UNIVERSITY OF CAPE TOWN

Investigating the Effectiveness of Supermarket Transmission Control Measures on the Spread of COVID-19 in the Presence of Super-Spreaders through Agent-Based Modelling

Minor Dissertation presented in partial fulfilment of the requirements
for the degree of Master of Science specialising in Biostatistics
in the Department of Statistical Science.

Author:
Timothy Mountford

Student Number:
MNTTIM002

Supervisor: Associate Professor Sheetal Silal

October 16, 2022

Investigating the Effectiveness of Supermarket Transmission Control Measures on the Spread of COVID-19 in the Presence of Super-Spreaders through Agent-Based Modelling

University of Cape Town:

Department of Statistical Sciences

Timothy Mountford

Abstract

An examination of the effectiveness of transmission control measures for COVID-19 in a supermarket setting, factoring for the inclusion of Super-Spreaders, must extend beyond the direct effects the control measure has on transmission in order to account for the indirect effects changes in human movement dynamics have on the spread of disease. The analysis makes use of Agent-Based Modelling simulation techniques to model changes in customer movement and disease transmission dynamics resulting from the isolated and combined implementation of COVID-19 transmission control measures. The bottom-up approach of agent-based modelling allows for the inclusion of heterogeneous, individual-level chances of infectiousness, compliance, and consumer behaviours, allowing for a more realistic representation of real-world behaviours. The model used for analysis is built entirely in the NetLogo environment, designed to be interactive, adaptable to user-varied inputs, and visually engaging. This allows for the model to adapt to changes in disease parameters and easily communicate model effects in a manner accessible to users in and out of the field.

Control measures considered include: Vaccinations, Capacity Limiting, Social Distancing, Staff COVID-19 Testing, and the use of Sanitizers. Results indicate high levels of effectiveness for the use of Vaccinations at reducing transmission with minimal impact on customer dynamics. The results also highlight the negative effects changes in customer dynamics can have on transmission, indicated by increased shop-queue transmissions resulting from the use of Capacity Limiting or other measures slowing customer entrance to the shop. The positive effects of interactions between control measures are highlighted by the additional implementation of Social Distancing in reducing these increases.

The implications of these findings involve the need to factor for changes in human movement dynamics when assessing the effectiveness of transmission control measures implemented in any environment. The findings further reinforce the benefits of implementing social distancing practises in conjunction with mechanisms that reduce the flow of movement, as well as the benefits of increased vaccination coverage in the population. Lastly, the findings provide an effective comparison of the control measures considered, allowing for the direct assessment of their implementation and the resulting effects on transmission and customer dynamics.

Keywords: COVID-19, Transmission Control, Agent-Based Model, Super-Spreader, Simulation, Supermarket

Acknowledgments

I would like to take this opportunity to express my thanks to two people in particular who were instrumental in my ability to put this research paper together.

First, I would like to thank Nicola Hattingh for her continuous care and support through some of the most intensive demands in focus required for completing this dissertation. She successfully provided consistent motivation and encouragement, while facilitating a space for me to focus entirely on my work without the need to worry about the demands of day to day life. She also provided considerable help and insight in the construction of the intricate design details featured in the simulation environment, without which the final visual presentation would fail to compare to the with what is present in this paper. I doubt that it would have been possible to complete this work without her, and words can't describe the appreciation she deserves.

Secondly, I would like to express my immense gratitude to my supervisor, Prof. Sheetal Silal. Despite her demanding role as the director of the Modelling and Simulation Hub, Africa (MASHA) and it's position as the driving cohort for the National COVID-19 Modelling team, she never failed to prioritise making the time to guide me in my research. The help she provided made it possible to build the comprehensive model in this paper, despite it's fair share of challenges along the way. I found it common for other research supervisors to openly express a lack of time to tend to the needs of their research students, but that was never my experience with Sheetal. Her ability to make time for me never failed to surprise me, especially in the final days leading to the deadline for submission. On top of her responsibilities in the COVID-19 modelling team, her role as a lecturer and supervisor to several students, and her facilitation of a course in-person on another continent, she made the time to provide helpful and insightful advice right up until the submission deadline. I have no doubt that she is the best supervisor I could have hoped for, and I am beyond grateful to be able to call her my mentor and role model as an academic and leader. Thank you Sheetal!

How To Access The Simulation

In order to access the simulation model, supplementary materials, and NetLogo software, use the following links provided:

1. Download the latest version of the NetLogo software from:
   `https://ccl.northwestern.edu/netlogo/download.shtml`
2. Download the simulation file and additional supplementary materials from:
   `https://github.com/TimothyM-Git/COVID-19SupermarketInterventions`

Please take note to read the information contained in the README file provided in the linked repository.

For information and instructions on how to use the simulation model, click on the info tab on the top left of the viewing window. The extent to which the whole interface of the simulation model is visible may depend on the screen size of the device used. In order to zoom in or out of the model to see the full interface, press 'Ctrl' and '-' to zoom out, 'Ctrl' and '+' to zoom in, and 'Ctrl' and '0' to reset to the original viewing size. Please note changes in text labels in the interface may occur due to "bugs" in the NetLogo software described in the README file provided.

Foreword

A note to the reader that this paper is encoded with hyper-links connecting all references to Sections, Figures, Citations, Tables, and Web-Addresses. Feel free to click on the number referenced, for the implement of interest, to be taken directly to the corresponding position in the paper.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Overview

The Outbreak of the novel coronavirus disease (COVID-19; previously 2019-nCoV) had its origins in Wuhan, China in December 2019 and has subsequently spread to countries all over the world; being declared a Global Pandemic by the World Health Organisation (WHO) on the 11th of March 2020 with over 118 000 collective cases in over 110 countries. Although the majority of COVID-19 cases are mild or asymptomatic, there is still a case fatality rate of around 2% meaning the virus can also be deadly for those who progress to a severe infection with severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2).[91][51]

The term "Super-Spreader" is one that has frequently been used in relation to Covid-19 through mainstream and social media. By its widest definition, it refers to a propensity to infect a larger than average number of people, this may be in relation to individuals, places, policies or social events. It is a combination of these super-spreaders and super-spreader events that are postulated to greatly contribute to the rapid spread of the virus; with an estimated 10% of infected individuals being responsible for roughly 80% of transmission[9]. However, data indicating this is vastly more qualitative than quantitative, indicating a need for further quantitative research in the field.

With Super-Spreaders indicated as a driving force in perpetuating the pandemic through substantial transmission, the need to study and understand the transmission dynamics in these environments is essential to controlling the spread of COVID-19. Investigating the effectiveness of control measures aimed at reducing COVID-19 transmission, in environments with super-spreader characteristics, provides valuable insight to guide action and policy in the best way to reduce the spread of COVID-19.

Supermarkets and Grocery Stores are places that provide essential services to the public and as such, they are environments that have needed to remain operational throughout the COVID-19 pandemic. With the high volume of people passing through supermarkets on a daily basis, supermarkets are an environment that allow for a variety of super-spreader elements to occur. As an enclosed space in which many people interact, they embody the role of a super-spreader place. The staff that interact with large volumes of customers become super-spreader people, as do the customers that have an above-average number of contacts or that fail to adhere to transmission control protocols. The combination of these factors makes a supermarket an ideal environment to evaluate the effectiveness of COVID-19 transmission control measures in the presence of Super-Spreaders.

Although available research indicates estimates of some control measure effectiveness at reducing COVID-19 transmission, many environmental factors have an impact on the extent to which different control measures may influence transmission reduction. The result is that many of the control measure impacts are described qualitatively, with a need for more quantitative research to support these research evaluations. Another important consideration in measuring control measure effectiveness is the indirect effect that their implementation has on transmission, as a result of changes in human behaviour due to adherence to control measure protocols. Often, these changes in behaviour have a direct effect of person-to-person interactions and, thereby on transmission.

The direct evaluation of the effectiveness of different transmission control measures is theoretically possible, however, it faces issues of practicality and ethics in real-world implementation. Although large-scale group-randomized trials, in which whole social groups or communities are allocated to different control measure groups, would be able to effectively assess and compare different control measures; studies of this nature would require large study durations and sample sizes to ensure sufficient power to estimate the effects of each control measure. Additionally, if any control measures are known to be more effective at reducing transmission in a population, it would be considered to be an ethical violation to enforce a less effective control measure on a community where more effective control measures are available, especially in cases regarding the life or long-term health of people involved.[29]

An alternative approach to estimating the effectiveness of different transmission control measures that is able to overcome these limitations is through the use of simulation-based modelling. Given the individual person-level differences inherent to super-spreader behaviour, the "bottom-up" modelling approach of Agent-Based Modelling is an ideal choice for capturing these interactions without the limitations of real-world trials.

This paper describes the development and use of an Agent-Based Model to investigate the effectiveness of several different transmission control measures under the influence of Super-Spreaders in a supermarket environment, in a South African context. The model developed simulates the movement of customers through a supermarket environment facilitating the direct and environmental transmission of COVID-19 between customers, and supermarket staff. Different transmission control measures are then compared and their effectiveness is evaluated based on changes in transmission dynamics and customer movement dynamics in the environment, with more effective measures resulting in larger reductions in transmissions with minimal impact on customer movement dynamics in the supermarket.

1.2 Rationale and Significance

Over he course of the past few years, a variety of measures have been developed and implemented worldwide with the aim of controlling the transmission of COVID-19. The intention of these transmission control measures is to maximize a reduction in the number of onward transmissions of COVID-19 in order to control outbreaks of the disease worldwide and minimize changes in day to day freedoms and behaviours. At present, research regarding the effectiveness of these control measures in most everyday settings is limited and largely qualitative in nature. This presents a need for more quantitative measurements of the relative effectiveness of the transmission control measures in use.

The majority of research available that focuses on the individual levels of effectiveness each control measure has at reducing transmissions, fails to factor for the impact that the implementation of each respective measure is likely to have in changing human movement dynamics. Thus, failing to account for the indirect impact that these changes have on transmissions resulting from changes in contact dynamics.

With the benefits that quality visual aids in research have been shown to provide with respect to comprehending and understanding risk[23][24]; the presentation of research in this area that is able to provide informative and engaging visual aid is likely to be invaluable not only in its ability to be understandable to larger, less data-literate audiences, but also provide an environment through which more individuals will be willing to interact with the research presented.

With the role that urban supermarkets play as essential services and super-spreader environments throughout the pandemic, these environments have become areas in which the understanding of transmission dynamics and potential control measure effectiveness is invaluable. The ability to make well-informed decisions regarding the effective implementation of measures to reduce COVID-19 transmission in these unavoidable super-spreader environments has the potential to make a considerable impact in the fight against COVID-19.

1.3 Research Question

What is the most effective use of available control measures to reduce COVID-19 transmission in a supermarket environment in South Africa, without impacting the customer shopping experience to a noticeable extent?

