get infected from infected person based on transmissibility and mitigation protocols

In order to model the Virus Transmission Probability, the dimensionless quantity R_0 is used, also known as the basic reproduction number (14). Equation 1 defines the characteristics of R_0. In a fully susceptible population, it represents how many secondary cases can be caused by a single infected agent.

$$R_0 \propto \tau \times \bar{c} \times d \tag{1}$$

In this equation, τ represents the probability of infection given contact between all susceptible customers and the infected customers, $\bar{c}$ represents the average rate of contact between all susceptible customers and the infected customers, and d represents the duration of infectiousness. Equation 1 can be rewritten in terms of transmissibility as follows:

$$\tau = \frac{R_0}{\bar{c} \times d} \tag{2}$$

R_0 was set to 3 since the pathogen that causes COVID-19 has an R_0 range of 3-3.8 (43)(15). Taking into account the standard quarantine period of 14 days and the average incubation period of COVID-19 of 7 days (about a week) (16)(17). The value of d was chosen as a number between 1 and 5 since an infected individual can spread the infection after the incubation period. When d is low, the transmissibility is high, based on Equation 2. An infected person is more susceptible to infecting others on the 6th day after infection, which is one day after incubation (d=1), as opposed to the 14th day, which is eight days after incubation (d=8). $\bar{c}$ was chosen as a reasonable estimate of 3 (18).

Initially, both customers' infection status is checked, as well as their node (aisle) as shown in Figure 4.4. The longer the two customers stay in the same node, the higher the chance that the susceptible customer will be infected. If there are any mitigation protocols implemented, then the factor will reduce the probability of getting infected. Explained in detail in section 4.3.

4.2 Experiment Simulation Setup

Simulation can be done in various languages using multiple libraries. In this project, Python is used for its versatility and libraries. The main aim of the simulation is to mimic behaviour of the customer similar to their real-life counterparts by using the customer mobility system and path recommender system. The simulation will be for all customers allowed inside the supermarket on a specific day. Python libraries pyglet and networkx were used to create visualisation and simulation for this project. Commonly used libraries in python for animations and application programming interfaces are pygame and pyglet, environments made by these libraries are rich in multimedia tools and can provide cross-platform windowing simulations. Network analysis can be performed with the networkx library utilising standard graph algorithms with non-linear data structures such as trees, digraphs, etc. Customers follow this path to reach the aisle, cash register, and exit. A file containing configuration parameters is loaded before the simulation is started. These parameters determine the list of potential customers and the store layout based on graphs.

According to Figure 4.6, the supermarket's floor plan follows a standard layout based on a study on supermarket layouts involving entrances, exits, and aisles (44). *Instacart dataset* is used to implement 134 aisles, and each aisle is represented by a node from `networkx`.

A *tick* counter keeps track of the simulation's progress. Typically, a tick represents five seconds of real-time. With the start of simulation on a particular day, `tick()` function is invoked by the simulation repeatedly. With each call, the tick counter is increased by 1 and the number of elements is updated at each tick. First, it evaluates whether to allow a customer into the supermarket or not, or update customer positions who are already inside the supermarket whether they leave, move around in the supermarket, or stay in the same position as part of their aisle stationary time or move towards the till counter. With the update in the position of any customer, the virus model formulates whether 2 customers are close to each other or not, if they are close to each other and one of them is infected, will transmission take place with the mitigation protocols if there are any. All these computational tasks are done at every tick. The raw results of the simulation are compiled and presented once the simulation has been completed, i.e. when the tick counter reaches a certain maximum value corresponding to the store closing.

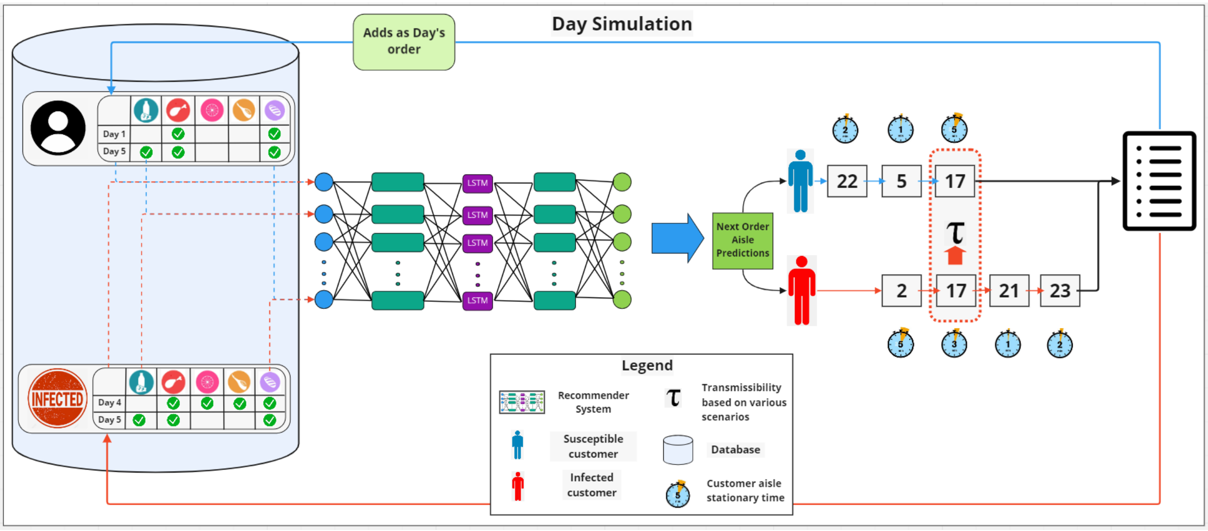

Figure 4.5: A Day simulation: how paths are predicted by the recommender system, customers would follow that path based on the time and might get infected if they are in the same aisle for some time.

From Figure 4.5, all the inputs of the recommender system are the items bought by customers in their previous visits. The customer only buys meat and bread on day 1, and then on day 5, the same customer buys milk, meat, and bread. Then these inputs will be used by the recommender system to predict the same customer's path on a particular day. Similarly, the recommender system will predict all paths for all the customers and the virus transmission model will keep on formulating if any customers are close to each other for more than 1 tick. Then the susceptible customer will get infected. As in Figure 4.5, both the susceptible customer and the infected customer are on the same aisle 17, one of them in the aisle for 5 ticks as stationary aisle waiting time (explained below in section 4.2.3) whereas the infected customer is in the same aisle for 3 ticks. Thus, susceptible customers will be vulnerable if there is no mitigation protocols and will get infected. These results are stored and used for evaluation, and the path will be saved back in the database for the next shopping day.

4.2.1 Supermarket store layout

The layout of a supermarket is based on a small-medium size supermarket. It has only one floor, with one entrance, one till/checkout counter, and one exit. It can be seen in Figure 4.6, that with an increase in every tick one customer is allowed inside the supermarket through the entrance. For this simulation to be closer to a real-life situation, the supermarket layout comprises 9 aisles, and 3 shelves for each aisle, thus making 27 sections, or nodes in between them.

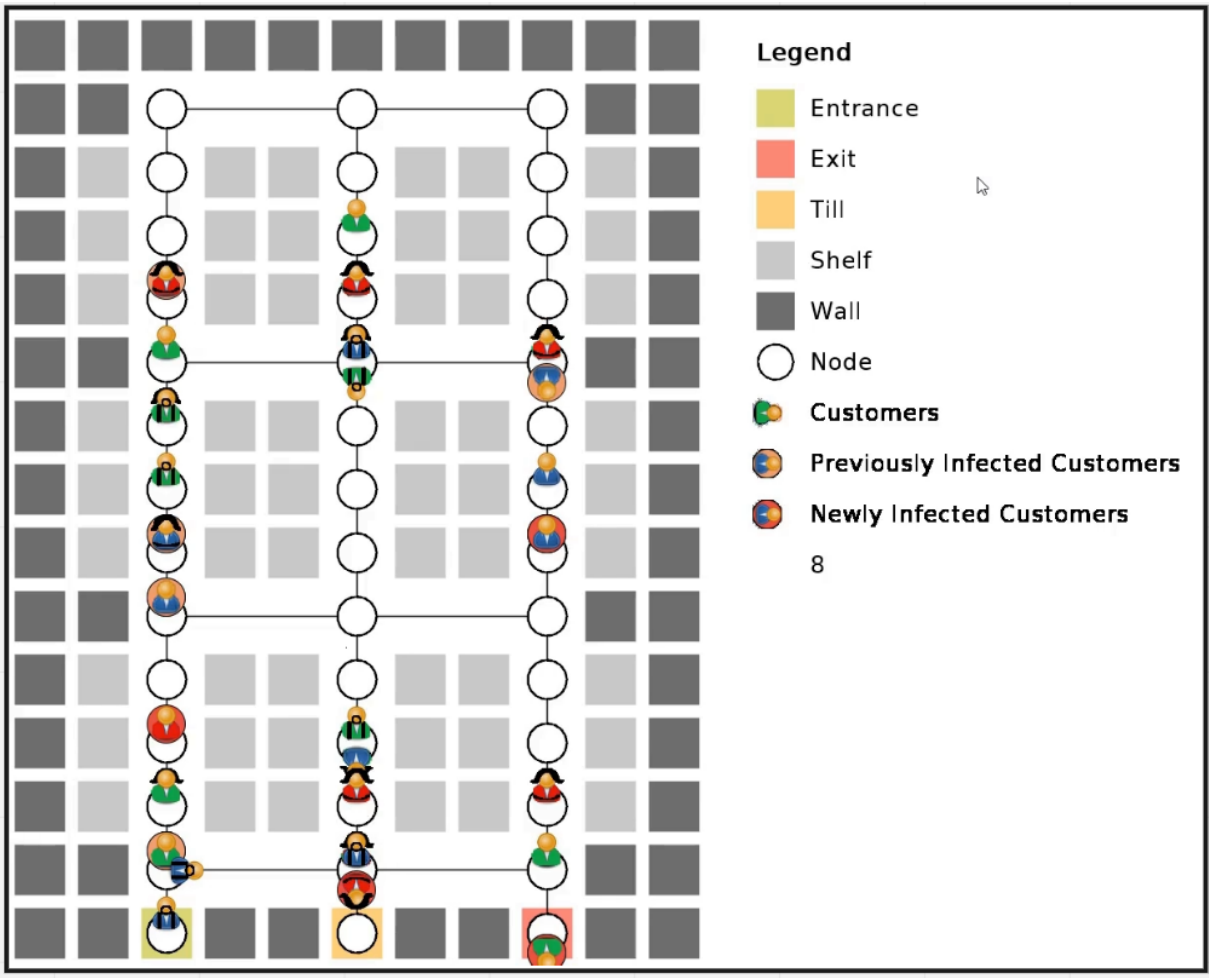

Figure 4.6: Supermarket store layout after n ticks

From Figure 4.6, 3 shelves can be on either side of each aisle, for example - on the bottom left-most corner, 3 wall shelves and 3 shelves on the first column make an aisle, and have 3 nodes in between. Similarly, there are 3 aisles in the first row stacked with 3 column aisle, making a 3 x 3 x 3 section. Each section has a node that a customer can arrive at. There are 5 items in each of the sections which denotes 5 kinds of different items that exist in each of the sections. The recommender system is trained with 134 items, thus for this supermarket, the total number of items is 135, which is 27x 5. These configurations can be changed, and the supermarket layout will fit accordingly. This also enables the feature that based on the number of items, various supermarkets can change their layout accordingly to accommodate their commodities. The customer path recommender system will only predict out of these 27 sections which will contain the item the customer is looking for. There are a few other nodes that act as a gateway for the customer mobility model to allow short passage to customers from moving aisle to aisle.

The supermarket consists of only one counter. Thus all customers who have at least one aisle stationary waiting time will move to the till counter once they are done with their shopping. This behaviour is to mimic a real-life scenario, where a customer who spends some time on at least one shelf, would plan to buy that stuff, and then to pay for that item will traverse to the till counter for payment. Once that is done, the customer will exit the supermarket. It can be seen from Figure 4.6, that customers are going towards the till counter before exiting the store. To mark customers who are initially infected, those customers have a different mark, with an orange circle on their back. Whereas, the customers who are in the same section as these infected customers and spend more than 1 tick with them will get infected if there is no mitigation protocol in place. Those newly infected customers' icons will change from any user image to an image with a red circle in the background. The counter will keep on increasing as newly infected customers are increasing. Note, that newly infected customers will not have any transmission because of the incubation period.

4.2.2 Customer Arrival

A bimodal gamma distribution is used to model the probability of customers' arrivals when adding them to the queue. Consequently, the probability density function (PDF) of customer arrival is modelled to mimic the entire simulation period. As a result, the probability of a customer joining the queue at a particular tick can be determined by the PDF for that tick, scaled appropriately by the total simulation time and of the distribution known as `xlim`. According to this value of probability, a customer will be added to the queue at random as True/False. The PDF for a Gamma Distribution is as follows:

$$f_{k,\theta}(x) \;=\; \frac{x^{k-1}e^{\frac{-x}{\theta}}}{\theta^k\Gamma(k)}\;,\; x > 0 \qquad (3)$$

The shape parameter k controls the overall characteristic of the distribution and the scale parameter θ controls its horizontal and vertical stretch. For $k \leq 1$, the gamma PDF is strictly decreasing, and for $k > 1$ it modifies into a left-skewed bell curve, which gets increasingly more symmetrical and less skewed as the value of k increases. With increasing θ, the distribution becomes broader and shallower, while maintaining its inherent skew and shape which is determined by k.

To model customer arrival, a Poisson distribution was used but decided against it because a

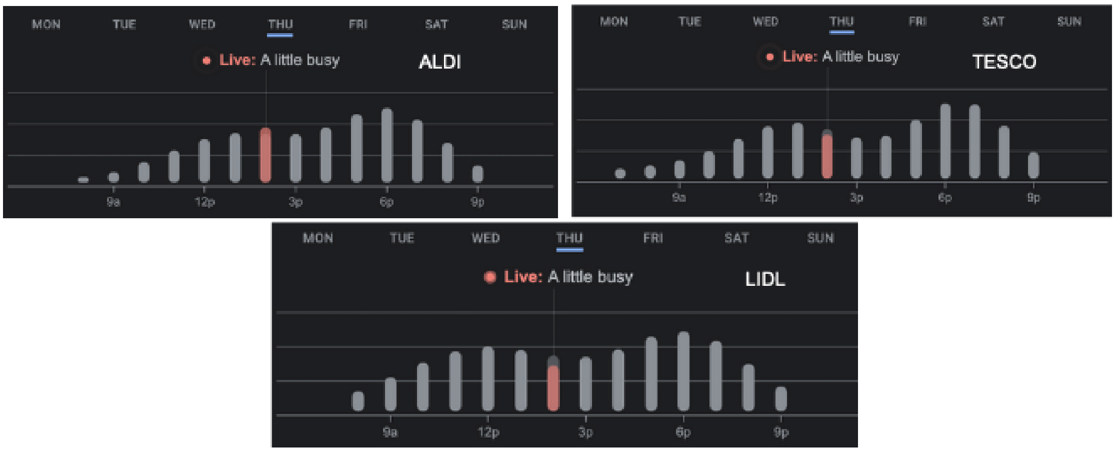

Figure 4.7: Bimodal Distributions of Footfall in different stores (1)

Figure 4.8: Modelled Bimodal Distribution for Customer Arrival

Poisson distribution is typically used to model the number of events that occur within a fixed period, instead, the main aim is to determine the probability that a single customer will enter the store at a particular time. Google (1) was also used to get footfall data for stores like Lidl, IKEA, Tesco, etc. To understand what the busy times are and what kind of distribution that would represent. Examples of sample data are shown in Figure 4.7. Due to the bimodality of footfall data, a normal distribution was not used because there can be multiple peaks of customers within a single day. Bimodal gamma distribution parameters were chosen with care to effectively model Google's footfall data. Figure 4.8 shows the final modelled distribution.