1.4 Research Objectives

With the above context, this project aims to achieve the following objectives:

1. Develop an agent-based simulation model that can effectively replicate the movement and transitions of customers in a supermarket.
2. Incorporate COVID-19 transmission dynamics into the agent-based model, to reproduce the underlying mechanisms of transmission in the supermarket environment.
3. Build an aesthetically attractive and effective tool to communicate the project's research outcomes simply, and in a way that is easily communicated to both academic peers and layman individuals outside of the field. Providing an effective medium to evaluate the impact of implementing transmission control measures in a supermarket environment with the flexibility to remain relevant amid changing input parameters.
4. Incorporate the effect of super-spreader behaviours on the spread of Covid-19 as a disease in the Agent-Based model produced.
5. Incorporate features of heterogeneous chances of transmission and infectiousness between individuals into the Agent-Based Model.
6. Develop features to demonstrate the effects of different transmission control measures on both COVID-19 transmission and customer movement in the environment in the Agent-Based Model.

1.5 Scope and Limitations

The scope of the analysis presented herein is limited to estimation of the relative effectiveness of the described COVID-19 transmission control measures in an urban supermarket environment. The transmission control considered include: Vaccinations, Capacity Limiting, Social Distancing, Staff COVID-19 Testing, and the use of Sanitizers.

Further limitations stem from the short duration of time from the discovery of COVID-19 to the presentation of the analysis conducted. The availability of research on COVID-19 is limited, albeit rapidly developing, which means the rates and values of disease-related parameters is subject to change with the presentation of further research. Further discoveries of new variants of COVID-19 as well as the introduction of newer control measures may present changes in disease dynamics that fall beyond the scope of this analysis.

1.6 Organisation of the Dissertation

The remainder of this dissertation is organised as follows: The following chapter presents the context of the problem and the relevant disease elements and tools central to the analysis through a comprehensive review of the available literature on each topic. Thereafter, the methods used and considered for the analysis conducted are described to frame the approach used to reach the research outcomes presented. This is followed by a modelling chapter describing the behavioural framework, parameters, model fitting, and implementation of the agent-based model presented. The results and estimates presented by the model are then presented and interpreted in the chapter of model results. The discussion of the results presented and their value in terms of answering the objectives and aims outlined is then provided in a chapter preceding the conclusionary remarks of the analysis. The pages following the conclusion of the paper contain the various additional appendices of figures and information referred to in-text.

Chapter 2

Literature Review

This literature review uses a thematic organisation to contextualise the proposed research with respect to available scholarly material. The systematic review of literature relating to the various aspects of the research problem begins with a description of the characteristics of the COVID-19 virus. These characteristics are provided in a biological context with a focus on the manner in which the virus is spread, alongside the related approaches to mitigation and transmission control. This is followed by describing the forms and dynamics of Super-Spreaders and the effects they have on transmission rates for infectious diseases. The focus is then moved to the Mathematical Modelling of Infectious Diseases and approaches to the Mathematical Modelling of Super-Spreaders. Finally a contextual focus on Agent-Based Modelling and its associated benefits is explored. The chapter is then concluded by outlining the Contextual Framework of available literature with respect to the research problem explored.

The approach to reviewing related literature takes a top-down investigation of the related fields. Starting by sourcing literature relating to topics on the broadest scale to gradually develop a contextual understanding of the research environment, before gradually narrowing down the focus of literature to papers relating to the scope of the analysis. The scope of the analysis is limited to COVID-19 transmission in an urban supermarket environment, and the transmission control strategies that may be imposed in this setting. As such information discussed from reviewed academic literature is limited to information relating to the development of such a model, and the effects that may need to be considered. A priority is given to available related literature contextualised in a South African setting.

2.1 COVID-19

2.1.1 History

The history of COVID-19 is a short compared to majority of well know infectious diseases, with the first reported cases of the virus occurring in December 2019. A number of patients were admitted to hospitals in Wuhan, China with an initial diagnosis of pneumonia. The potential for a COVID-19 outbreak was predicted in the early stages of its discovery, with a reproductive number for the virus deemed to be considerably larger than 1, ranging from 2.24 to 3.58 expected further cases of COVID-19 produced by each positive case of COVID-19.[69][51]

The first confirmed case of COVID-19 in South Africa was detected on 3rd of March 2020, with the first local transmission being confirmed on the 20th of March 2020. Six days later the South African government announced a mandatory nationwide lockdown, urging citizens to Isolate themselves and limit interactions in an attempt to slow the spread of the virus[88]. Given the proportion of the South African public living in informal settlement areas, the levels of personal interaction between these individuals is much higher and limited resources make isolation difficult if not impossible for many. By the beginning of February 2022 there have been over

3 500 000 confirmed cases of COVID-19 and over 90 000 related deaths in South Africa, as can be confirmed on the nationally produced public-facing dashboard produce by the Department of Health.[54] [51]

2.1.2 Biology and Transmission

COVID-19 is one of the many pathogens that targets the respiratory system of its host. COVID-19 is a relatively new virus that forms part of a group of coronaviruses (CoVs). These include the well known and documented severe acute respiratory syndrome (SARS)-CoV and the Middle East respiratory syndrome (MERS)-CoV, both of which have also been categorised as viruses that are a considerable threat to public health.[51]

There is evidence that the origin of the COVID-19 virus in Wuhan, China may have been zoonotic given the large proportion of infected people who had exposure to the wet animal market. However, majority of the cases transmitted around the world today are spread through person-to-person contact. Person-to-person transmission occurs primarily via direct contact or through droplets spread by coughing or sneezing from an infected individual.[69] [51]

Yesudhas et al. (20121) describe the main transmission mechanism of COVID-19 to be through respiratory droplets from an infected individual being inhaled or absorbed by a healthy individual[92]. Beyond this mechanism, there also exists evidence for surface to person (fomite) transmission as well as aerosol transmission in poorly ventilated spaces[3][73][77]. The indicated availability of these transmission mechanisms for the spread of COVID-19 requires transmission models to include the effects of transmission using all of these pathways.

2.1.3 COVID-19 Transmission Control Measures

Given the short period of time since the emergence of the novel coronavirus, there is still much to be learned about the virus and the treatment and control of its spread. New information is learned about the virus almost every day and using this information, the strategies adopted for controlling the further spread of the virus can be adapted to optimise their implementation for reducing transmission. Control measures currently in place fall into one of two categories; namely, those that help slow or reduce disease transmission and those that help combat symptoms of the virus. The main controls aimed at slowing or reducing transmission, proposed by the CDC, are [10][51]:

- **Vaccination**:
  Susceptible individuals are able to receive doses of vaccinations against COVID-19. These vaccinations help induce a level of immunity to COVID-19 by inciting the development of viral antibodies for the COVID-19 virus. In an effort to increase the vaccine uptake in many parts of the world, the use of company enforced vaccine mandates for staff, as well as government enforced vaccine mandates on all individuals have been proposed and implemented around the world.[26] Company enforced staff vaccine mandates have been suggested for use with a focus on essential service areas involving increased levels of contact and risk for transmission.[52]
- **Social-Distancing**:
  The primary use of Social Distancing measures describes individuals keeping a distance of at least 2 meters between one another, to reduce the chance of direct transmission through large respiratory droplets that settle to the ground in this space[92][83]. Vardoulakis et al. (2020) and Kennedy et al. (2020) describe Social distancing as a self-governed public intervention practice that is suggested to play a major role in reducing direct transmission between individuals, making the importance of compliance essential to its success[32]. An evaluation of this in practice is seen in the paper by Tupper et al. (2020)[81], describing its role in reducing transmission through reducing direct contact and reducing opportunities for transmission to take place. The population may also act to minimize person to person contact as much as possible by avoiding large gatherings. This includes the use of mandatory nationwide lockdowns to ensure isolation, however, *in the supermarket context proposed; supermarkets operate as an essential service throughout the pandemic and would remain operational regardless of any lockdown implementations.*

- **Capacity Restriction**:

  The placement of a restriction on the maximum number of people allowed in a venue at one time serves to reduce the number of potential person to person contact the people in the venue can make. This relates to the sentiment behind the avoidance of large gatherings discussed under social distancing above. Olivier et al. (2020)[56] and Charpentier et al. (2020)[12] comment on the use of capacity limiting as a means of reducing the number of contacts individuals make by reducing the number of people permitted in a shared space.

- **Quarantine, Self-Isolation & COVID-19 Testing**:

  Infected Individuals must isolate themselves and avoid all contact with others as far as possible. Brett et al. (2020) [7] describe the benefits of isolating infected individuals and the associated success this strategy can have in implementation, with respect to the difficulties involved in doing so accurately and effectively. The difficulties described involve the need for positive case identification, which relates to the use of testing for COVID-19. The evolution of testing capacities for COVID-19 and their associated sensitivities are described in more detail in *Sections 4.8 and 4.8.6.* Stock et al. (2020)[78] describes the benefits to the regular testing of essential-service workers by highlighting evidence of unidentified asymptomatic cases of COVID-19 among essential-service workers and the impacts this has on facilitating the transmission of COVID-19. An important factor to consider is the financial cost of regular testing, as of December 2021 the South African Government mandated that the cost of a COVID-19 antigen test is limited to a maximum of R150 and the related cost limit for RT-PCR testing is R500.[70]

- **Face masks**:

  When in public individuals wear masks covering the face and nose in order to prevent mucus particle expulsion. With the majority of transmission cases coming from respiratory transmissions through direct contact, face masks and other implements of personal protective equipment (PPE) are described by Tupper et al. (2020)[81] in their ability to reduce the chances of transmission in the presence of available contact. *At the time of writing the use of face masks is mandatory in all public spaces in South Africa, so the consideration of scenarios without the use of masks may be unrealistic. Additionally, data availability regarding the transmissibility of COVID-19 is largely focused on values given in the context of mask use*

- **Sanitization**:

  Alcohol-based sanitizers are to disinfect hands and surfaces on which the virus may be present, rendering any COVID-19 particles present, inactive. The use of sanitization strategies for disinfecting hands and surfaces is described in more detail in the papers by Pradhan et al. (2020)[63] and Vardoulakis et al. (2020)[83] referring to the role these strategies play in reducing surface to person (fomite) transmissions through the inactivation of active viral contaminant on hands and surfaces. The role of sanitizer in reducing transmissions is associated with the similarities described for face masks and other PPE by Tupper et al. (2020)[81]. There are varied sources of literature supporting the potential role fomite transmission place in case creation as seen in the papers by Santarpia et al. (2020)[71] and Kanamori et al. (2020)[30]. However, the extent of this role is difficult to evaluate given the difficulties associated with being able to confirm the origin of transmissions to fomites by excluding airborne transmission potential. This point is highlighted in the papers by Pradhan et al. (2020)[63] and Meiksin (2020)[46].