4.2.3 Customer Aisle stationary time

During the initial load, the customer path recommender system will predict the paths of all selected m customers. The customer mobility model will try to find the best path suited for these predicted aisle vectors. And when the simulation starts, based on the customer arrival model, customers will go inside the supermarket. But when a customer reaches a particular section in the aisle, he/she will spend some time on that spot known as customer aisle stationary time. In real life, most customers spend some time in each of the sections they intend to buy an item from, to get the best-suited item for the best price they deem fit. In this simulation, customers are assigned aisle stationary time on each of the sections they will visit. The time allotted will be based on 2 factors: the probability of each customer visiting that particular section of an aisle. This is to cater to the fact that a customer will spend more time in the aisle section they have the highest probability of. Since the probability of visiting each section is given by the recommender system, stationary time will be assigned for all those nodes at which a customer would shop. The second factor affecting how much time, or what would be the range of stationary time, will be decided by Poisson distribution as explained in (45). Poisson distribution gave a good relationship between the in-aisle stationary time and the probability of visiting that particular aisle. The range of the stationary time will be obtained from Poisson distribution and each time will be independent of all time allotted for other nodes, it will be solely dependent on the probability of visiting that aisle (45). The PDF of a Poisson distribution is as follows:

$$f(k, \lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{4}$$

The number of events in the Poisson distribution is defined by k. In this simulation, k will be the total number of times or ticks a customer would spend on a specific section of an aisle. The probability of these events in the distribution will be defined by λ.

Each customer who enters the supermarket would have some aisle stationary time calculated by Poisson distribution and the probability of visiting that aisle. The clock on top of the customer in Figure 4.9 symbolises their aisle stationary time at their respective nodes. It can be seen from the left part of Figure 4.9 that both customers are on their respective aisle nodes 22, and 2. Both customers have been given a stationary aisle waiting time of 2 and 5 ticks. This is to mimic a real-life situation, where each customer is spending some time shopping and deciding what to buy and what not to buy. Then after 2 ticks of the simulation, the customer with 2 ticks as aisle stationary time will move to another aisle. Whereas the other customer will continue to shop in the same aisle as he/she had an aisle stationary time of 5 ticks. This can be seen from the right side of Figure 4.9, that the first customer is moving towards another aisle whereas the second customer has 3 ticks left on their aisle stationary

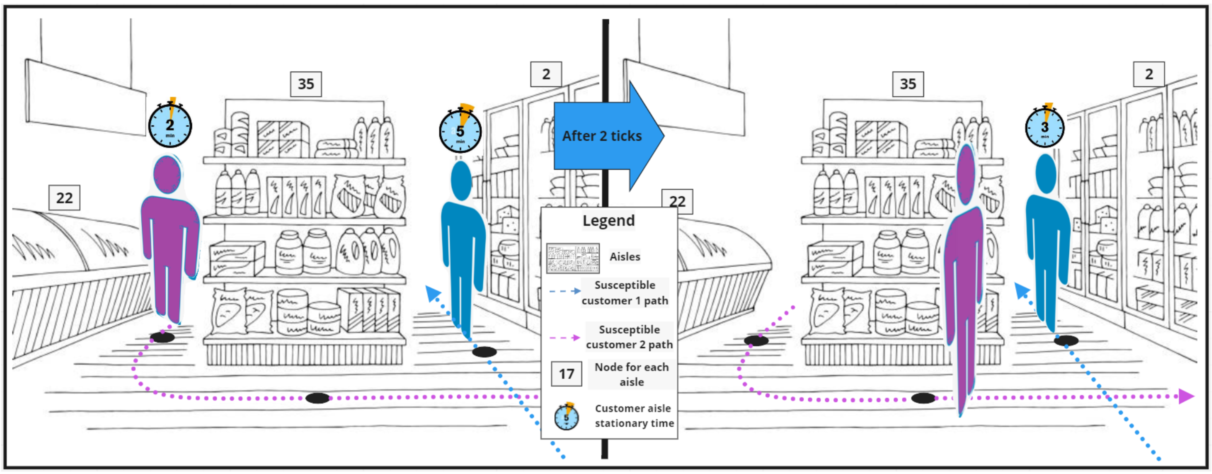

Figure 4.9: Customer Aisle stationary time for 2 customers. After 2 ticks, one of the customer moves to different aisle.

time. This was done for all customers and the simulation is run based on this configuration. But this also highlights one of the biggest factors that with increasing stationary aisle time, the risk of getting infected increases linearly.

4.3 Implementing Mitigation Protocols

Due to covid-19's high negative impact, a lot of research has been conducted in recent years. But the protocols used are not all new. In various sectors of society, masks and social distancing have been prevalent. The effectiveness of these protocols against the SARS virus was evaluated with covid-19. The majority of protocols were effective in limiting the spread of the Covid-19 virus.

4.3.1 Masks

Masks have been part of many sectors of society for so long. As a non-pharmaceutical intervention, it has been effective in a lot of cases in various sectors. As mentioned earlier in sections 2.8 and 3.4.1, different masks are efficient against virus transmission in some way. Some masks have higher efficiency than others, whereas some have more reusability. As it can be seen from Figure 4.10, virus transmission is relatively very high when none of the customers are wearing masks. On the other hand, even if some of the people are wearing masks, the virus transmission could still be high if the infected person is not wearing a mask, as they will spread virus droplets in the air and on the surfaces of the supermarket making other customers vulnerable. Virus transmission is lower if the infected person is wearing a mask, and the probability of the susceptible person getting infected will be based on the efficacy of the mask used by the infected person. But it will still have some probability of infecting other customers. Lastly, if all customers are wearing masks then the probability of virus transmission will be very low.

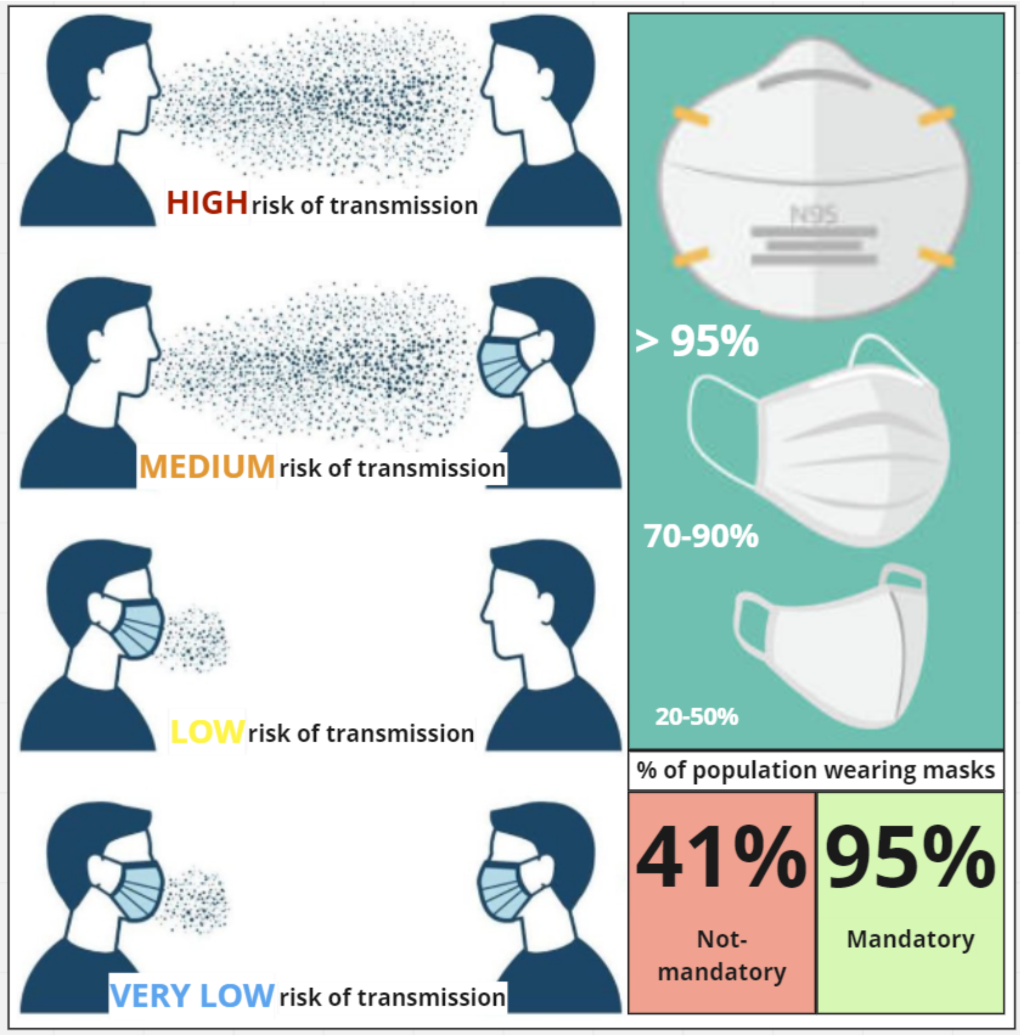

Figure 4.10: Effects of different masks against virus transmission

From 2.8 and (23), it is found that the efficiency of the mask is linearly proportional to the outward and inward efficacy of the mask. The table 4.1 shows the inward and outward efficacy of the masks based on how they were made, what materials were used and for how long the customer wearing masks will be exposed to the virus. In this simulation, the efficiency of the masks is calculated from (23) in the worst-case scenario in terms of their outward and inward efficiency. For example, if cloth masks have outward efficiency of 20-50%, which is

Table 4.1: Efficiency of Different types of masks

Types of Masks	Inward Efficiency	Outward Efficiency	Overall Efficiency
N95 masks	98-99%	>95%	95%
Surgical masks	72-85%	70-90%	72%
Cloth or Homemade masks	20-80%	20-80%	25%

based on the type of material used to make the mask, the tight fitting of the mask, etc. Higher will be the efficiency if all these factors are implemented well. But in this simulation, worst-case scenarios are considered because the ability or the use of a mask by the customer is not considered. From (11), it was found that even with effective masks, customers were not wearing the masks properly, or even if they were using them correctly they were frequently adjusting them and thus not fully utilising the effectiveness of masks.

From section 2.8 and (11), the effectiveness of masks alone is not enough to limit the transmission of the virus. As it can be seen from Figure 4.10, the majority of the population should wear masks. It was found that the effectiveness of masks is higher even if the majority of the customers are wearing an ineffective mask. From (11), it was found that the average number of people infected by the infected customer is inversely proportional to the total number of people wearing masks and the efficiency of the masks they are wearing. The relation is as follows:

$$R_e = (1 - mp)^2 \tag{5}$$

In this equation, R_e is the average number of people infected by the infected customer, and m is the efficiency of the masks in trapping virus particles inside the mask. And p is the percentage of people wearing masks. It can be seen from equation 5, that if m and p increase, then R_e will decrease. Indicating that if a broader section of customers is wearing effective masks in the supermarket, then transmission of the virus will be highly reduced by the factor above. For example, if 50% of the customers are wearing masks and the masks they are wearing have an efficacy of 50%, then the average number of people infected will be reduced by $R_e = 0.56$. Thus the probability of susceptible customers getting infected will be reduced from 100% to (100 - 56 =) 44%.

Mandatory vs non-mandatory

With the above equation, the percentage of people wearing masks is significantly important. The question arises, of what steps governments/companies should take to make customers aware of the importance of wearing masks. From masks (12), it was found that when policies like masks are mandatory were introduced a lot of people while going outdoors for any important activities were wearing masks. It was observed that nearly 95% started wearing masks when the policy was mandatory. But when wearing masks was not mandatory, then the number of people wearing masks went down. It came down to nearly 41%, taking the factor of both the phases which is before and after of covid -19 peak transmission. It is seen that when cases are not that high, the policies and people are a bit lenient.

4.3.2 Social Distancing

As mentioned earlier in section 2.9, masks are not 100% efficient, and with human error in mind, their effectiveness against virus transmission is not guaranteed. From previous work (26), it was also found that virus droplets sometimes pass through the masks if the user is in close contact with the infected person for a longer period. Thus for the reasons mentioned in 2.9, social distancing is also important and it can be synergised with all other non-pharmaceutical protocols. The only factor affecting the effectiveness of social distancing is based on the customers themselves. Customers to protect themselves, just have to be sure they maintain some distance (1.8 m) as seen in (26) between themselves, and virus droplets from the infected customer would evaporate before it reaches them. The variables required to calculate social distance are as follows (26). Every customer or a person has his/her social radius which he/she maintains when going to a commonplace, social radius is the distance a person keeps with any stranger without being subjected to overcrowdedness. Similarly, even when buying items in the supermarket customers would maintain their social radius with other customers. Another element is the relative velocity between the 2 customers both in vector dimensions of x and y. The most important factor is the euclidean distance between the 2 customers which would tell how far are these two customers. The last 2 factors affecting social distance are the relaxation distance between the two customers and the force amplitude which is the repulsion force amplitude when 2 customers are too close to each other. The formula can be written for dimensions x and y as follows:

$$F_x^{soc} = Ae^{\frac{-\epsilon}{B}}\frac{1}{2}\frac{x_i - x_j}{d}(1 - c_x\frac{x_i - x_j}{d}) \tag{6}$$

$$F_y^{soc} = Ae^{\frac{-\epsilon}{B}}\frac{1}{2}\frac{y_i - y_j}{d}(1 - c_y\frac{y_i - y_j}{d}) \tag{7}$$

where

$$d = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{8}$$

$$\epsilon = d - 2R \tag{9}$$

$$c_x = \frac{v_{xi}}{\sqrt{v_{xi}^2 + v_{yi}^2}}, \quad c_y = \frac{v_{yi}}{\sqrt{v_{xi}^2 + v_{yi}^2}} \tag{10}$$

In the above equations, F_x^{soc} represents the interaction between the two customers whereas d represents the Euclidean distance between the two customers and R is the social radius. x_i, y_i represents the x, y coordinates of the first customer where x_j, y_j represents the x, y coordinates of the second customer. Similarly in equation 10, v_{xi} and v_{yi} represent the velocity in x and y direction. And c_x and c_y represent the dimensionless components of the velocity between the customer. From (26), the relaxation distance between the two customers is set to B=0.3

m. And the force amplitude A is set as 2.1. If the value of F_x^{soc} is less than a threshold value, then the two customers will be close to each other making them vulnerable to virus transmission. A threshold value is set based on the social distancing norm, that customers should maintain 1.8 m between each other (27) as virus droplets would not reach that far and affect the customer.

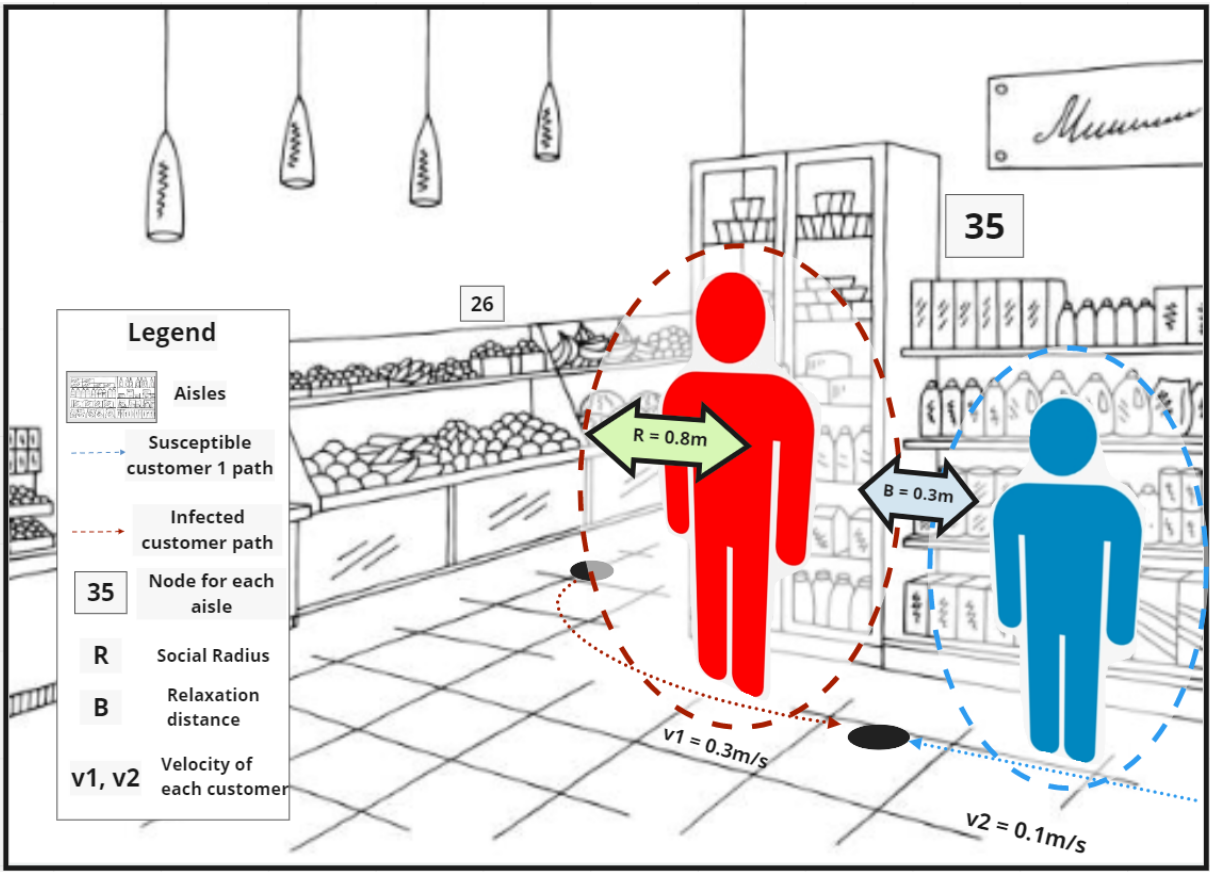

Figure 4.11: Customers maintaining social distancing by keeping social radius of 0.8m with others

Mandatory vs non-Mandatory

The most important factor is the R in the above equation 9, as it is the social radius the customer would maintain when they are inside the supermarket. From (26), the value of R is set to be between 0.2-0.5 m when there are no restrictions. Even when there are no restrictions, customers tend to have some interpersonal distance from strangers, however, they may be close to each other unintentionally, if it's crowded.

With covid-19, the government may force a policy or can ask customers to maintain social distancing, and thus each customer can maintain a social radius of 0.8 m and they can maintain social distancing with other customers based on equations 6 and 7. Thus in this simulation, these values are set, assuming that 95% of the population will maintain social distance and in doing that would maintain a social radius of 0.8 m.

From figure 4.11, it can be seen that the customers are following social distancing and maintaining a social radius of 0.8m. And then based on Equation 6 and 7, their social interaction would be higher and would maintain a distance of 1.8 m between the two.

4.3.3 Sanitizers

Even when all the customers are following these non-pharmaceutical interventions, they are still susceptible to virus transmission because of the surroundings inside the supermarket. Especially, in indoor settings, airflow and ventilation are limited and subject to contamination. If proper sanitization is done, customers might be still vulnerable to virus transmission because of the presence of virus droplets on surfaces and in the air.

Table 4.2: Effective contact time(min) for chemical constituents (2)

Active Ingredients	Type of Sanitizer	Effective contact time	Formulation type
Ethanol	Alcohol	2	Ready-to-use
Isopropyl	Alcohol	10	Wipe
N-propanol	Alcohol	10	Dilutable
Benzalkonium chloride	Non-Alcohol	2	Dilutable
quaternary ammonium	Non-Alcohol	2-6	Dilutable

As discussed in 2.11, proper sanitization is as important as any other mitigation protocol. From (10)(2), it was found that if customers use sanitizers, their hands would be protected from the virus for some time, as sanitizer would disinfect any virus. There are 2 broad types of sanitizers, alcohol-based, and non-alcohol-based sanitizers. From (10), it was found that alcohol-based sanitizers are more effective and their effects last for nearly 10 min.

Table 4.3: How long SARS-Covid virus reside on surfaces at favourable temperatures (2)

Surface	Time(h)
Aerosol	3
Glass, counter top,plastic,stainless steel	72
Cardboard, paper,fabrics	24

Table 4.2 is a summary of how long does the effectiveness last after using sanitizers with these main chemical constituents. Thus, these sanitizers wipe out protein present on top of the hand, on which viruses feed, thus killing them. From table 4.3 (10) it can be estimated that alcohol-based sanitizers would give 98% effectiveness if customers touch any contaminated surfaces for only 10 mins (alcohol based) and 2 min(non-alcohol based). From non-alcohol-based sanitizers their effectiveness is not as high as alcohol-based. Their effectiveness is between 50-70%.

Table 4.3 gives insight into that covid -19 virus can sustain on surfaces for a very long time in a favourable temperature and humidity. The environment can get contaminated by an infected individual unintentionally and can be a source of transmission to other customers if they touch those surfaces and then touch their mouth, nose, or eyes.

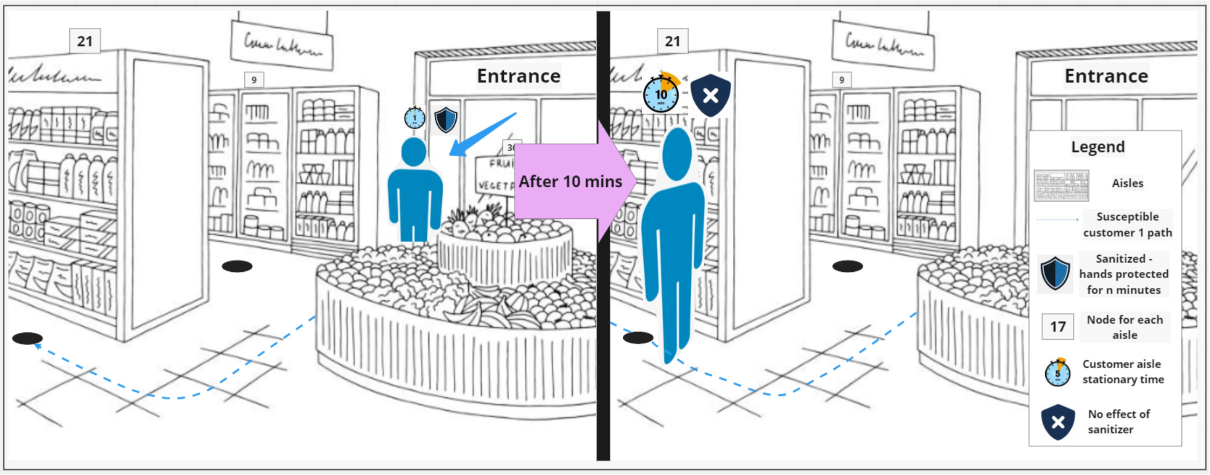

Figure 4.12: Customers use sanitizers while entering the supermarket and immunity for their hands for some time.

In this simulation, a sanitizer dispenser is provided at the entrance of the supermarket. Once a customer comes in and uses that hand sanitizer, they would have protection against covid-19 only for n mins based on the type of sanitizer placed. But once those minutes are over, they become vulnerable to virus transmission. It can be seen from Figure 4.12, that customers have immunity for their hands once they are inside the supermarket. But after that is done, they might get infected from virus transmission.

4.3.4 Vaccination

Covid-19 can sometimes affect customers despite all these measures. Long-term, the immune system of the human body is one of the best ways to prevent virus transmission, since it will prevent the customers from becoming critically ill. To ensure that people are safe after vaccination, many organisations and governments have spent a lot of money developing vaccines. Immunity cannot be guaranteed 100 percent by vaccination. However, vaccinated people have a lower chance of transmission than non-vaccinated people. In this simulation, the 3 most commonly used vaccines are implemented, that is astrazeneca, pfizer, and a category of other vaccines. As mentioned above in section 2.12 are the characteristics of each vaccine after 1st and 2nd doses.

Table 4.4 states the efficacies of each of the vaccines after customers have administered 1st and 2nd doses.

In this simulation, virus transmission was adjusted when customers were administered with

Table 4.4: Effectiveness after 1st and 2nd doses of different vaccines against delta variant

Vaccine	**1st dose**	**2nd dose**
AstraZeneca	30%	67%
Pfizer	35.6%	88%
Other vaccines	30.7%	79.6%

1st or both doses. For these cases, all the customers were either administered 1st dose or all were administered 2nd dose of the same vaccine, to analyse how effective these vaccines could be in these situations.

Once all these protocols were implemented, 100 simulations were done for each of the scenarios. Many of the protocols can synergize with each other and have additional control over the virus transmission between customers in the supermarket. Various combinations were tried and the results were recorded. Note, that 1 simulation is run for all customers in a single day for a given period.

5 Results and Analysis

Once 100 simulations were done for every combination, results were analysed. 1 day between a starting and ending time signifies 1 simulation. Every tick is set to 5 seconds. Table 5.2 lists down all configuration details. Below are the results of all different scenarios :

5.1 Default Transmission

This section discusses the results obtained after the default transmission of Covid-19 without any mitigation protocols in the supermarket. Stats like newly infected customers, exposure time, previously infected customers, and the total number of customers were recorded.

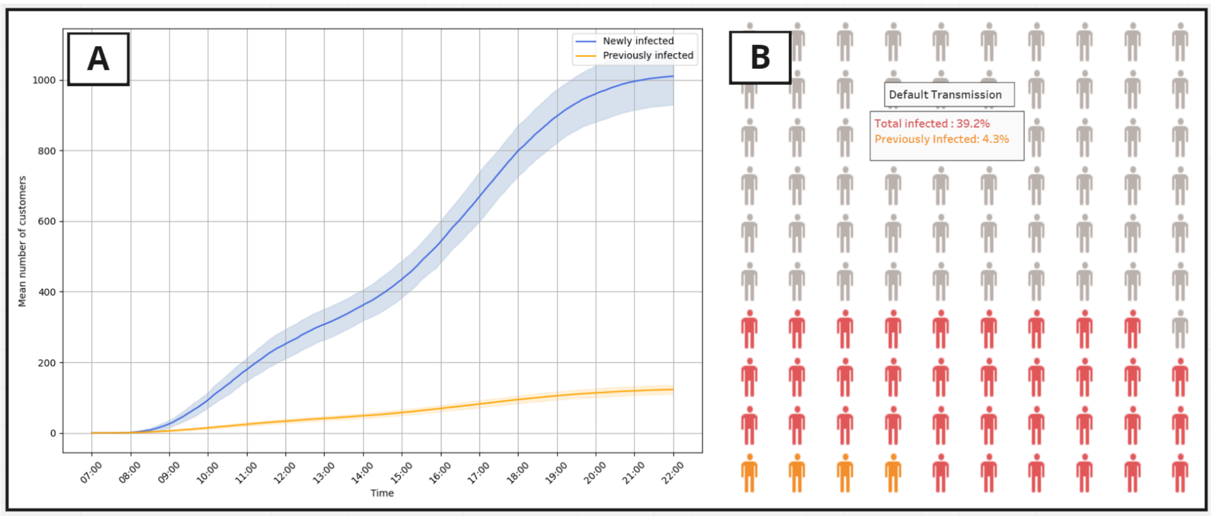

Figure 5.1: Transmission of virus in the supermarket without any mitigation protocols. **(A)** Newly infected customers throughout the day. **(B)** Waffle chart showing % of customers who got newly infected.

From Figure 5.1, it can be seen that a lot of customers get infected due to viruses over some time, as the number of initially infected people increases. It can also be seen that nearly 39% got infected from 4% previously infected from virus transmission. Note, virus transmission is only from previously infected customers not from newly infected customers, because of their incubation period.

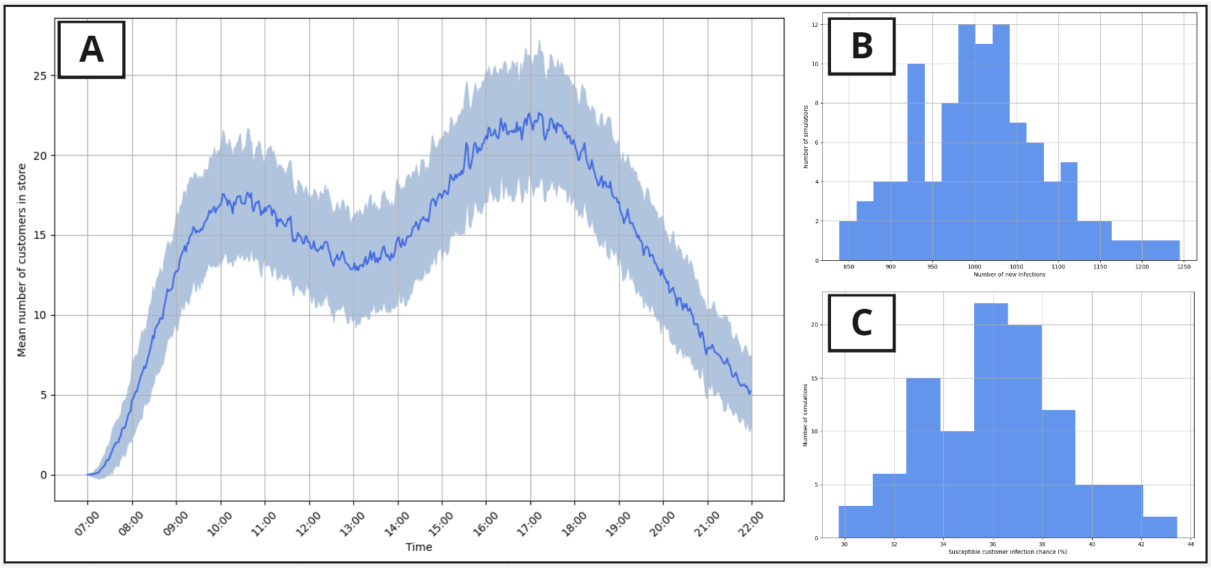

Figure 5.2: Across 100 Simulation **(A)** Average number of customers in the store. **(B)** Distribution of newly infected customer. **(C)** Distribution of chance of getting infected

From Figure 5.2, the average number of people in the supermarket throughout the day for 100 simulations is almost similar to Figure 4.8, as customers are allowed based on the gamma distribution. It also shows that 1000-1050 is the mode for the number of newly infected in all simulations. Additionally, there is a 35-36% chance that a customer might get infected.