The main controls aimed at treating symptoms are [11]:

- Ventilation: Critically infected individuals that have extreme difficulty breathing are ventilated to ensure delivery of ventilation to the lungs.
- Oxygen: Severely infected individuals that have difficulty breathing are provided with oxygen to ensure adequate supply to the lungs.

In the context of a supermarket environment, no treatment strategies are likely to be imposed in the setting.

2.1.4 COVID-19: Vaccines

Over the course of the last century, vaccination has been the most effective method of preventing death caused by infectious diseases.[18] The use of variolation to combat disease dates back as far as the eleventh century in Chinese literature, however, the use of vaccination as a deliberate prevention technique began in 1881 through the work of Louise Pasteur.[61] Over the years the process of vaccine development has been refined and developed in an effort to improve vaccine efficacy with minimal toxicity and holds its place as the cornerstone in preventing the spread of infectious disease.[50]

Vaccines are generally developed on the basis of inducing the development of an immune response within the body in order to enable a stronger immune response within the body should the target virus come into contact with the body in future. The methods used to induce this initial immune response vary between two well-known techniques, being an adenovirus vector-based technique as used by Pfizer's Covid-19 vaccine and the mRNA-based technique used in the Johnson & Johnson vaccine[50]. These are the two most widely distributed vaccines in South Africa and many countries worldwide.

Introduced in the early 1990's mRNA-based vaccines are type of vaccine with foundations, similar to adenovirus vector-based vaccines, in the use of messenger RNA (mRNA) to induce an immune response in the body. Messenger RNA is encoded from genome DNA and is used by the body to make proteins. In mRNA-based vaccines like the Pfizer produced vaccine, the mRNA sequencing for the construction of Covid-19 spike-proteins is injected intramuscularly into the body. Each virus has a unique spike-protein surface structure, and when the body comes into contact with a new virus it will create antibodies that will seek and destroy cells with that structure.[72]

The administered mRNA is taken into cells within the patient, and the body's cells use this mRNA to create the spike-proteins they describe. The body's immune system recognises the spike-proteins as a foreign body and produces antibodies to fight and remove them. Once these antibodies have been developed, the body can more readily produce them should they encounter the foreign cells with those spike-proteins again. This way if a patient who has received the Covid-19 vaccine is infected, their bodies will be able to more readily produce the antibodies to fight off the infection before it takes hold. [72][50]

Adenovirus vector-based vaccines, like the Johnson & Johnson vaccine, are the most extensively studied and well-used type of vaccine to date. They are based on the use of human adenoviruses, a large family of non-enveloped, double-stranded DNA viruses in the genus *Adenoviridae*. The processes underlying the way adenovirus vector-based vaccines help the body produce an immune response for a disease are very similar to those of the mRNA-based vaccine. The difference is that instead of directly administering the mRNA into the cells of the body, the mRNA is administered within a different virus structure. This allows one to take advantage of the inherent ability of the virus to transduce cells for a desired therapeutic outcome. Additionally, the vector viruses can be genetically altered to improve efficacy and safety, reduce administration dose, and enable large-scale manufacturing. As a safety precaution, genes are removed from the vector virus to prevent it from being able to reproduce in the body.[27][74][50]

Vaccines are widely regarded in various sources of literature to be the most effective means of combating and eliminating the spread of vaccine-preventable diseases[57][75]. Omer et al. (2009) and Siddiqui et al. (2013) highlight the greatest barriers preventing their optimised capabilities in preventing the spread of disease are founded in issues of reduced acceptance and coverage of vaccines. The issue of vaccine hesitancy has been highlighted by the World Health Organisation and Centre for Disease Control as one of the greatest threats to public health globally. With vaccines regarded as one of the most effective tools in public health for preventing the spread of infectious disease, they are likely to play an essential role in controlling the spread of COVID-19.[21]

2.2 Super-Spreaders and Super-Spreader Events

The existence of super-spreaders and super-spreader events have been reported in literature for over a century however, there is limited information on them found in scientific literature. The term ”super-spreader” indicates a propensity of more people than the average person or event.[9]With this definition in mind, the definition of Super-Spreaders can be stratified into four main groups:

- Super-spreader People: Individuals likely to spread the virus to a greater than average number of other individuals.
- Super-spreader Places: Locations that are more likely to facilitate the spread of the virus than the average location. [38]
- Super-spreader Events: Social events that are more likely to facilitate the spread of a virus than the average social event. [44]
- Super-spreader Policies: Rules or regulations that are more likely to facilitate an increased spread of the virus.

The description of Super-Spreaders that is most frequently referred to is made in reference to super-spreader people. The definition of a super-spreader individual makes reference to their propensity to produce more transmissions than the average individual, however this may be as a result of different underlying mechanisms. Kumar et al, further defines super-spreader individuals by grouping their transmission amplification mechanisms as either clinical or behavioural. The clinical components describe individuals with more transmissible strains, higher viral loads, or more severe symptoms. The behavioural components are the larger group of the driving mechanisms. They describe behavioural aspects of an individual's lifestyle that may contribute to more transmissions. This will include individuals who are likely to have more person to person contacts due to their profession, high levels of socialising, or those who frequent spaces with large crowds[38]. Another element to consider regarding super-spreader individuals, not presented as a focus in the academic definitions of super-spreader individuals, is the presentation of super-spreader behaviours that involve an active non-compliance with measures taken to reduce transmission. The occurrence of Super-spreader events is recorded for a variety of infectious diseases such as Measles[16], Ebola[2], TB[36], and SARS virus[41]. Kumar et al. (2020) describe the first recorded instance of a super-spreader, otherwise known as Typhoid Mary, who was the first recorded asymptomatic spreader of a disease who spread typhoid fever to 53 others as she continued her work as a cook. [38]

Super-spreader events are difficult to identify beforehand and most super-spreader events are identified in hindsight, however Kumar et al. describe a variety of social and clinical characteristics that can typically be seen in super-spreaders. These range from clinical characteristics such as a more severe cough to social characteristics such as risk-taking behaviour or working in crowded locations. These characteristics may provide insight into the identification of likely super-spreaders before they are able to distribute the virus.[38]

2.3 Mathematical Modelling of Infectious Diseases

The use of mathematical models in epidemiology has grown rapidly over the past century, providing valuable insights into population level characteristics of infection due to individual behavior and biology. [48]

Mishra et al. indicates that, unlike chronic disease epidemiology, the study of infectious disease requires specific dynamic models in order to capture the transmission of disease from infectious to susceptible individuals and incorporate positive and negative feedback characteristics of the infectious processes. These mathematical models allow us to extrapolate from current information about the state and progress of an outbreak, predict future outbreaks and quantify the uncertainty of these predictions. [31]

Mishra et al. describes the mathematical model that defines the transition dynamics of an infectious disease as a compartmental model. The compartmental model categorizes hosts into three or four key stages of infection.

There are two widely used models in the mathematical modelling of infectious diseases, these are namely; the SIR and the SEIR models respectively. These models separate individuals in the population into groups susceptible to the disease, infected by the disease, and recovered from having the disease. The SEIR model extends this by including an exposed group of individuals who have been infected but incubate the disease for a period, unable to transmit the disease, until they become infectious and are then able to infect others. The SEIR model is better suited to the structure of COVID-19 as individuals infected with COVID-19 have a two week period of incubation before they become infectious to others.[51] This is the conceptual structure that will be considered for use in the analysis conducted in this paper, with individuals defined between these disease states and the addition of two additional vaccine states.

2.4 Mathematical modelling of Super-Spreaders and Super-Spreader Events

In order to factor for the effects of Super-Spreaders on the spread of disease in mathematically-based epidemiological models; the effects of Super-Spreaders and Super-Spreader events must first be represented in the form of a mathematical formulation or procedure, in order to incorporate their associated effects to the model's operation. There are four distinct approaches suggested by literature for the mathematical modelling of Super-Spreaders in epidemiological models, they are as follows:

- Stochastic small-world (SW) and scale-free (SF) networks [76][42]
- Compartmental Models
- Branching Processes
- Agent-Based Modelling

Although these methods provide an effective means of including some super-spreader effects on disease transmission, many of the approaches described are limited to the inclusion of effects relating to a single super-spreader effect of either super-spreader people or events and fail to account for the effects of other super-spreader types. These approaches are explained in more detail below.

The use of **Stochastic small-world (SW) and scale-free (SF) networks** for modelling super-spreaders is an approach proposed by Small et al. (2006) is a model for the SARS Virus[76]. The approach involves a combination of compartmental disease-states and person-linkage structures, with individuals belonging to a single disease-state and links being created between individuals. The approach includes a small-world structure by defining two linkage types for local and foreign links. The local links represent close connections such as family, and foreign links represent connections to other groups of individuals. This approach attempts to model the effects of super-spreader people through representing super-spreaders as individuals with a large number of foreign links, thereby facilitating spread between groups. This approach expands on many other models allowing the model to ignore the assumption of a homogeneous, fully connected population. Lieberthal and Gardner (2021) [42] extended this approach, which included probability-dependant super-spreader capacities through the assignment of links, to the additional inclusion of time-dependant super-spreader effects. This is achieved through a process of centrality and clustering between individuals, and the distance between clustered groups is then representative of a stochastic arrival time for a potential transmission between groups.

The next approach using **Compartmental Models** was shown in papers by Kochańczyk (2020) [37] and Yayehirad (2020), but has been replicated in other epidemiology studies. The approach builds on the standard compartmental models described in the section above, assigning a proportion of the population to super-spreader metapopulation compartments and assuming increased transmission rates for individuals in these groups.

The approach to represent Super-Spreaders through **Branching Processes** proposed by Muller & Hosel (2020) approaches modelling super-spreader people with the assumption that all individuals may be super-spreaders if they fail to be diagnosed or traced. It follows the concept of contact tracing by allowing infected individuals to be diagnosed or traced by fixed probabilities, representing super-spreaders as those that fail to be diagnosed or traced. Thereby allowing them to continue spreading the disease.

The final approach considered by Kim et al. (2018) [34] provides the most flexible approach to modelling super-spreader effects, allowing for the representation of super-spreader people and events with distinct individual-level heterogeneity in contact rates, such that each individual has varying contact rates and clustering of contact frequency. Super-spreader individuals are represented by individuals with larger numbers of contacts and transmission probabilities.

Of the approaches considered, the Agent-Based modelling approach is the most flexible, yet expensive in terms of computing requirements and model building effort. This is as the model must be built from the ground up with little to no existing functions and structure. This ground-up formulation, while limited by the inability to use known and trusted mathematical formulations, provides immense flexibility in the way the models are designed for individuals and their environments.

2.5 Agent Based modelling

Wilensky and Rand (2015)[90] describe Agent-Based Modelling (ABM) and a computational modelling paradigm that, through it's use in modelling a system, is able to describe the associated rules and procedures defining the Agent's behaviour. ABM is a simulation-based modelling technique that attempts to define the complex systems it aims to represent, through the perspective of the agents that move within the system. Bonabeau et al. (2002)[6] describes the autonomous decision making behaviour of the agents in the system modelled as the cornerstone of the Agent-Based Modelling approach.