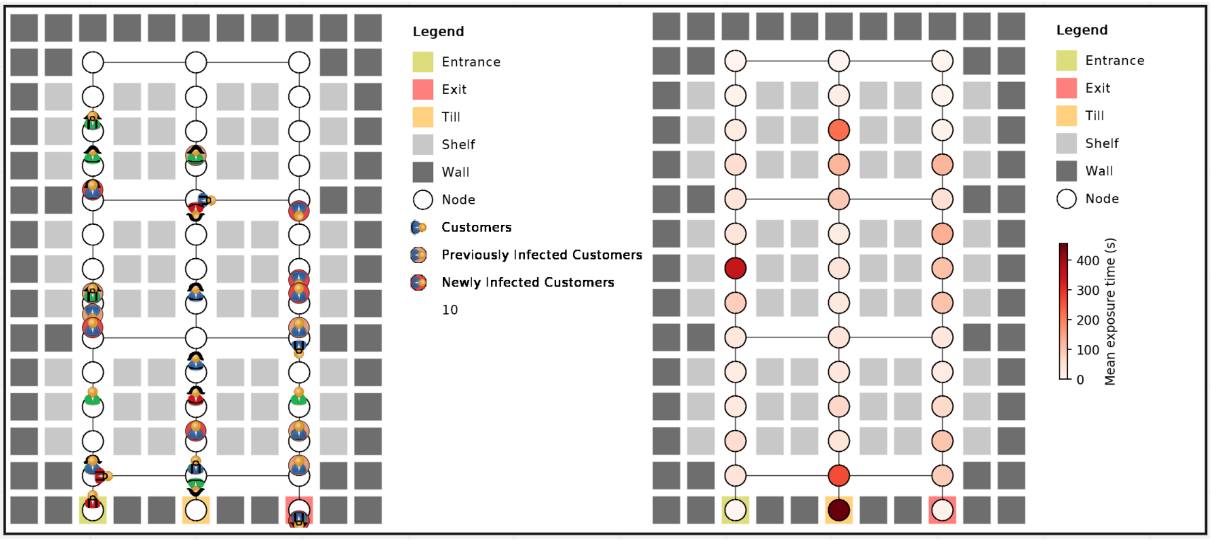

Figure 5.3: Total exposure time in each node in the supermarket for across 100 simulations.

Since the transmission of the covid-19 virus among the customers was high, the exposure time for all customers in nodes where they shop was observed which can be seen in Figure 5.3. And it was found that near the left aisle and the till counter exposure time was significantly higher, signifying that that particular aisle is visited by a lot of customers, and once all customers are done shopping they all will go to the till counter, which is riskier than all other nodes.

5.2 Customers using different types of masks

As explained above, in sections 4.3.1 and 3.4.1, the 3 most common masks were implemented based on their effectiveness. 100 Simulations were done in the same setting with all customers wearing the same type of masks. And stats were recorded.

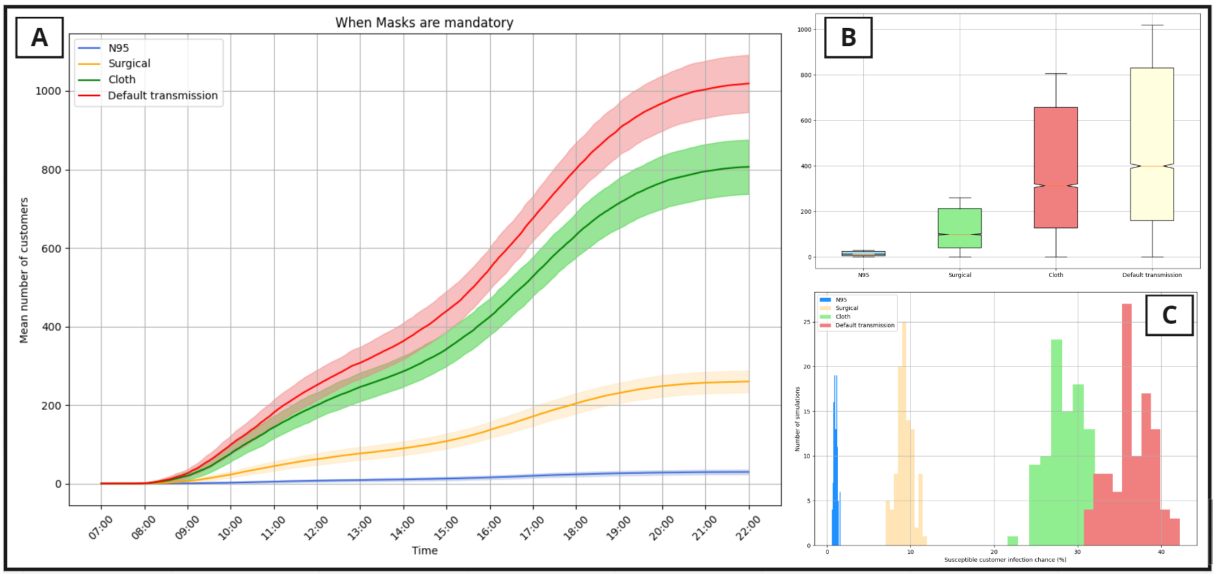

Figure 5.4: Comparing 3 commonly used masks: **(A)** Newly infected customers when masks are mandatory. **(B)** Box plot with mean of newly infected customers for different types of masks. **(C)** Chance of getting affected when customers are wearing each type of masks.

It can be seen from Figure 5.4, that even with masks there are customers who are newly infected from the previously infected customers. But there is a clear reduction in transmission of the virus after the use of masks. N95 seems to have brought virus transmission to its minimum, due to high efficiency. Since this setting is when wearing masks is mandatory, signifying the importance of the population wearing masks. It can be seen with N95 masks newly infected customers are less than 50 signifying real efficient mitigation protocol against covid-19. Surgical masks on the other hand are a lot better than cloth masks signifying good substitutes for N95 if not available. Whereas, cloth masks are the least efficient, but are still better than default transmission, signifying that even if the population is wearing an ineffective mask, it will still have a positive impact on virus transmission. From C, the difference between the chance of getting infected when customers are wearing N95 versus customers wearing cloth masks is almost 26% displaying how effective wearing higher efficiency masks could be.

The same scenario was rerun when the wearing of masks policy was not mandatory. Again some percent of the population were wearing masks (41%). It can be seen again in Figure 5.5 that masks were effective in reducing the transmission of the virus. However, masks are not as effective as compared in the previous case, signifying that even if customers wear highly efficient masks, it would not be enough to reduce transmission of the virus. Thus with high efficient masks, the majority of the population should wear masks. In C, it can be seen that for default transmission and cloth masks the density is spread throughout and ranges to 1k.

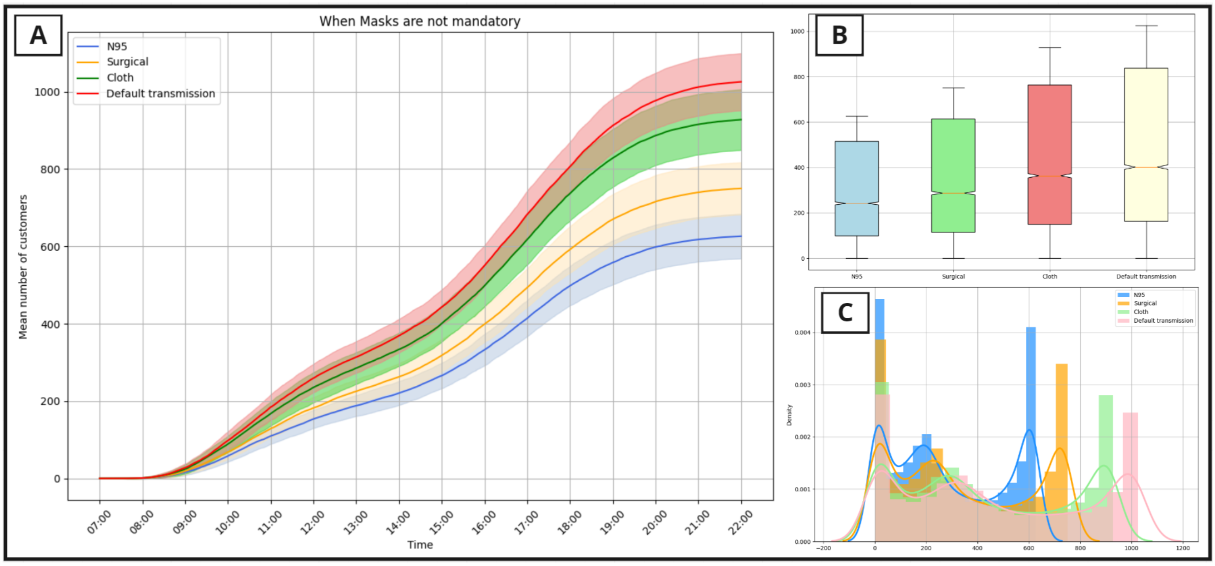

Figure 5.5: Comparing 3 commonly used masks: **(A)** Newly infected customers when masks are not mandatory. **(B)** Box plot with mean of newly infected customers for different types of masks. **(C)** Density plot when customers are wearing different masks.

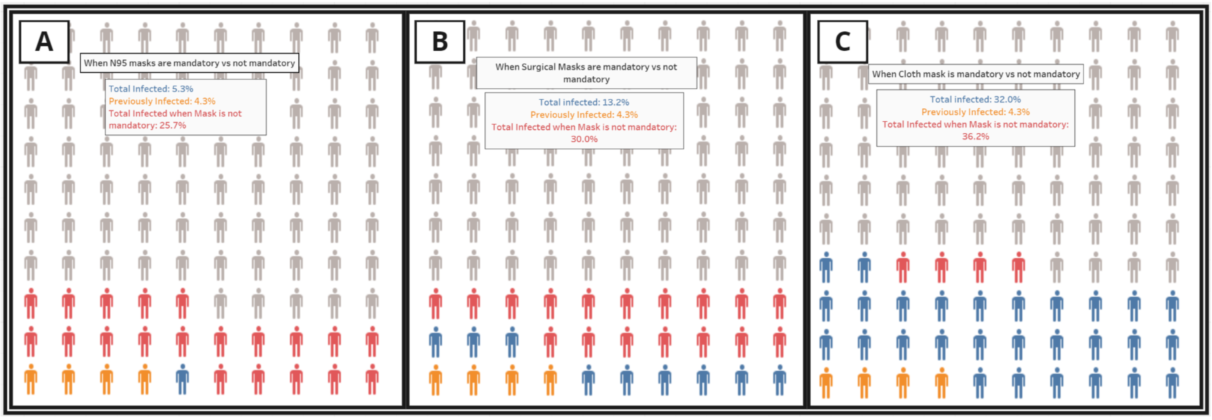

Figure 5.6: Waffle charts: **(A)** N95 masks are mandatory vs not mandatory **(B)** Surgical masks are mandatory vs not mandatory. **(C)** Cloth mask are mandatory vs not mandatory .

Figure 5.6, tells what percentage of customers got newly infected from previously infected customers. This is when all customers were wearing each type of mask for 100 simulations. Stats, after each simulation, were stored, and the mean of newly infected customers was recorded. It can be seen from A that when customers were wearing N95 customers only a few customers got infected as it was only 5.3%. Whereas when masks were not mandatory, nearly 25% more people got infected. Similarly, for surgical and cloth masks, the total percentage of customers who got infected was less when masks were mandatory, and the percentage of newly infected customers increased when the policy was not mandatory. In conclusion, N95 masks were better than both surgical and cloth. Cloth masks had poor efficiency signifying that the material with which they are made is important, or if they are tightly fitted or not, making N95 and surgical masks clear winners. But the percentage of customers wearing masks is also as important as the type of masks.

5.3 Customers maintaining social distance

After implementing masks, social distancing was implemented as mentioned in sections 3.4.2, and 4.3.2. Social distancing was implemented keeping in mind that all customers would follow social distancing rules when the government mandates it. In the simulation, customers are assigned different values of social radius as mentioned in table 6. When social distancing is mandatory, 100% of customers are designed to maintain social distancing which might not be always possible in real life. And results were recorded across 100 simulations and analysed.