The reason autonomous decision making is so central to ABM is due to the approach in ABM design, through which the model seeks to represent complex systems by defining the decision making behaviour followed by these agents. By defining and assigning a predetermined set of rules for the agents to follow, the model is able to gradually reproduce the complex emergent behaviours seen in the target system; resulting as a product of the repetitive interactions between the system's agents.

Agent Based modelling contrasts population level modelling by taking a bottom-up approach of modelling, building the model around the behaviour of individuals as opposed to the population as a whole. The approach to model development begins by developing an understanding of individual-level behaviours and operating structures for the individuals members of the system. This understanding is leveraged in defining procedural rules that are followed on an individual-agent level. Through the definition of these structures, the interactions between agents defined by their assigned behaviours, allow for more complex population-level behaviours to emerge through observation of the system.

ABM's ability to replicate these complex systems, is the motivational force behind it's replacement of more traditional mathematically-base methods. Bonabeau et al. (2002)[6] states that even very simple agent based models are able to result in the emergence of complex behaviour that equation-based methods would struggle to replicate. The major advantage that ABMs have over traditional mathematical modeling approaches is it's ability to explicitly define heterogeneous characteristics between individuals in a population, where the majority of equation-equation based modelling strategies make the assumption of homogeneous-mixing within the populations they define.

Bonabeau et al. (2002)[6] decribes ABM as more of a mindset than a technology, reflecting on the necessary ability to structure and break down a problem into a structure that can be defined by the behaviours of the agents that govern it.

2.6 Benefits of Agent Based Modelling

Agent based modelling is a powerful modelling approach which features many unique benefits that aid in it's ability to reproduce complex higher-level emergent phenomena. Bonabeau et al. (2002)[6] outlines some of the key benefits of ABM below, with the additions of some features described by Wilensky and Rand (2015)[90].

1. *ABM is able to replicate emergent, complex phenomena*

   The combination of the described behaviours and the resulting effects of their repeated, iterative interactions between agents, their environments, and each other, results in the description of emergent population-level phenomena far more intricate than the behaviours defined for individual agents. This indicated the ability to replicate these complicated systems through more than just the sum of the agent behaviours described, but including the additions the competitive interactions they share.

2. *ABM provides a natural description of a system*

   There are many cases of systems that may seem more intuitive to model from an agent-based perspective. It can be much simpler to model human population behaviours through the behaviour of individual agents as it follows the thinking pattern the person approaching the problem would instinctively adhere to.

3. *ABM is flexible*

   The ability to define characteristics at an individual-agent level, provides the flexibility to describe systems through multiple perspectives, allowing the emergence of the same population-level effects through different avenues of individual-level behaviours. The added flexibility of the ability for parameter values to vary from individual to individual, allows the ability to describe behaviours that population-level structures would be unable to define.

4. *ABM provides deeper model feedback*

   With the added ability to record model outcomes at an individual-level, as well as a population level through aggregated collections, ABM allows an added layer of depth in the complexity of data that may be provided in a model.

2.7 Consumer Dynamics and Behaviours

In order to establish a clear understanding of the super-market setting and the way in which customers behave and interact with the environment described, it is important to determine the important elements of consumer dynamics and behaviours specific to their engagement with supermarket spaces. A challenge faced in the review of literature is to understand these specific customer behaviours and dynamics is the primary focus of literature relating consumer behaviour specifically to their purchasing practices. However, papers like the paper by Pazzaglia et al. (2021) [58] discussing the uses of people-counting techniques, make mention of elements in customer behaviour that provide valuable insight into the customer dynamics required. Pazzaglia et al. makes mention of the unidirectional flow of customers in supermarkets, discussing the role of queues and the compartmental nature of the shopping process that facilitates unidirectional flow. Highlights are made regarding movement from entry as customers arrive at the shop, to in-shop product collection, followed by till process queuing, checkout processing, and termination by exiting the shop[58]. This informs a structural layout of a potential layout framework. The grocery shop case analysis of burstiness parameters discussed by Ahrens et al. (2019)[1] makes specific mention of factors inducing irregular shop visits, providing insight into the nature of different shopping requirements in terms of basket-size or shopping extent. This highlights the potential need to account for variation in shopping extents between customers and the effects this will have on shop-times. The paper by Arndt et al. (1977)[4] on the time dimension of shopping behaviour provides some contextual understanding of customer shopping times, placing emphasis on the shop queuing mechanisms and service structure for customer processing. Although the paper may be outdated, insights provided with respect to queue importance and customer processing present timeless implications that remain relevant in modern-day shopping practices.

2.8 Contextual Framework

In order to provide a clear understanding of the way in which the various components of literature reviewed are synthesised to contribute to the development of an informed analytical model for the proposed research, this section provides a conceptual framework outlining the relationships between the reviewed fields and the way their combination frames the model's development. *Figure 2.1* below shows a graphical interpretation of this synthesis.

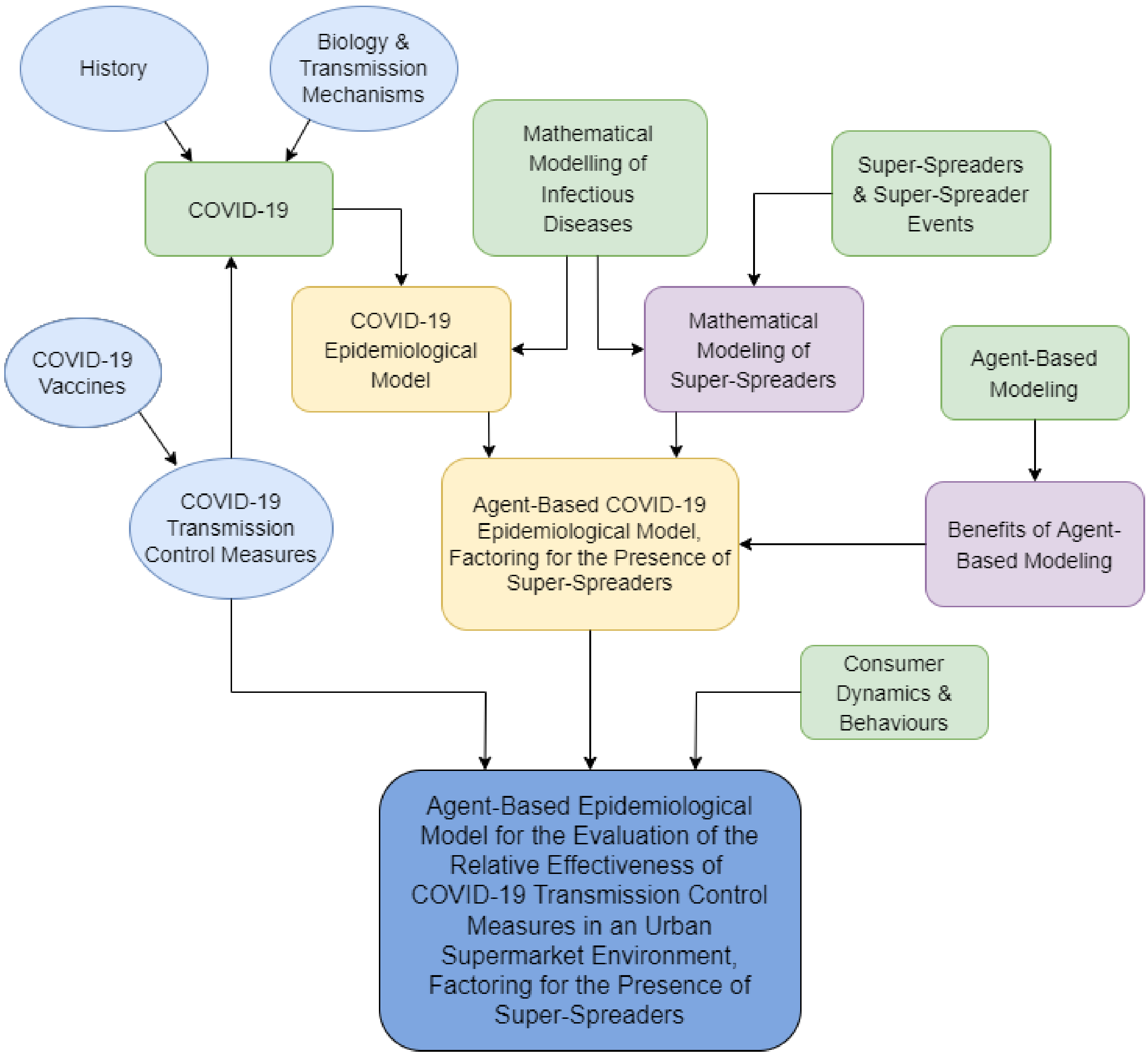

Figure 2.1: Flow Diagram Outlining the Synthesis of Literature to Guide the Proposed Research

Looking at the figure above, the broader sectional concepts presented are shown in *Green*, the more specific concepts with a reviewed section are seen in *Purple*, theoretical sections describing the combination of concepts are shown in *Yellow*, contributing sub-sectional concepts are seen in *Light Blue*, and the final synthesised objective is seen in *Dark Blue*.

The sub-sectional concepts in light blue describe the different contextual components of research that provide a rounded understanding of COVID-19 as a virus, they provide the necessary context for understanding the mechanisms for transmission, the risks of infection and related need to prevent transmission, and the control measures available for doing so. These control measures also form a key component of the proposed research model, as they are foundational to the research question presented. The combination of these elements provides a contextual understanding of COVID-19, the first of the broad topics relating to the research question (shown in *green*).The next of these topics is the presentation of the Mathematical Modelling of Infectious Diseases (MMID). This section provides context to the need to produce epidemiological models and highlights the most frequently used approach in doing so.

The next literature section that contributes to the review is the section on Super-Spreaders and super-spreader events. This section provides a contextual definition of what Super-Spreaders are and describes the effects they may have on the spread of infectious diseases. This is then linked to the mathematical modelling of infectious diseases in order to describe the ways that epidemiological models have approached an incorporation of the effects of Super-Spreaders on disease transmission. The combination of the MMID and the context of COVID-19 would provide context for the formulation of COVID-19 epidemiological models. The next topic of literature presented is that of Agent-Based models. This section describes the use of agent-based modelling from the perspective of its use as a general modelling technique, being sure to illustrate that it is defined without limiting its context to the use of ABM in epidemiology. This is due to the fact that agent-based modelling is widely used in many fields, and epidemiology models describe a very small subset of its use. This is further elaborated on in the section highlighting the benefits of its use as a modelling technique. This, in combination with the context of Epidemiological models that account for super-spreader effects and COVID-19 epidemiological models, forms the context of an Agent-Based COVID-19 model that accounts for the effects of Super-Spreaders in transmission. The final broad literature topic provides a contextual description of Consumer Dynamics and behaviours, which provide the necessary context for the setting of the research presented as a supermarket environment. Combining the elements of the contextual Agent-Based model mentioned, with the use of available COVID-19 transmission controls and consumer dynamics, provides all the necessary understanding of available academic sources to situate the research task proposed and formulate the modelling approach to its analysis.