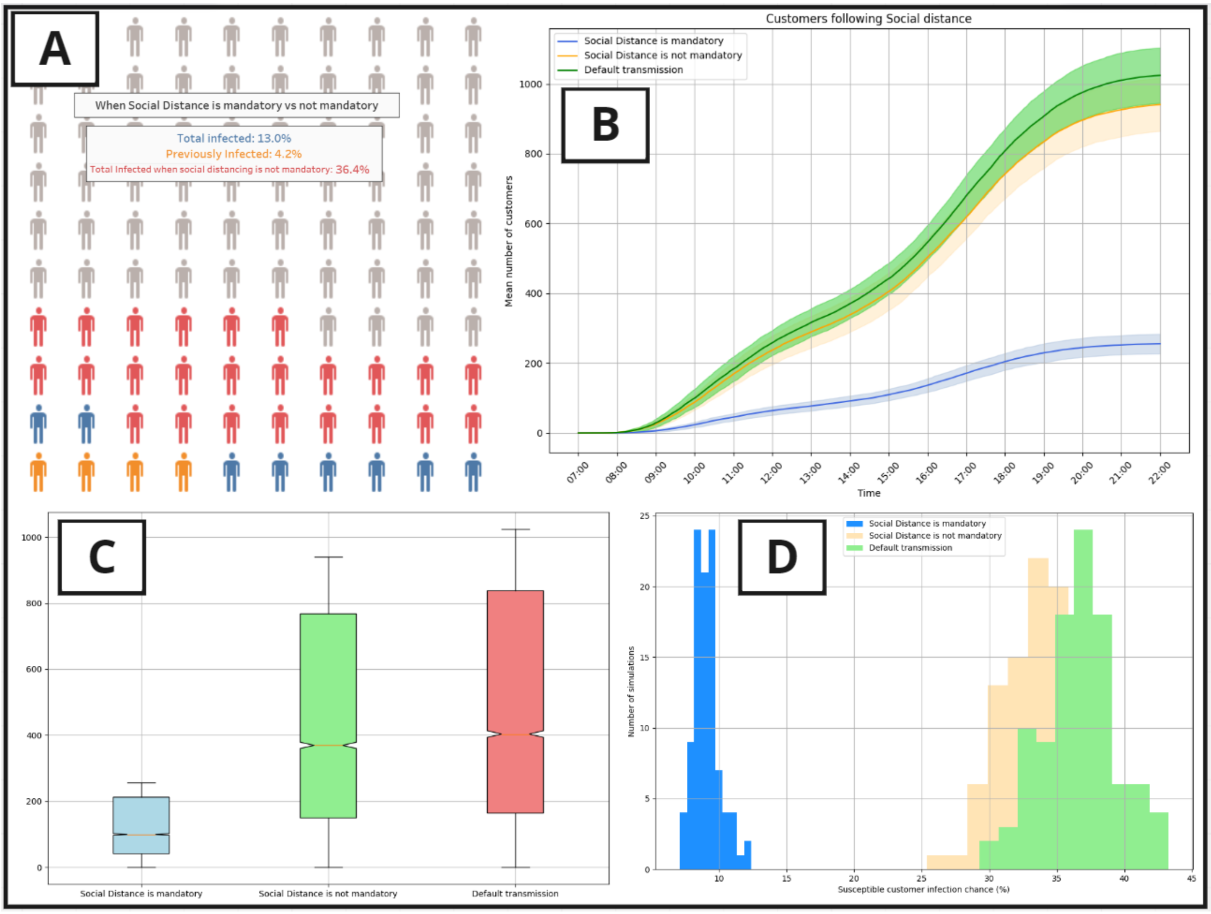

Figure 5.7: When social distancing is mandatory vs not mandatory : **(A)** Waffle chart representing % of customer getting infected **(B)** Newly infected customers **(C)** Box plot **(D)** Distribution of chance of getting infected

From figure 5.7, it can be seen that when customers follow social distancing, there is a good reduction in the transmission of the virus. But that is not the case when social distance is not mandatory, as it is almost close to the default transmission stating that even if some people are following social distance, there is still a greater chance of getting infected from the ones who are not following. From A, C the difference between the scenarios when customers are following social distancing and the scenario in which they are not following social distancing is a lot, 13% vs 36.4%. Even the chance of getting infected increases from 8% to 32% which is nearly 4 times. In conclusion, social distancing is only effective when everybody is following.

5.4 Customers using alcohol-based vs non-alcohol hand sanitizers

As mentioned in sections 3.4.5 and 4.3.3, the importance of proper sanitation and ventilation was explained.

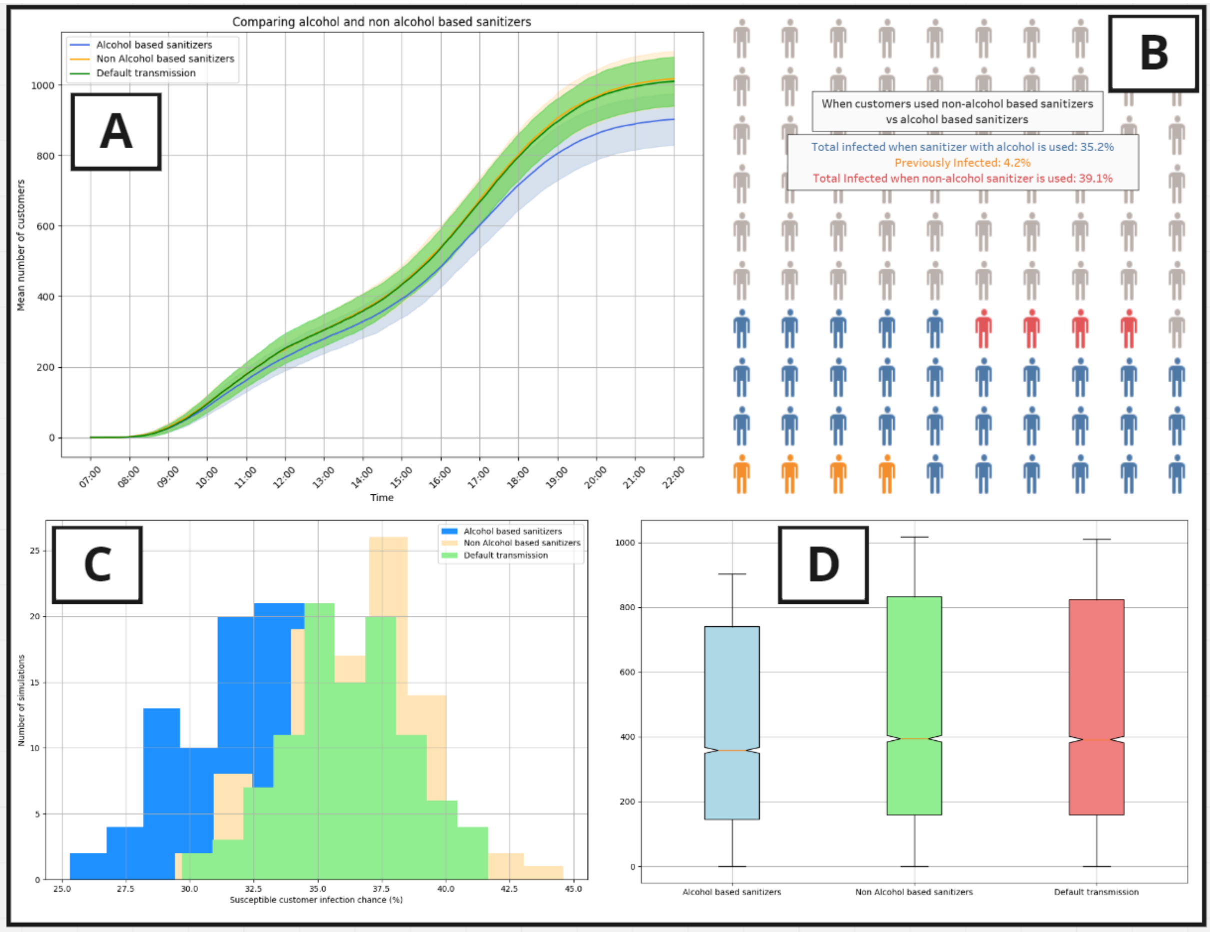

Figure 5.8: Customers using alcohol based sanitizers vs non-alcohol based sanitizers : **(A)** Newly infected customers **(B)** waffle chart indicating % of customers getting infected **(C)** Distribution of chance of getting infected **(D)** Box plot

For every simulation, all customers defaulted to having used the sanitizer which would have been provided at the entrance of the supermarket. Once the customer is inside the store, he/she would have immunity only for their hands for some time (which will be based on the type of sanitizer used), and once that time is over, they will be vulnerable to infection. From previous work, it is found that alcohol-based sanitizers were more effective than non-alcohol ones.

From Figure 5.8, it can be seen that sanitizers did not have a great effect in reducing the transmission of the covid-19 virus. It could be because of various things like, what other mitigation protocols are the customers following because if customers are not wearing a mask, then the use of sanitizers would not be that effective. Another reason could be that with the use of sanitizers, customers gain immunity only for 10 min max.Since most of the customers spend more than 24 min in the supermarket (Mean shopping time = 1440 sec) they would get infected after 10 min. From other figures, it can be seen that the use of non-alcohol-based sanitizer is minimum. In conclusion, sanitizers are important and only effective if customers use them multiple times when inside the store. And sanitizers can be synergised with other mitigation protocols to provide even better results.

5.5 Vaccination

The vaccine gives immunity against the covid-19 virus, even though it's not 100%, but it protects customers against any severe implications. Each of the vaccines has different effectiveness against delta variants. In this simulation, the virus transmission model is set based on delta variant data as mentioned in sections 3.4.4, and 4.3.4. Each vaccine's effectiveness against delta variant in the supermarket is observed and stats are recorded for analysis.

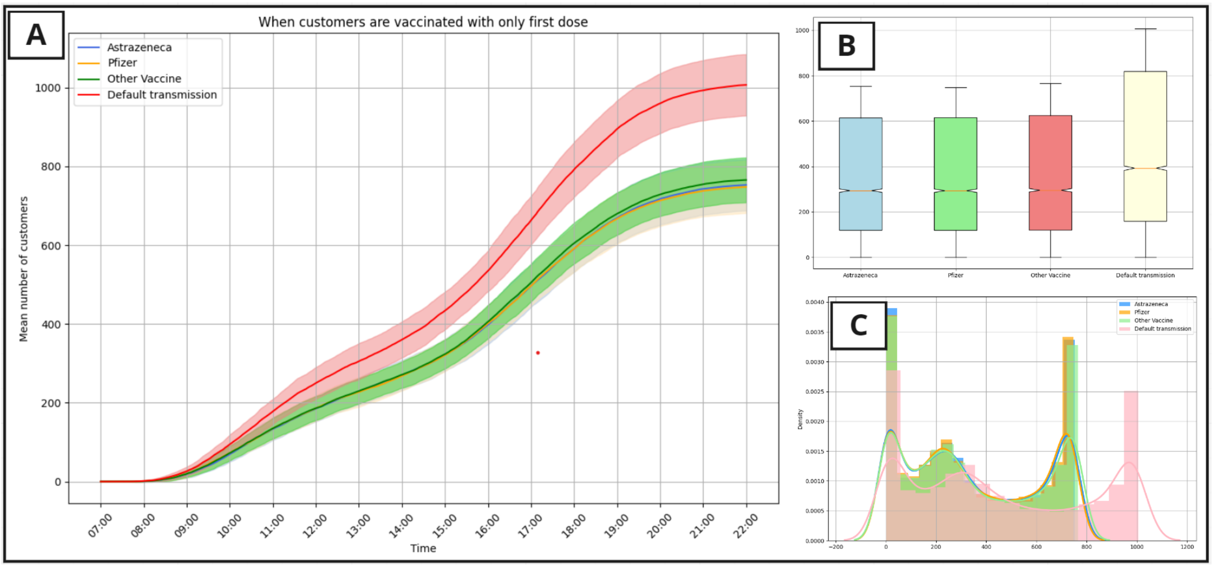

Figure 5.9: Comparing different vaccines after customers are administered with 1st dose of Astrazeneca, Pfizer, Other vaccines **(A)** Newly infected customers **(B)** Box Plot **(C)** Density plot

From Figure 5.9, it can be seen that when customers have been administered only 1st dose of any vaccine, transmission of virus is reduced, signifying the importance of the vaccine. But there are not a lot of differences between each of the vaccines, as from table 4.4, it can be seen that their efficiency against delta variants are close to each other, after 1st dose. Box plot and density plot tells that all vaccines are almost equivalent in terms of their effectiveness against covid-19.

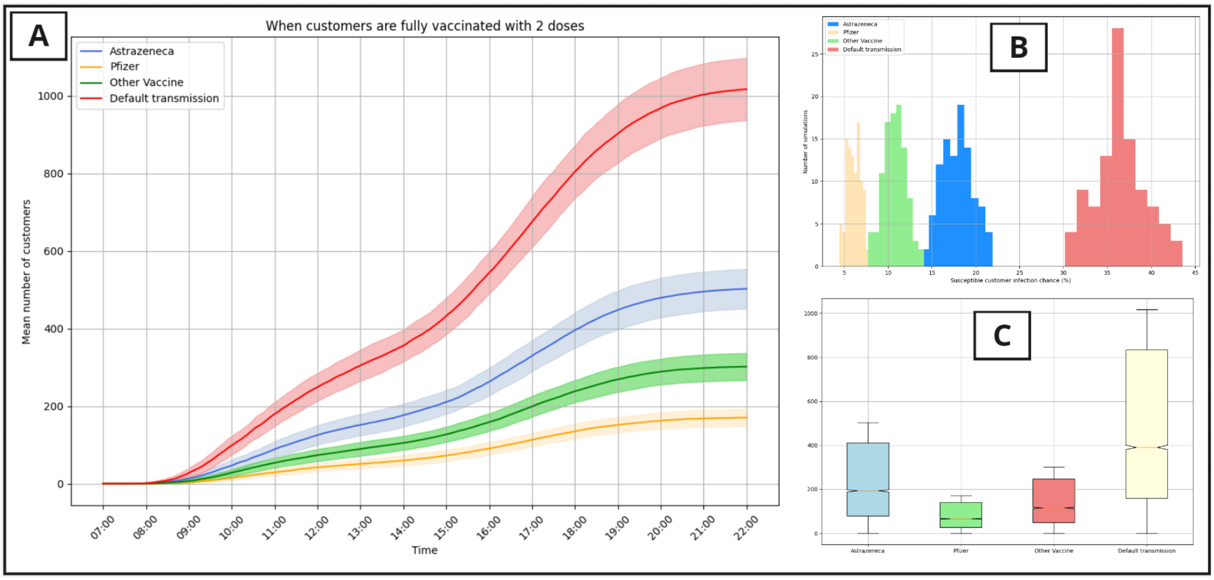

Figure 5.10: Comparing different vaccines after customers are fully vaccinated with Astrazeneca, Pfizer, Other vaccines **(A)** Newly infected customers **(B)** Chance of getting infected after vaccinated with both doses. **(C)** Box plot

From figure 5.10, there is a clear difference between all three types of vaccines. It can also be seen that their efficiency increases against covid-19 virus signifying their significance in reducing covid 19 transmission. The chance of any customer getting affected by virus transmission has also reduced a lot from 30% to less than 20%. It can be seen that the Pfizer vaccine has been the most effective.

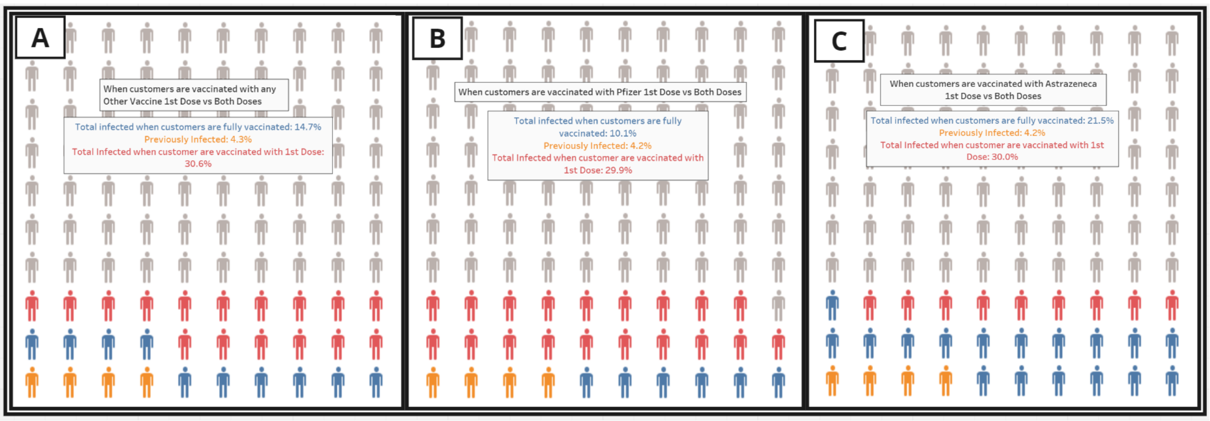

Figure 5.11: Waffle charts for both 1st and 2nd dose vaccines: **(A)** When customers are vaccinated with any other vaccine. **(B)** When customers are vaccinated with Pfizer. **(C)** When customers are vaccinated with any Astrazeneca.