2.9 Research Gaps in the Field

As COVID-19 is a relatively new virus, there is still a lot about the virus that is unknown and this lack of information presents several challenges regarding modelling the transmission of the disease.

Information regarding transmission rates and the associated transfer times between stages of infection are prone to change as more data becomes available and more is learnt about the virus. Limited data also contributes to model fitting being unreliable, however the model may be fit more accurately as more data becomes available.

The majority of research available that focuses on the individual levels of effectiveness each control measure has at reducing transmissions fails to factor for the impact that the implementation of each respective measure is likely to have in changing human movement dynamics. Thus, failing to account for the indirect impact that these changes have on transmissions resulting from changes in contact dynamics. Available research is also framed in the context of very unspecified environments due to the novel nature of COVID-19, this paper serves to start filling the space of a more context-specific evaluation of COVID-19 control measures.

With the role that urban supermarkets play as essential services and super-spreader environments throughout the pandemic, these environments have become areas in which the understanding of transmission dynamics and potential control measure effectiveness is invaluable. The ability to make well-informed decisions regarding the effective implementation of measures to reduce COVID-19 transmission in these unavoidable super-spreader environments, has the potential to make a considerable impact in the fight against COVID-19.

Chapter 3

Methodology

3.1 Method Considerations

A large majority of epidemiological models fall into the category of *Compartmental Modelling*. These are mathematical models that make use of ordinary differential equations, taking a top-down approach in modelling emergent phenomena from a population perspective. The approach breaks down the population into a series of mutually exclusive and exhaustive compartments, with transitions between compartments defined by the corresponding differential equations. The result is a deterministic, compartmental, mathematical model that makes the assumption of homogeneous mixing within the population[49]. The bulk of these models are built off of the SEIR model, which splits the population by classifying individuals by their epidemiological status of Susceptible, Exposed, Infectious, or Recovered[31]. The use of Compartmental models has been seen as a frequently used approach to modelling COVID-19 transmission, however in a review paper of several COVID-19 compartmental models discussed by John-Baptiste et al. (2021)[28] the authors highlight the limitation these Pure Mathematical approaches have in being able to accurately represent real-world dynamics in public health outcomes. The primary downfall of the approach is it's assumptions of homogeneity for the compartments described, real-world population groups regularly fail to live up to these assumptions, and the complex model adaptations necessary to try to capture some of the key heterogeneous effects in these populations makes the implementation of these models difficult.

Another method to modelling the analysis that was considered is the use of *System Dynamics Modelling*. System Dynamics modelling is a simulation based modelling technique that has grown to have a wide array of applications in many different industries. System dynamics modelling makes use of an approach to problem structuring that approaches a problem by breaking it into smaller parts and processes. This technique makes use of a method—cognitive mapping structure of the problem, and an associated computer-based supporting system. The aim is to structure situations so that they are characterized by feedback dynamics. Thus the method is subsequently suitable as a visual interactive modelling method. This enables the use of visual interactive system dynamics modelling methods, providing the benefits of problem-structured visual aid.[20]

System Dynamics modelling takes the approach of structuring the problem such that moving parts or components take the form of working items that transfer between distinct guiding compartments which conduct a fixed reliable process on any components with which they interact. Using this approach would involve defining customers as working items and providing them with disease-related characteristics as they pass through various stages in the shopping process.

The major limitation of both of these approaches is the assumption of a uniform homogeneous mixing population. This prevents the inclusion of heterogeneous chances of infection, compliance, and consumer behaviours. The inherent nature of individual-level variation that underpins Super-Spreaders and super-spreader behaviours, necessitates the ability to include elements of heterogeneity in these components. Another limitation is that these approaches ignore random effects in the model. This can become a problem if the susceptible or infectious group is small, as the variability in model outcomes is masked. The ability an Agent-Based Modelling approach has to include all of these elements of heterogeneity, while retaining the capability of effectively capturing the emergent epidemiological phenomena we aim to observe, makes the choice of Agent-Based Modelling optimal.

3.2 Agent-Based Modelling

Wilensky and Rand (2015)[90] describe one of the key benefits to agent-based modelling over other equation-based modelling (EBM) techniques is it's distinct ability to model heterogeneity in a population well. This is because agent-based modeling approaches make the definition and assignment of parameter values at an individual agent level, whereas other EBM techniques take the approach of defining parameters to groups or populations.

De Angelis et al. (2019)[17] comments on the limits these more traditional population-level modelling approaches have in their ability to integrate decision making in their model complexity. The development of agent-based models has opened the possibility of describing the way that decisions are made, and their effects. Agent based modelling enables features that allow changes in model processing and procedure control to depend on operational changes in parameter values as the model runs, giving it superior modelling capabilities in being able to capture the effects of complex decision making tasks.

The individual agents in the described environment follow the outline set of rules according to the environmental conditions in which they're placed, as well as the interactions they have with one another. This approach defined by agent-based modeling leverages computing power and the use of repetitive, adaptive procedural interactions to replicate complexities in population-level effects far beyond the scope and limitations of traditional mathematical approaches.

Sections 2.5 and 2.6 in the Literature Review chapter provide further discussion into the benefits of the use of Agent-Based modelling over more traditional approached, as well as defining a more foundational definition of what agent-based modelling entails.

Wilensky and Rand (2015)[90] expand on another major benefit agent-based modeling approaches have over the use of other equation-based mathematical approaches. The benefit they discuss is the additional detail available for recording results. Where other mathematical approached are limited to population-level data estimates for any responses and effects measured; agent-based methods are able to record response data at both an individual-agent level, as well as at an aggregated population-level, providing an added layer of depth and information to the data produces in a model's analysis.

Agent based systems provide an environment in which we can:

1. Capture our understanding of systems.
2. See how actions at the individual level create emergent phenomena within the population as a whole.
3. Validate theory against real data at both the individual and population level.
4. Test "what if" scenarios to inform future decisions and planning.

As powerful as agent based modelling may be, there are several limitations which should be considered before investing time and resources into model development.[15]

Ward et al. (2016)[86] highlight some of the problems with agent based modeling approaches, with the issues faced by the approach of agent-based modelling falling into two main categories. The first is focused on the issues inherent to simulation-based approaches and the lack of robust model-fitting procedures available. The model description is described to depend on an abstract/realism approach as described by Ward et al., in which the components of realism come from the attempt to replicate the real-world system the model aims to describe, by defining as many real-world features as possible and making use of real-world parameter data to define the model's operation. This is the most likely approach to be used in the development of the model used in this paper, due to the well-defined and researched descriptions of epidemiological processed and parameters.

The other approach is the abstract approach, which aims to simplify the behaviours of more complex mechanism to a few behaviours, focusing on adjusting the way those behaviours are defined by observing their outcomes in relation to the target process.

The second category of issues highlighted by Ward et al. (2016)[86] is focused on the processing requirements of agent-based modeling approaches. In this way the benefit mentioned by Wilensky and Rand of more detailed data collection serves as a double edged sword. As the collection of such data requires keeping track of all the defined parameters, for each of the agents present in the model, at each time-point in the model's simulation. This is necessary to govern agent behaviour according the value of their parameters, as well as the values of those with which they interact. With this in mind, the more complicated the model developed becomes, the more intensive the processing demands will be.

An issue that ties these categories together relates the lack of robust model-fitting techniques to a reliance on sensitivity analysis in order to establish confidence in model outcomes. The process of sensitivity analysis, as will be described in the Agent-Based Model chapter below, is an extremely computationally heavy method of assessing model reliability. The need to perform factorial design approaches to varying parameters means that there are often many iterations that must be performed, which combined with a computationally demanding method, leads to very large demands in processing power and time.

However, with the rapid improvements in computer performance in recent years, the benefits of the modelling approach are gradually beginning to outweigh any costs in computing demands.

3.3 Queuing Theory

The Agent-Based Model considered makes use of customer queues within the shop in order to appropriately represent their real-life counterparts. These queues are later defined using Kendall notation in order to describe the queue structure followed by customers in the corresponding shop areas. Although the queuing structure is not subject to change within the model, an understanding of the notation used is shown as follows[94]:

Queuing theory uses the Kendall notation to classify the different types of queuing systems, or nodes. Queuing nodes are classified using the notation A/S/c/K/N/D where[79][66]:

- A is the arrival process
- S is the mathematical distribution of the service time
- c is the number of servers
- K is the capacity of the queue, omitted if unlimited
- N is the number of possible customers, omitted if unlimited
- D is the queuing discipline, assumed first-in-first-out if omitted

Further abbreviations frequently used for the description of the Arrival Process and Service Time include:

- M represents a Poisson process
- D represents a Deterministic process
- G represents a General, Independent process

Queuing theory is most commonly applied in optimisation settings, in which various different queuing structures and formulations are tested against one another. Different structures are routinely assessed according to evaluations metrics such as average queuing durations, queue lengths and successful service counts. The approaches queuing theory based analyses take in terms of analysis is primarily with the objective of optimising performance and task completion. Although the use of queuing theory analyses is not suited for epidemiological transmission modelling, having a well defined and universally understood definition of the queuing structures considered in the environment; will serve not only to ensure accurate representation in building the model, but also aid in the ability to fully describe the queuing structure in the setting of communicating research. The consideration of queuing theory methods may also provide insight into the optimisation of the customer queuing structure to consider in the model. This would allow improvements in Customer Dynamics related outcomes, which may in turn serve to better control transmission and control measure implementation by streamlining the shopping experience.

Although there are additional, more complicated descriptions with respect to the definition of the Arrival Process, Service Time, Queue Discipline, and Queue Structure; these extensions fall outside the scope of the analysis conducted in the paper due to the small role Queuing Theory plays in the model being described.

Customer waiting behaviours that frequently form part of Queuing Theory include balking, Reneging, and Jockeying. These are defined as follows:

- **Balking** describes the decision a customer makes to avoid joining a queue that is unsatisfactorily long
- **Reneging** describes a customer's decision to leave a queue when their waiting time becomes unsatisfactorily long
- **Jockeying** describes a customer's choice to switch to a shorter alternative queue

3.4 Simulation Software

3.4.1 Netlogo

Netlogo is an open-source integrated development environment available for the building, running and monitoring of Agent Based Models. Netlogo allows for the design and programming of a full Agent Based Models in its own programming language. Netlogo also has its own simulation window to observe the dynamics of the produced agent based model[89].

One of Netlogo's major limitations is that it can quickly become very computationally expensive to run complicated models. This is as the model needs to record and account for the parameters and processes for every individual in the system. Complicated models with more parameters to keep track of can quickly become computationally difficult to keep track of and more individuals in the system act to further increase the number of these factors.