Lastly from figure 5.11, when comparing what percentage of people who got newly infected from virus transmission when the customers were vaccinated with various vaccines. The stats are an average of 100 simulations where all customers are vaccinated with similar vaccines. It can be seen from A that all other vaccines apart from Pfizer and Astrazeneca are also effective, instead all other vaccines have a better efficacy than Astranzeneca. Note, other vaccines are just a means of efficiency of all vaccines. Whereas Pfizer seems the best option as only 10% customers got infected. In conclusion, it can be said that vaccines are good and have a positive impact in reducing transmission of viruses. And vaccination can clearly be synergizer or combined with all other non-pharmaceutical interventions to improve the odds against transmission of virus.

5.6 When Masks and social distancing is mandatory for customers

From the above sections, 5.2 and 5.3, it can be seen how masks were efficient in reducing the transmission of the virus, similarly, social distancing also reduced virus transmission significantly. This scenario is the combination of both masks and social distancing when both protocols are mandatory for customers inside the supermarket.

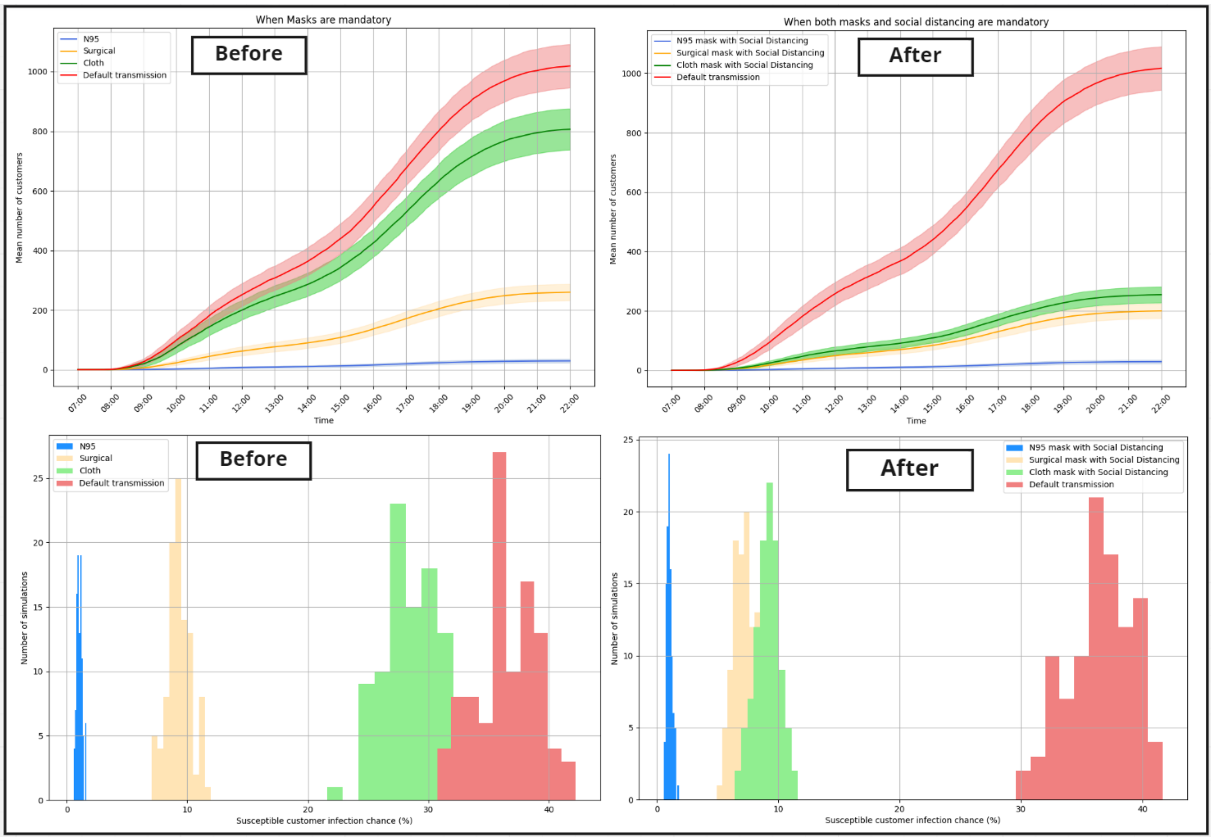

Figure 5.12: Before and after implementing social distancing with different types of masks when both the protocols were mandatory for customers.

From previous works (23), it can be seen that masks can be synergized with all other non-pharmaceutical and pharmaceutical interventions. In this section, masks and social distancing were combined. Combining both efficiencies was done based on the compound method (the best efficient protocol is taken and all other fractions are added on top of it). There can be a lot of other better ways to implement it. But it is not a part of this project. Once these mitigation protocols were implemented, stats were recorded for 100 simulations and analysed.From Figure 5.12, it can be evident that when both mitigation protocols were combined, effectiveness increased significantly. This signifies that mitigation protocols should be combined to find the best policy to reduce virus transmission effectively. Note, that this protocol was recorded when both policies were mandatory. Denoting the importance of government policies with mitigation protocols. It can be seen from the figure that N95 masks continue to efficiently curtail virus transmission. But the most important part is that with social distance, surgical masks and cloth masks have improved efficiently, signifying that even with less effective masks, higher efficiency can be achieved by combining it with other mitigation protocols. From sections 5.2, and 5.3 it can be seen that protocols are efficient when the policy is mandatory to follow these protocols. Even the chance of getting affected has reduced heavily from 30% to 10% which is a gain in long-term strategy in reducing virus transmission.

5.7 When masks are mandatory and customers are vaccinated with 1st dose.

When there is a pandemic, both pharmaceutical and non-pharmaceutical interventions are important. As one can cater for a gap in the other mitigation protocols. Like in covid-19, masks were used by customers in supermarkets and it was seen in section 5.2 that masks were effective when mandatory. But there are a lot of gaps in this protocol, as it relies a lot on how people wear it. Similarly, vaccines are important to provide immunity against covid -19 which is a safe bet, as it will protect customers. Note, that none of the vaccines grant 100% immunity against all variants of the virus. It can be seen from section 5.5 that vaccines are highly effective when both doses are administered to the customer. This scenario deals with the case when customers are administered only 1st dose, as an individual who has been administered with 1st dose cannot immediately take the second dose. He/she has to wait for some time to take the second dose. During this period, customers should not be lazy believing that they are vaccinated and would not get infected. The main aim of this scenario is to check how efficiently are vaccine's 1st done when customers are wearing various masks. 100 simulations with this scenario were run and the stats were recorded.

From figure 5.13, it can be seen that when masks were introduced, the efficiency against the transmission of the virus increased. When customers were administered the 1st dose of any vaccine, it was not that effective. But when customers are wearing masks, and it's mandatory,

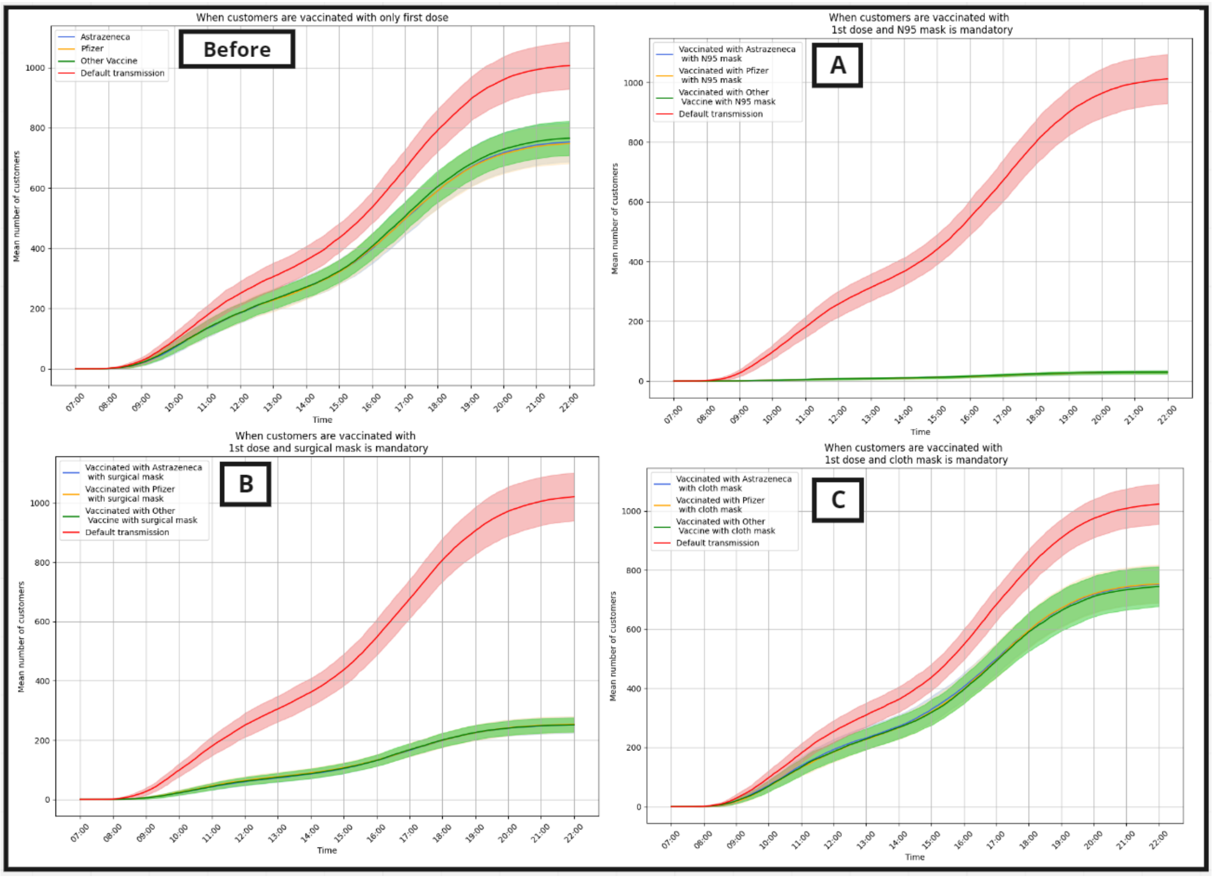

Figure 5.13: When customers are vaccinated with 1st dose and are asked to wear **(A)** N95 masks. **(B)** Surgical masks **(C)** Cloth Mask

the scenario is a lot favorable, as masks synergize well with vaccines as well. Thus in these scenarios masks can be efficiently used to curtail virus transmission in the supermarket when customers are only vaccinated with 1st dose. Similar to section 5.2, N95 masks were highly effective, whereas cloth masks did not have a lot of influence on the result.

5.8 When customers are fully vaccinated and masks are mandatory

This section is an upgraded version of the previous scenario. This is a similar scenario where masks are mandatory and customers are fully vaccinated with both doses. From section 5.5, it can be seen that Pfizer is better than other vaccines and more effective in containing the transmission of the virus. In this setup, customers are fully vaccinated with each of the vaccines and were asked to wear different types of masks. 100 simulations with this configuration were run and stats were recorded for analysis.

From figure 5.14. It was found that with N95 masks, virus transmission is least because of the high efficiency of N95 masks. But for surgical masks, it was found that with the use of masks,

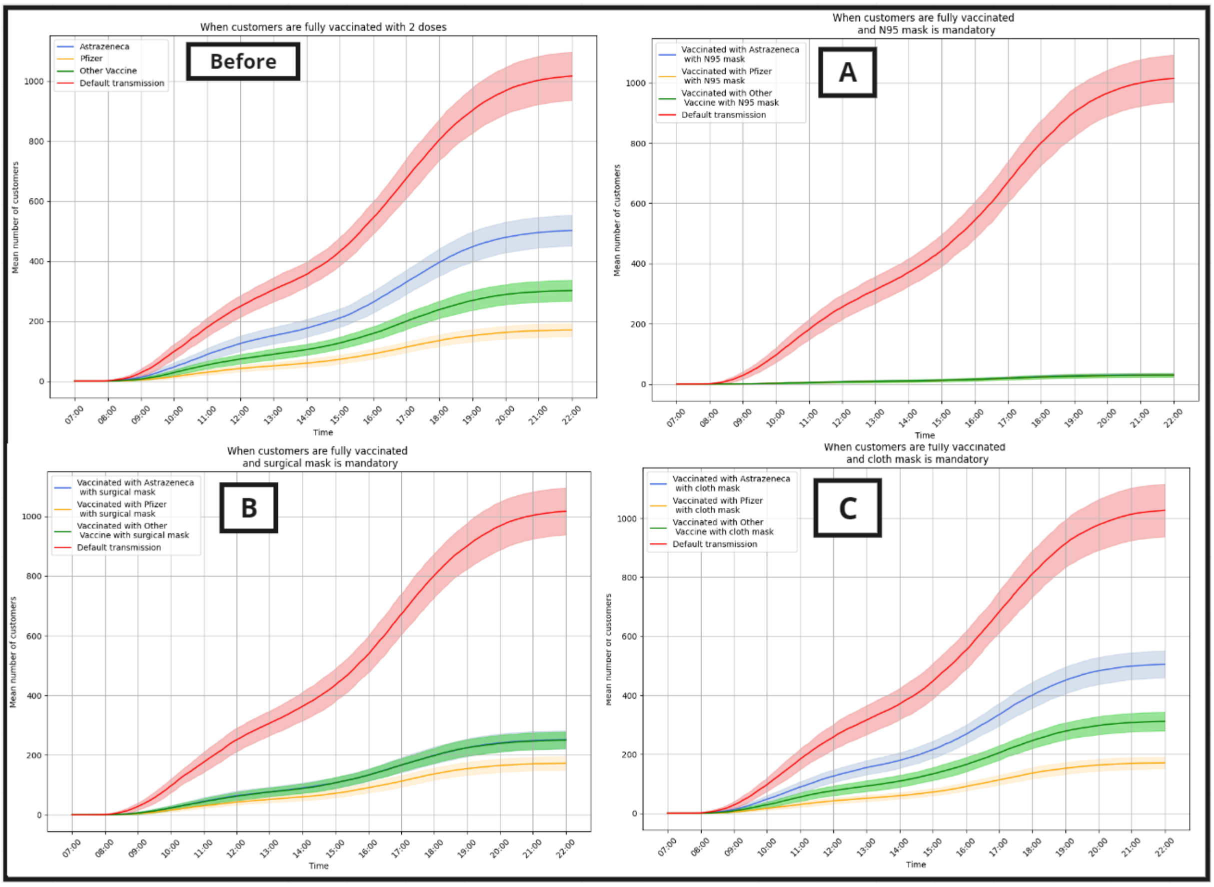

Figure 5.14: When customers are fully vaccinated and are asked to wear **(A)** N95 masks. **(B)** Surgical masks **(C)** Cloth Mask

the efficiency of customers with AstraZeneca and any other vaccine against transmission of covid increased, signifying that if a customer's vaccine is not that strong then proper use of effective masks can fill that gap. When customers are fully vaccinated, their efficiency is higher than that of only 1st dose and with a mask, it would even be higher. But that is not always the case, as it can be seen that for cloth masks, there aren't any improvements in efficiency in the overall scenario, stating that optimal choice of the mask is important.

5.9 When customers are vaccinated with 1st dose and social distancing is mandatory

This scenario is based on combining social distancing with vaccine effectiveness against transmission of the virus. In this scenario, customers are vaccinated with 1st dose of the vaccine and are asked to maintain social distance from each other. This is due to the fact mentioned earlier that a customer cannot be administered the second shot of vaccine immediately after the other, thus social distancing would help in reducing transmission of the virus. After 100 simulations, stats were recorded.

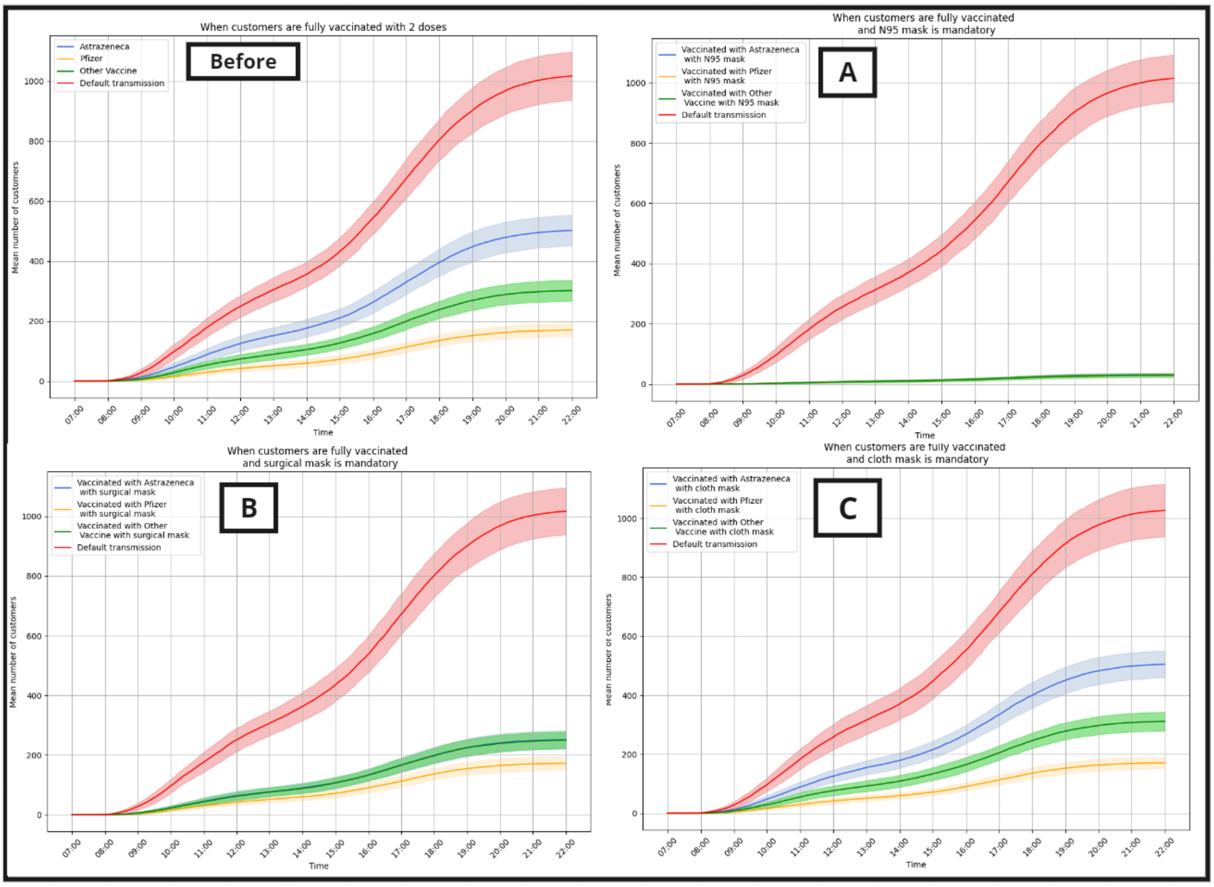

Figure 5.15: When customers are vaccinated with 1st dose and maintain social distancing **(A)** Newly infected customers. **(B)** Box plot **(C)** Chance of getting infected from virus

From figure 5.15, there is a clear difference in vaccine efficiencies, when combined with social distancing, scenario effectiveness increases for all customers with any of the vaccines. Indicating that when customers are maintaining social distance, there is not a bigger impact of vaccines. From the box plot and histogram, it is evident that with social distancing, vaccines 1 dose is not that effective, and social distancing has a sole impact on the scenario signifying that social distancing customers would maintain appropriate distance, and not affect others.

5.10 When customers are fully vaccinated and social distancing is mandatory

Similar to section 5.7, it is an upgraded scenario of the previous scenario. In this scenario, customers are fully vaccinated and are asked to maintain social distancing. Against the delta variant, Pfizer has proved to be more effective. Stats were recorded for 100 simulations for a particular day.

From Figure 5.16 it can be seen that with social distancing, the effectiveness of each vaccine improved further. In this case, fully vaccinated customers maintain resilience against virus

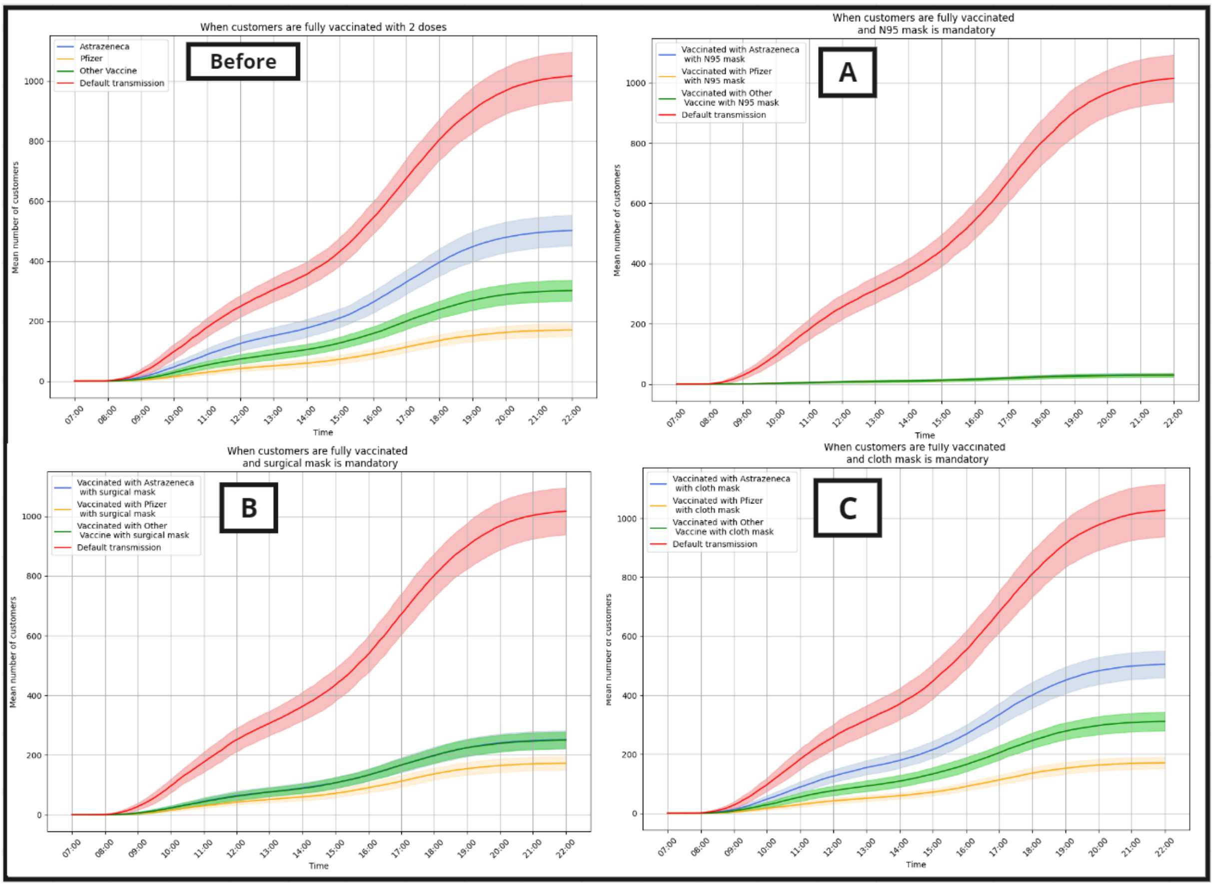

Figure 5.16: When customers are fully vaccinated and maintain social distancing **(A)** Newly infected customers. **(B)** Box plot **(C)** Chance of getting infected from virus

transmission. Thus, it can be said vaccination with both doses has the best overall effectiveness against the covid-19 virus. And when customers are only vaccinated with 1st dose, they should continue to take extra caution.

5.11 Comparing best and worst of each protocols

This scenario is about comparing the best and worst of each of the protocols. From the above sections, a lot of pharmaceutical or non-pharmaceutical mitigation protocols were implemented and combined to effectively reduce the transmission of the virus. But all these protocols are not highly efficient in all cases. Based on sections 5.2, 5.3, 5.5, and 5.4, the best of each protocol like N95 masks were highly efficient when masks were mandatory. Similarly, in vaccines, Pfizer was highly effective when the customer is fully vaccinated with it. Once this was done, the worst cases of each protocol were also compared to analyse the effectiveness of each set of a protocol. 100 Simulations for all these scenarios were done and results were recorded.

As it can be seen from Figure 5.17, the best of all protocols were N95 masks(mandatory), Social distancing (mandatory), fully vaccinated with Pfizer vaccine, sanitizer with alcohol. It is evident that N95 was highly effective when compared with others, social distance and

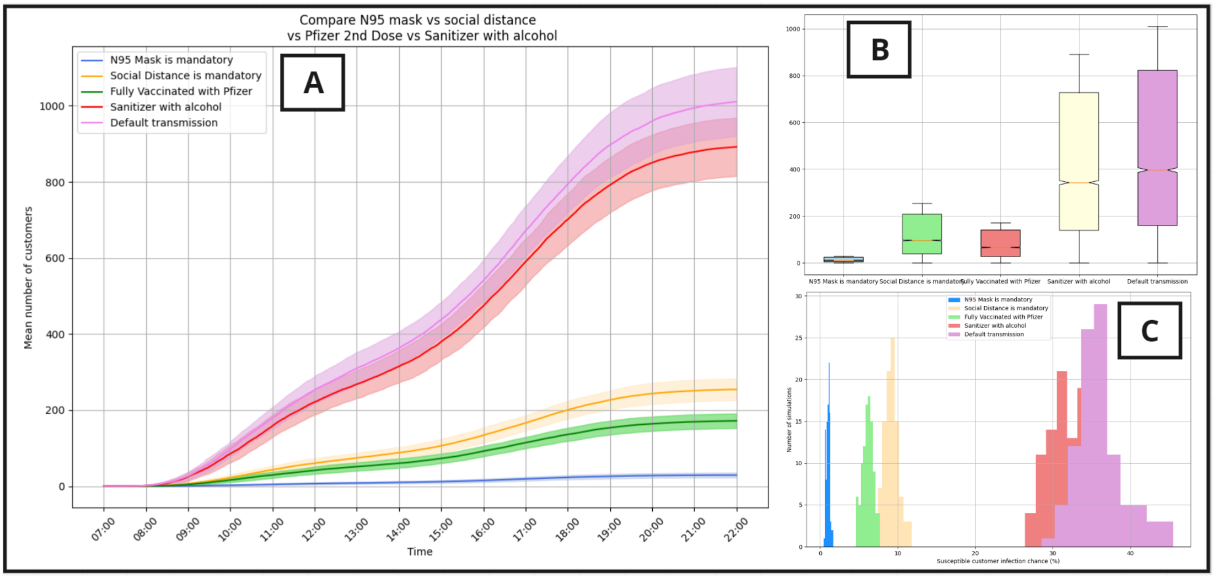

Figure 5.17: Comparing best cases in each of the protocols (Masks vs Social Distancing vs vaccine vs sanitizer) **(A)** Newly infected customers. **(B)** Box plot **(C)** Chance of getting infected from virus

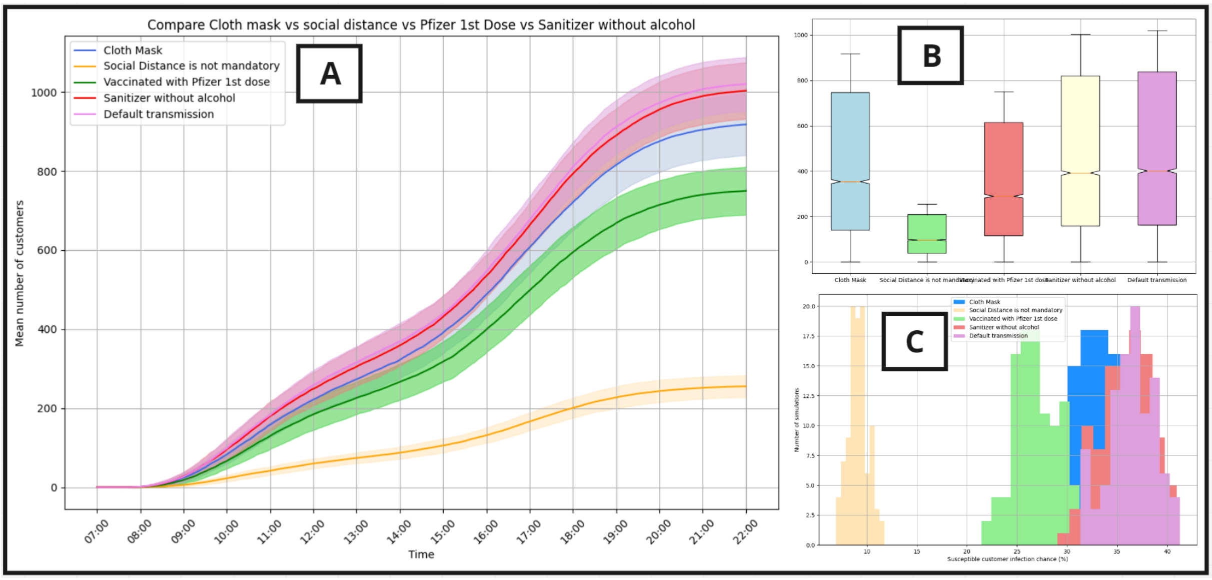

Figure 5.18: Comparing worst cases in each of the protocols (Masks vs Social Distancing vs vaccine vs sanitizer) **(A)** Newly infected customers. **(B)** Box plot **(C)** Chance of getting infected from virus

vaccine are close to each other and highly effective. Whereas sanitizers were not that effective because customers stay for a longer time making them vulnerable. From the box plot and histogram, it can be seen that the chances of getting infected are less when wearing an N95 mask, maintaining social distancing, or being fully vaccinated with Pfizer.