Another limitation is that information from the model must be collected and adjusted successively at each time period. This means that information cannot have gaps in time to be generated, as movements and adjustments rely on the current situation to determine what is to happen next. In this way information for the next time period cannot be generated without knowledge of the current period.

One more limitation of the Netlogo Software is that it does not have any built in functions or packages to conduct thorough statistical analysis, and requires the use of an external tool for any advanced analysis of its data.

3.4.2 Netlogo's BehaviourSpace Tool

Netlogo has a BehaviourSpace Tool which can be used to run simulations simultaneously with predetermined adjustments to the model parameters. The maximum number of iterations that can be run simultaneously is limited by the number of processing cores available on the device used, with a maximum of one iteration per available core. The tool then compiles user specified information at each time period in the model and saves it in the form of a single `csv (Comma Separated Value)` file. This Information can then be analysed and assessed in another external analysis software such as R or STATA.

3.5 Data Handling

The data produced through the simulation process described above is further analysed through the use of statistical programming software. The chosen statistical programming software for further analysis is `R` and `RStudio`[65].

The data compiled is loaded into the R environment and separated into response measure information from each respective scenario. The comparison metrics for each run are then calculated from response measure data to be used for scenario comparison. The separated data allows for the calculation of variability and a measure of uncertainty of the values for each comparison metric. Thus comparisons between scenarios are performed through a comparison of metric distributions, rather than single values through an individual simulated run.

3.6 AIC and Distribution Fitting

Histograms of the calculated metrics are plotted in form of Exploratory Data Analysis to better understand the metric distributions for each hesitancy scenario. In attempting to compare the distributions model fitting is conducted to find relative parsimonious approximations of these distributions so that they can be plotted together for comparison. The best approximation is selected according to Akaike's Information Criterion (AIC). AIC measures the difference between a models predicted response values and the true values the model is attempting to predict. The difference is measured according to Kullback-Leibler distance[8]. In this way AIC acts as a form of likelihood providing penalisation for additional parameters in interests of model simplicity. AIC can hence be used as a measure of relative support for different models or distributions on a given dataset. [85]

Chapter 4

Agent-Based Model

The Agent-Based Model developed captures and describes the complex changes in population Customer, Transmission, and Disease Dynamics through a bottom-up approach, by defining sets of rules and behaviours that agents in the model follow on an individual, single-agent level. The choice of an Agent-Based Modelling approach to modelling the effectiveness of different transmission control measures in a shop environment in the presence of Super-Spreaders comes from the individual natures of super-spreader behaviour, person-to-person contacts, and consumer practices. Specifically, the manner in which interaction and compliance behaviours, as well as consumer shopping needs and practices vary between each individual in a population. This makes modelling at an individual level the best choice for capturing the effects that these individual needs and behaviours have on changes in Customer, Transmission, and Disease Dynamics in the population, allowing for the existence of heterogeneous chances of infectiousness, compliance, movements, and interactions. The benefits of model development in the NetLogo environment that go beyond the use of general Agent-Based Modelling, involve the catching and engaging visual environment available for describing and interacting with the model developed.

This chapter begins with an overview of the agent-based simulation model developed, describing an introduction to the environment and behaviours it aims to replicate. This is followed by a description of the environment layout and the benefits of the visual communication the environment provides. Thereafter, the rules and procedures for Environment, Customers, and Staff are described and explained. This is followed by a description of model assumptions and restrictions, model parameters and selected values, which precedes the Model Fitting process including a sensitivity analysis of the parameters used. The scalability of the model in then assessed to reflect on the model's ability to shop environments with higher customer loads. The different Transmission Control Measures and their implementation in the model are then described, followed by the final section describing the use and monitoring of the simulation environment.

4.1 Simulation Overview

This model simulates the transmission and spread of the COVID-19 virus in a human population within an urban supermarket, including the use of transmission control measures and factoring for the inclusion of the presence of super-spreader behaviours.

There are a number of factors which contribute to the perpetuation of a disease within a single population[93]. The presence of vaccinations on a vaccine preventable disease act to reduce the presence of disease and the use of transmission control measures act to reduce the chances of further transmission, while the existence of super-spreader behaviours reduces control measure compliance and inhibits their effectiveness at reducing transmissions.

This simulation model replicates the arrival of customers to an urban supermarket. Customers move through the shop environment, collecting a varied number of items from different areas in the shop before moving to the tills. Customers then wait for a member of staff to become available to process the check-out of their purchases before exiting the shop. Infectious Customers infected with COVID-19 interact with other customers, staff, and the shop environment to facilitate the transmission of COVID-19 to other individuals in the simulation. Different transmission control measures can be selected for implementation in the shop environment. When implemented, the customers and staff changes their behaviours to enact and respond to each control measure, with super-spreader individuals exhibiting reduced compliance to the required behaviours for control measures within their control.

4.2 Environment Layout

The agent based model developed highlights a considerably more intricately designed visual representation of the described environment than those seen in the publicly available Model Library and compared to other related Agent-Based Models. The visualisation of the environment displays a supermarket shop environment with both 2D and 3D representations of the environment available. The shop on display aims to replicate a universally familiar supermarket environment with a variety of products stocked throughout the shop as seen in *Figure 4.1* below.

The shop environment consists of an array of artfully designed components that serve to enhance the environment and captivate the observer. Beyond the key components that make up the structure of the analysis for the model, the additional elements are described in more detail in *Section 4.2.1* below. Although these design elements provide no computational value in the Agent-Based Dynamic model; the time and effort used to push the limits of the Turtle Designer facilities in NetLogo, to create the featured design elements, enabled the inclusion of these features to increase the aesthetic value of the model's visual environment. This is done in an effort to maximize the benefits of the visual-aid component in communicating research comes, as explored in the section to follow below.

Figure 4.1: 2-Dimensional Representation of the Simulated Shop Environment

The key components that facilitate model analysis in the environment consist of:

- A single shop entrance queue for customers entering the shop
- A single shop entrance (shown in green)
- 6 main points of interest in the shop for customers to collect items
- A single till queue for customers to wait for an available till station
- 3 till stations for staff to process customer check-outs
- A single shop exit (shown in red)
- 3 working staff to run a single till station each
- 2 substitute staff to run a till station for any self-isolating staff
- 5 staff houses for substitute staff and staff in isolation

The use of these key components functions to replicate their real-world application. The definition of their underlying mechanisms is described in more detail in *Section 4.4*.

4.2.1 Benefits of Visual-Aid in Research

Several studies by Garcia-Retamero et al. have provided indications that the addition of visual aids in the presentation of research serves not only to improve diagnostic inferences and metacognitive judgment calibration, but to highlight that the benefits of the use of visual aid are specifically effective in improving understanding in the presentation of risk-related research [23][25][24].

The course of the COVID-19 pandemic has highlighted the importance of providing clear and informative communication of research to the larger public and community as a whole. Issues of limited literacy have been a considerable limitation faced by academia and researchers alike in their ability to communicate research outcomes to the public. Engaging and relatable visual aids have become an essential tool in crossing literacy gaps in order to allow members of the public with no related academic experience to understand the growing understanding research has developed regarding COVID-19. In the months following the discovery of COVID-19, the world has had to fight the spread of the COVID-19 virus amongst the equally virulent spread of related misinformation. Much of the issues with misinformation are linked to healthcare and the importance of adhering to the suggested COVID-19 control protocols. The most effective tool that researchers can use in combating this sensationalised misinformation, is the production of quality, engaging research that aids in teaching others using reliable, peer-reviewed, scientific information.

Beyond making simple and relatable visual aids to make research understandable, providing an entertaining and interactive interface for engaging with the information provided serves to improve willingness and eagerness to engage with the material.

The agent-based model developed combines all of these communication tools to provide a platform that simplifies communication of research outcomes, encourages engagement with the work, and easily adapts to visual presentation environments. If a picture paints a thousand words, an engaging, realistic, and interactive simulation can tell an entire story.

The simulation environment features over 30 unique and realistic turtle designs, individually made for use in this model

The shop environment consists of the following artfully designed sections, available for closer inspection in *Appendix B, Section 8*:

The products sections consist of:

- 11 Shelves of food, toiletries, plants, and cleaning supplies (*Figure 8.4*)
- 9 Refrigerators of cheese, dairy, refreshments, and fresh produce (*Figure 8.5*)
- 2 Produce Islands of fresh fruit and vegetables (*Figure 8.6*)
- 3 Freezers of assorted frozen foods (*Figure 8.7*)
- 2 Islands of prepared foods (*Figure 8.8*)
- 1 row of in-queue merchandise (*Figure 8.9*)

The extra design elements consist of:

- 1 African Acacia (*Vachellia abyssinica*) tree (*Figure 8.12*)
- 2 Pincushion Protea (*Leucospermum spp.*) bushes (*Figure 8.13*)
- 1 Parking lot which becomes more or less populated depending on the number of customers present (*Figure 8.14*)
- 1 Generic Car (*Figure 8.15*)
- 1 Sanitizer Stand which becomes visible if the **Sanitization** control measure is used. (*Figure 8.16*)

The staff sections consist of:

- 3 Till Stations for processing customer check-outs (*Figure 8.10*)
- 5 Staff Houses for substitute staff and staff in isolation (*Figure 8.11*)

4.3 Simulation Assumptions

The following assumptions are made with respect to the structure of the simulation environment. These are assumptions that are made prior to model development in order to aid in the definition of behaviours, movements, and structure of the simulation environment.

The Structural Assumptions made include the following:

- Only the balking customer waiting behaviour is considered:

  Customers that arrive at the shop will decide to leave based on the lengths of the shop and till queues independently. Once a customer enters the system, they will only leave by exiting the shop. This aids in simplifying the monitoring and collection of metrics such as customer arrival counts or processing times. If customers were to exit the system without completion of the uni-directional flow described in *Section 2.7* in the Literature Review, the inclusion of their headcount in relation to their effect on preceding processes such as queues, would require the need for more complex measurement implementations.

- There are 3 customer shop-sizes exclusively:

  The basket-size of each customer, representing the number of items they collect or the extensiveness of their shop is defined by the customer's assigned "shop-size". The number of shop-size levels is limited to 3 in order to simplify the model development. These shop-sizes are representative of a *Small, Medium,* and *Large* shopping extent. These are assigned as values of 1,2, and 3 respectively, such that a larger number indicates a more extensive shop with the collection of more items.

- Shop-size correlates with the number of points visited in the shop:

  As the shop-size is defined to be representative of the relative number of items collected in the shop, it follows that the associated increase in the number of items collected with increased shop-size correlates to an increase in the number of points visited to collect those items.

- $(M/S/3/\infty/\infty/FIFO)$ customer till service for checkout:

  The queue for the till stations in the shop show an independent Markovian (M) arrival process, with customer arrivals depending solely on their independent completion of the shopping process. Service Times (S) are drawn from a Poisson distribution to allow for service times to be specified in discrete time. Additionally, the Service time for each customer is correlated to the shop-size/number of items collected by the customer, with larger shop-sizes(more items collected) corresponding to longer service times allocated. Define TSS as the multiplier for service time allocation by customer shop-size, such that TSS is representative of a "Till Service Speed" with a lower TSS indicating increased speed and shorter service time. Factoring for the above, define the allocation of the service times S to be distributed as $Poi(TSS * Shop - Size)$ in discrete time. The FIFO queue discipline indicates a first-in-first-out system in which the first customer to arrive will be the first to be serviced. The number of servers is defined to be 3 as the model layout specifies 3 till stations, and there are no limits placed on the number of people who can join the queue or the number of people that may arrive at the tills.

- $(M/D = 1/1//\infty/\infty/FIFO)$ customer entrance to the shop:

  The queue for the shop entrance is defined similarly to the till station queue, with two key differences in its structure. Firstly the service time follows a Degenerate distribution with a fixed, deterministic service time of 1 min in the base model. Secondly, as there is a single entrance, the number of servers is set to 1.

- There are 5 fixed periods in the day with independent distributions of customer inter-arrival times:

  The definition of these fixed periods is done to simplify the definition of changes in customer arrival times throughout the day when implementing these features. The periods are defined to represent; an initial slower period of customer arrivals, a notable increase in customer arrivals for a "lunch rush" followed by a quieter period before the end of the work day, considerable increases in customer arrivals after the end of the standard work-day, ending with a final quieter period as the shop prepares for closing.

- Customer proportions with respect to disease states are representative of the larger national population:

  This assumption is stated for two main reasons. Firstly the ability to represent larger populations through the customer population aids in the definition of the proportions that arrive at the shop, as rates can be selected from more readily available population estimates. Secondly, with the statement of this assumption, observations in transmission dynamics can be interpreted in the model findings to provide insight regarding larger scale disease interactions.

- Disease transmission occurs solely through person to person contact and environmental (fomite and aerosol) transmission:

  This assumption is stated in order to simplify and reduce the need to define extra, more complicated means of transmission between individuals in the system.

- Customers will only arrive in one of the following disease states: Susceptible, Infectious, Partially Vaccinated, Fully Vaccinated:

  This assumption is stated in order to simplify and reduce the need to define extra, more complicated disease states for individuals in the system. Additionally, the assumption to limit to these states makes the definition of the relative proportions of each of these easier to source in literature.

- Shop Staff do not receive any transmissions external to the shop

  This assumption is stated in order to simplify and reduce the need to define extra, more complicated means of transmission for staff members. Once the model had been developed, transmission mechanisms allowing external staff transmission were implemented. This defined the chance of external transmission through the allocation of an average number of contacts per day[40], divided by the remaining hours in the day to account for the short amount of time for interactions to take place after-hours, multiplied by the prevalence in the system, followed by multiplying by the chance of direct transmission given contact, and lastly accounting for any staff immunity. This method was tested at a variety of transmission chance rates and no noticeable effects were noted in any transmission or customer dynamics outcomes. Therefore, its inclusion was left from the model to aid in simplicity.

- The chances of being infectious are directly proportional to the assigned number of direct contacts each person has:

  The more direct contacts an individual makes, the more opportunities for transmission exist for that individual. Such that when grouped into 5 levels of direct contact counts, the chance of being infectious for each respective group is at a ratio of 1:2:3:4:5 where the highest count level has a chance of infectiousness five times that of the lowest count level. This relates to a direct relationship between the opportunity for transmission to take place and the probability of it happening.

- An individual's propensity to exhibit super-spreader behaviours, such a non-compliance with control measures, is directly proportional to the number of direct contacts that individual has:

  A frequently cited description of super-spreader individuals refers to their proportionally higher number of interactions with others. This assumption makes a link between the risk-seeking nature of increased socialisation in a pandemic setting and the risk-seeking behaviours of avoiding compliance with control measures.

4.4 Rules and Procedures

The Rules and Procedures described in this section define the process of procedures and steps taken throughout the simulation procedure from the setup and initialisation of the simulation (Procedures shown in green) through all processes undertaken throughout the simulation period. As the Agent-Based simulation model developed is a single unified model that allows for complex interactions between Customers, Staff members, and the Environment in which they exist, the Procedures and Rules followed by the model would be best represented through the use of a single large flow-diagram connecting all of the model components. However, this flow-diagram would quickly become very large and complicated. For ease of illustration and interpretation, the flow-diagram of the model rules and procedures has been divided into three sections illustrating and interpreting rules and procedures for the **Environment and Patches**, **Customers**, and **Staff** respectively.

4.4.1 Environment and Patch Procedures

The simulation process begins with the setup and initialisation of the environment itself. *Figure 4.2* on the page below shows the process of procedures following on from the initialisation of the model. All **Setup and Initialisation Procedures** are shown in **Green**, with primary setup procedures shown in *Dark Green* and secondary setup procedures shown in a *Lighter Green.* The primary setup procedures are the processes that initiate the procedure flow-diagrams for three procedure groups. The Environment Setup procedure is the primary set of steps used to initialise the environment and patches, after clearing and resetting the model it is used to run the secondary setup procedures for the following:

- Design Setup: This step is focused on model aesthetics and sets the layout of the environment through setting patch colours and placing design items.
- Set Global Values: This step is used to ensure global counts and times are set to zero to be aggregated through the simulation process. The step also ensures all selected and calculated rates, speeds, and proportions set using model variable sliders and choosers are calculated for the model parameters elaborated on in *Section 4.5* below.
- Patch Setup: This step is used to initialise the contaminant levels in all locations to 0, and to assign the locations for the environment's tills, queues, staff homes, and points of interest (POI) in the shop.
- Control Measure Setup: This step sets and adjusts the parameters used for implementing any chosen transmission control measures, elaborated on in *Section 4.8.6* below.
- Staff Setup: Described in the Staff Procedures section.

The next procedures used are the **Time Related Procedures** shown in **Yellow**. These procedures are responsible for changes in global parameters throughout the simulation period as they are triggered by changes in time values. They can be described as follows:

- Time Setup: The procedure is used to define the operating hours of the shop, such that it opens at 7am and closes at 7pm daily (staff leave at 8pm). The initial values for Day, Hour, and Minute are also set to begin on the first day at 7am. Lastly, the different time periods of the day with varied customer arrival rates are defined and the distribution inter-arrival time for the first customer period is set.
- Time Step: This describes processes that happen continuously for each time step/minute throughout the simulation period. This includes updating the counts and global values for monitors (described in *Section 4.9*), making all areas exposed to environmental contaminant dissipate at their assigned dissipation rate, and reducing the time until the next customer arrival. When this next-arrival time reaches zero, a customer will arrive. Thereby initiating the Customer Procedures described in the following section.
- Increment Minutes: This step is initiated every 10 min/time steps to reduce computational demands and is used to progress the time monitors and update the visual components relating to the viewing of environmental contaminant and the cars in the parking lot.

- Increment Hours: This step is triggered when the Minutes variable reaches 60, and it is mainly responsible for adjusting the arrival rate of customers if the time change moves to the next period of the day with a marked change in expected customer arrivals.
- Increment Day: This process is triggered when the hours variable reaches the assigned end of the working period, it is responsible for triggering; the addition of any external exposures for staff transmission, the progression of disease, and the testing of staff for COVID-19 if this transmission control measure is implemented. This is elaborated on in *Section 4.8* and the section on Staff Procedures below. The staff procedures triggered daily are shown in **Purple** and described in the section on Staff Procedures below.

The Staff procedures shown in **Purple** may result in very rare cases in which all Staff members are known to be COVID-19 positive and are self-isolating, in these cases the shop is closed and any arriving customers are lost. If the shop has been closed, it will remain closed until a staff member recovers and may return to work.

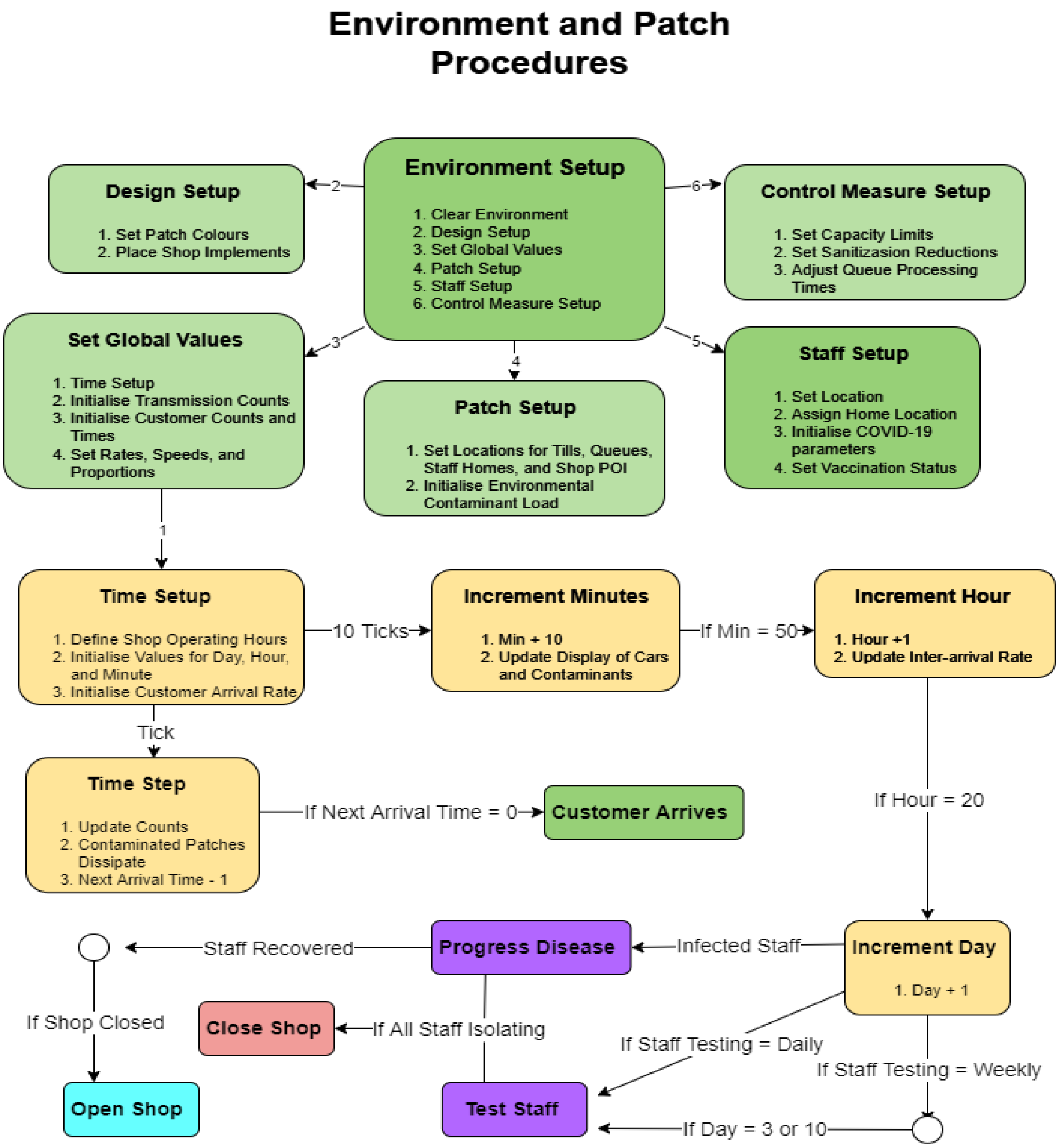

Figure 4.2: Flow Diagram showing the Sequence of Procedures for the Model Environment and Patches

4.4.2 Customer Procedures

The Customer Rules and Procedures can be considered to make up the bulk of the model processing and are considerably more demanding on computational resources for the model. This is as the Environment Procedures are run for the single environment and Staff Procedures are run for the three to five staff depending on the procedure, but the Customer Procedures are run for each of the many customers in the environment at a given moment in time.