When the worst cases of each protocol were compared, the results were close to each other indicating that if customers are following the worst possible case in any of the protocols, they would still have some effectiveness in reducing transmission of the virus. It can be seen from

Figure 5.18, that apart from social distancing all other protocols were not that effective, but were still better without any mitigation protocols. It can also be seen that the chances of getting infected are high and close to default settings which indicates the importance of proper mitigation protocols and timely vaccinations.

5.12 Combining best and worst scenarios of each protocol

In the real world, mitigation protocols are not implemented at random or only 1 of them is implemented. Various protocols are implemented on top of each other to provide layers of barriers to virus transmission. In this scenario, all the best possible as mentioned above in section 5.11 are combined and compared with default transmission, similarly, all worst cases were combined to see how effective these worst case scenarios are as compared to default transmission protocols. Results were recorded after combining all scenarios.

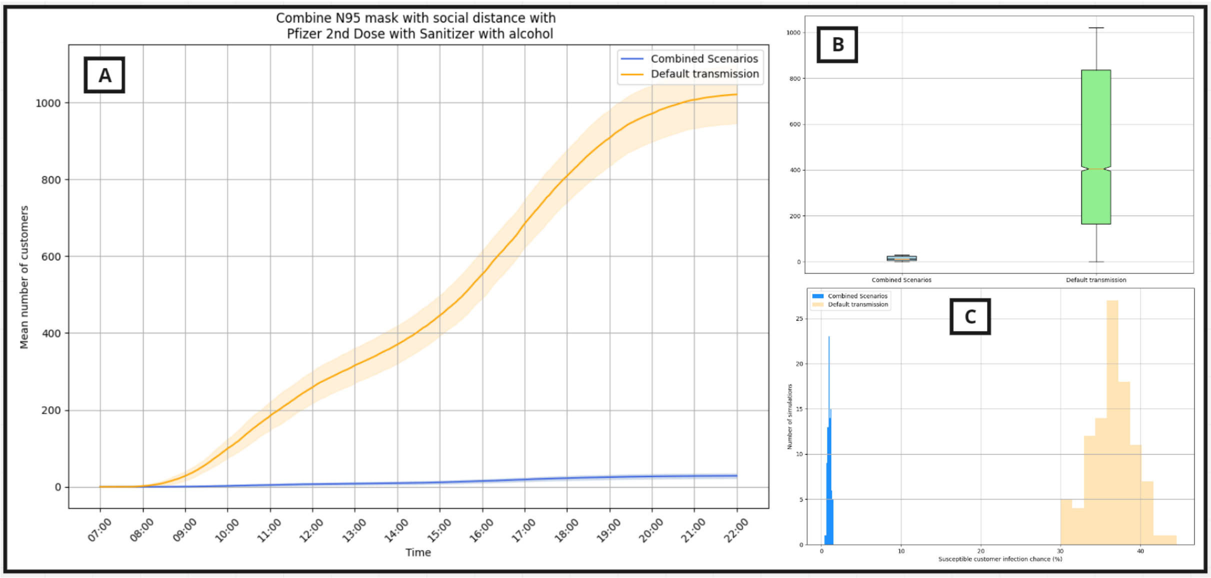

Figure 5.19: Combining best cases of each protocols (Masks vs Social Distancing vs vaccine vs sanitizer) **(A)** Newly infected customers. **(B)** Box plot **(C)** Chance of getting infected from virus

It can be seen from Figure 5.19 that when all protocols were combined, that is when all customers were N95 masks, maintained social distancing, and are fully vaccinated with Pfizer, and lastly have used alcohol-based - sanitizer, the transmission of the virus is a bare minimum, signifying that when these protocols are combined, they have high synergy and work together to better the chances of not getting infected from the covid-19 virus.

On the other hand Figure 5.20, is combining the worst cases of each of the protocols, like customers wearing cloth masks and not everyone maintaining social distance. Customers have

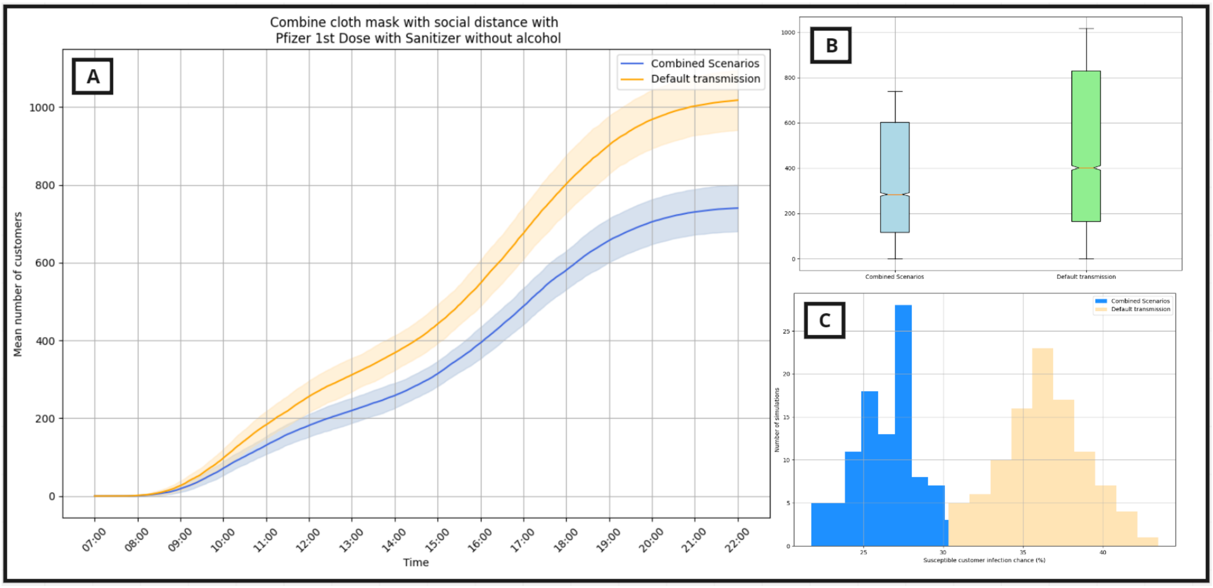

Figure 5.20: Combining worst cases of each protocols (Masks vs Social Distancing vs vaccine vs sanitizer) **(A)** Newly infected customers. **(B)** Box plot **(C)** Chance of getting infected from virus

vaccinated with only 1st dose of Pfizer and even the sanitizers are not alcohol-based, making it be of the worst-case scenario. But it was still found that, even with those protocols, it is better than the default transmission where there are no mitigation protocols.

Metric	**Mean**	**Standard Deviation**
Number of Daily Customers	2913.75	41.08
Number of infected customers	121.95	11.1
Number of susceptible customers	2791.8	40.97
Mean shopping time (sec)	840.69	10.28
Total exposure time (sec)	9977.8	816.65
Mean exposure time (sec) per susceptible customer	1.79	0.14
Total exposure time (sec) per infected customer	41.16	1.95
Proportion of susceptible customer with any exposure	0.3581	0.0289
Number of new infections	998.21	81.58
Proportion of infections per susceptible customer	0.05746	0.0125

Table 5.1: Simulation Results : The mean and standard deviation for default transmission of each metric across 100 simulations.

Below are the table listing down parameter values taken for all simulations.

Table 5.2: Parameter values

Parameter	Default value/Assumptions	Reference
Store Opening Time	7 AM	
Total hours open	15 Hours	
Number of shelves in each aisle	3	
Number of aisles	9	
Number of items per section	5	
Basic Reproduction Number for delta variant, R_0	3-3.5	(15)
Infectiousness duration, d	2-5 days	(15)
Average contact between susceptible customer and infected customer, $\bar{c}$	3	(18)
Tick duration	5 seconds	
Customer arrival probability modelled using bimodal gamma distribution	arrival_probability = (gamma.pdf(x, a=3.5, scale=4.5) * 3) + (gamma.pdf(x, a=18, scale=2) * 4)	(1)
Initial infection rate	1.2362	(22)
N95 masks	0.95	(23)
Surgical masks	0.72	(23)
Cloth/homemade masks	0.25	(23)
Mandatory/Not Mandatory %	95% , 41%	(12)
Astrazeneca 1st dose/2nd dose	30% , 67%	(29)
Pfizer 1st dose/2nd dose	35% , 88%	(29)
Other vaccines 1st dose/2nd dose	30% , 79%	(30)
Sanitizers Alcohol/Non-alcohol	99% , 60%	(10)
Repulsion force between customers, A	2.1 m/s^2	(26)
Relaxation distance between customers, B	0.3 m	(26)
Social Radius, R	0.2-0.5m (default) / >0.8m (mandatory),	(26)

6 Conclusion

For all the damage which covid -19 virus did around the world. Its impact has been huge. This work was done with the aim to model transmission of covid-19 virus inside a supermarket to find out various strategies which can be implemented to reduce covid-19 virus or any other virus in the future such that the loss is less.

6.1 Summary

For the modelling of covid-19 virus in a supermarket, 2 different models were created. The first agent-based customer mobility model, in which agents' or customers' behaviour will be based on the customer's personal choice. Based on each customer's previous historical data, their path or shopping behaviour will be predicted by the machine learning model. This recommender system is based on RNN and gradient boosting algorithms. Once the items which a customer would buy are final, the customer mobility model will map out a particular path in such a way that it will cover all the nodes and then traverse to the till counter for payment before exiting the supermarket. For the simulation, a supermarket layout was created on which these customers will follow their predicted path and buy items. Meanwhile, there will be another virus transmission model, which will keep on calculating the transmission factor between any two customers who are in the same aisle for more than 1 tick. If the customers were close to each other, then based on the duration of infectiousness of the infected customer, the average number of contacts between them, and the duration for which they were close to each other, the other susceptible customer will be infected. But if customers are following some or any of the pharmaceutical or non-pharmaceutical interventions, the transmission of virus between them will be reduced.

For the start of the simulation, the initial setup of the supermarket layout and picking some customers are loaded first. Then their paths will be predicted by the recommender model. Since the simulation is for a day, it will start at 7 in the morning, with an increase in every tick which is 5 seconds, and customers will be allowed to go inside the supermarket. Customer arrival inside the supermarket is regulated by gamma distribution which makes sure that everybody is not allowed inside the supermarket simultaneously. Initially, some of the customers were marked as infected. Virus transmission will incur only from these customers as newly infected customers will be in their incubation period. Once the customers are inside the supermarket, virus transmission models will be formulated based on the interaction between the infected customer and all susceptible customers. If customers were following mitigation strategies then the transmission was reduced. It was found when masks were mandatory, the transmission of the virus was effectively reduced even with ineffective masks. Also, it was found that N95 masks were better than other masks. Similarly, another mitigation protocol was implemented which was social distancing, and it was found that when social distancing was mandatory, virus transmission was reduced. However, it was not the case with sanitizers. Non-alcohol-based sanitizers were ineffective as compared to alcohol-based ones. Even alcohol-based sanitizers did not make a bigger impact because sanitizers provided protection only for some time, and if the customer stayed inside the supermarket for more than that time, they would be vulnerable to the virus. Lastly, vaccines were implemented and each customer was administered with 1st dose of 3 most commonly used vaccines it was found that with 1st dose, their efficiency was not that high and it was required that customers should follow other mitigation protocols like masks and social distancing to reduce the transmission of the virus. When customers were fully vaccinated, there was a significant improvement in the effectiveness of vaccines against the transmission of the virus. It was also found that various mitigation protocols can be combined to fill the gaps in other protocols and effectively reduce transmission of the virus. It was found that when customers are vaccinated with 1st dose, masks, and social distancing improved their effectiveness significantly, signifying that these mitigation protocols filled the gap when customers are vaccinated with only 1 dose. Government policies like when to make these protocols mandatory are also very important and it was found that when protocols were mandatory, they were highly effective. From these strategies, it was found that these protocols synergize well with each other and can be combined to effectively reduce virus transmission. Even the worst cases of these protocols were more effective than the default transmission indicating that even small efforts can make a difference. This simulation can also be used to find hotspots or places where chances of infection are high and proper layout and protocol can be also implemented to reduce transmissions.

Since the customer shopping behaviour prediction is based on a customer dataset, it can be used in various supermarkets with ease. Similarly, the transmission of the virus can be controlled by various policies and protocols. Government can cater and look into these results to find out the best ways to reduce virus transmission based on the current situation of the customer. These simulations can be used to model any supermarket big or small, based on the requirement making it generic for all. These simulations can be used to reduce virus transmission and consequently reduce the economic and societal impact of such pandemics.

6.2 Limitations

Following are the limitations of the paper, as they could be improved with more effort and research.

The first one is the implementation of social distancing, since the layout of the supermarket was not based on specific items but the aisle, 2 customers were positioned on the same node even though they were standing on the edges of the aisle. This would trigger a virus transmission model and the customer can be marked as infected.

Second, when combining two or more mitigation protocols, a proper mathematical approach should be followed instead of using the best method of them and then adding the rest of them in fractions.

The proper synergy between the use of sanitizers with all other protocols was based on the fact that customers would have protection just from using sanitizers. It should be tightly coupled with the use of masks. For example, if customers are wearing masks then the use of sanitizers can be considered whereas if customers are not wearing masks, then sanitizers would provide no protection making customers vulnerable.

6.3 Future work

Once the above-mentioned limitations are fixed, there is plenty more work that can make models, even more, closer to their real-life counterparts. Modelling can be extended further by improving the customer mobility model, virus transmission model, and the customer shopping behaviour predicting model.

Store layout can be a vital point in transmission, it can be seen from the scenario that near till counter, a lot of customers get infected, this problem can be solved by introducing multiple tills and maintaining social distancing at that place, or online payment system or self check out zones in various parts of the supermarket. Multiple entries and exits can be made to ensure no congestion. Customer entry into the supermarket should not only be based on gamma distribution but also their path, like if their predicted path is to an aisle where not a lot of customers are using then this particular customer can be allowed to go in. Customers' personal health history could also hold importance in virus transmission, as it was found that elders were more susceptible to covid-19.

Majorly, customer behaviour, transmission, and effectiveness of mitigation protocols depend a lot on the group of customers in the supermarket. Groups can be divided in various ways, like groups of children would have a different pattern as compared to adults, similarly, the way they would follow mitigation protocols would be completely different from adults. Groups can be done based on many things like the age of the customers, gender of the customers, ethnicity of the customer, even location of the supermarket, time of the day, day of the week, start or end of the month. All these factors can affect the simulation significantly and can be worked upon in the future.

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