The Customer Procedures begin with a single initialisation procedure shown in **Green**. This procedure is responsible for creating the customer and assigning them most of their required parameter values. It begins by setting times for each shop process at zero to be aggregated as the customer moved through the environment, a similar step is used for disease parameters such as the incubation period and contaminant exposure. Customers are then assigned their super-spreader level which is then used in calculating their chance of being infectious. This incorporates the feature of in-homogeneous chances of infectiousness by allowing individuals who have more contacts, and hence more chances for prior exposure, an increase in their relative likelihood of being infectious that is proportional to the number of contacts they make. Once a chance of being infectious is assigned, their disease state is assigned according to proportions described in *Section 4.5* below. The initial destination is then set to the Shop Queue/Entrance (same location).

The movement of customers through the environment is conducted through the use of setting destinations, taking steps towards destinations, and waiting. The **Movement Procedure** shown in **Yellow** is triggered at every time step and works by decreasing an assigned `wait-time` by 1 or taking a step towards an assigned destination if there is no wait-time remaining.

Other procedures triggered at every time-step (tick) are the **Disease-Related Procedures** shown in **Purple**. These are split between Infectious Customers that can spread COVID-19 and Receptive Customers that are able to become infected as follows:

- Infectious customers have the processes of making a direct transmission to a proportion of receptive customers they make sufficient contact with, and a process of spreading environmental contamination in the areas they come in contact with.
- Receptive Customers have the processes relating to environmental transmission in which they Check Exposure to contaminants and when in contact with contaminants they update their aggregated exposure period and the contaminant levels they were in contact with. The combination of these is used to calculate their chance of receiving an environmental transmission.
- When a transmission takes place, the customer moves to the Exposed disease state and sets their immunity such that they cannot receive another transmission. The transmission counts corresponding to the transmission are also updated.

The Customer **Staging and Location Procedures** are shown in **Blue** and describe the steps and behaviours the customers follow in each corresponding area in the shop environment. They can be described as follows:

- Join Shop-Queue: This procedure is the step responsible for assigning the size of the shop the customer will need to do in the shop. In terms of movement, the procedure assigns the customer a queue-position describing their place in the queue and their destination is set to their `personal-space` distance (described in *Section 4.8.6*) behind the customer placed ahead of them. This procedure is also the step responsible for any customer balking that takes place. Before joining the queue, if the shop or till queue lengths are above/at the assigned thresholds the customer will leave and the lost customer count is increased. The balking procedure is one of the two Customer **Terminal Procedures** which are shown in **Red**.
- Shop Queue Movement: This Procedure is used to assign respective destinations and wait-times for customer movement in the shop queue. This is done by assigning a wait-time of 1 at each step until the customer in the position ahead moves forwards, then assigning the destination as with the Join Shop-Queue procedure. This step is also responsible for the implementation of Capacity Limiting and

Sanitization if the control measures are in use, these are described in *Section 4.8.* They involve processes for the customer in the first position, such that they only enter the shop if the Capacity limit hasn't been reached and that Infectious customers have reduced contaminant spread with the use of sanitizer, which also results in an increased wait-time between customer entries.

- Shop Movement: This step describes customer movement as they pick up items in the shop. The customers will visit a number of points of interest (POIs) corresponding to the size of the shop they are there to do. A POI is selected at random from the available 6 and the customer moves between these until they have visited the required number of points before moving to join the till queue.
- Join Till-Queue: This process happens in the same manner as the Join Shop-Queue procedure without the assignment of any parameter values or any balking.
- Till Queue Movement: This process happens in the same manner as the Join Shop-Queue procedure Shop Queue Movement with customers moving along the till queue as the customer in the first position gets assigned to any available Till-Station. When one becomes available, a check-out processing time is assigned roughly proportional to the size of the shop done by the customer.
- Till Checkout: This procedure involves waiting until the checkout processing time is complete before moving to exit the shop.

The final remaining procedure is the other **Terminal Procedure** for customers, in which the customer will leave the shop. When this is initiated, all customer times are assigned to their respective global aggregates, the number of customers processed is increased, and the customer is removed from the environment.

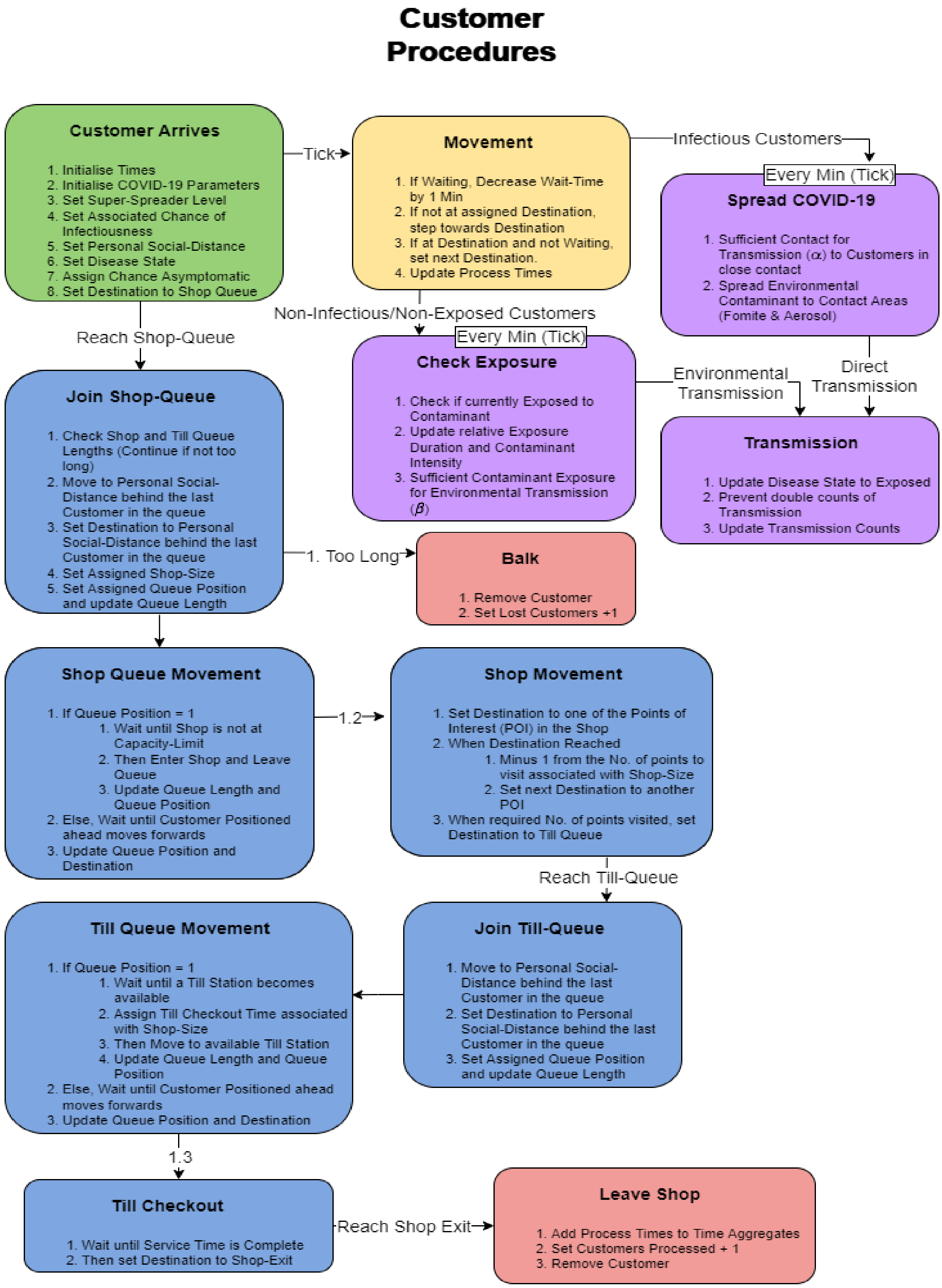

Figure 4.3: Flow Diagram showing the Sequence of Procedures for the Model Customers

4.4.3 Staff Procedures

The last set of model procedures to be described are the rules and procedures relating to Staff in the model. The initial primary setup procedure is triggered by the Environment Setup procedure described in *Section 4.4.1* above. Just as with the diagram in that section, this is shown in **Dark Green**. This procedure begins by creating the five Staff members in the model, beginning by assigning each member a home location at one of the staff houses. The staff COVID-19 parameters are then initialised as was done for the customers initialised in the staff procedures above, followed by the vaccination status of each member as determined by the *Vaccine Scenario* described in *Section 4.8*

The secondary setup procedure shown in **Lighter Green** then sets Staff locations with three members at a Till Station each and the remaining two as substitute staff at their homes. Thereafter, it sets the staff working status for each member.

The **Operational Procedure** for **Working Staff** shown in **Yellow** describes the process followed by each staff member at the till stations. It works by having staff set their tills as available until a customer arrives at their station. They then set the till to unavailable until the checkout processing time assigned to the customer is complete. At this point the procedure is responsible for the implementation of sanitization at the tills as described in *Section 4.8* when the control measure is in use at that level. If so, the staff member then removes environmental contamination on the till surfaces and allows a wait-time of 1 time-step before setting the till as available for another customer.

The **Disease-Related Transmission Procedures** are shown in **Blue** and are performed in the same way as the corresponding customer procedures in the Customer Procedures section above. This is because transmission for customers and staff members rely on the same transmission mechanisms.

The additional **Disease Procedure** for staff, shown in **Purple** and seen in the Environmental and Patch Procedures in *Section 4.4.1* above is the Progress Disease Procedure. This is as Staff members are present in the simulation environment over several days, as opposed to the few minutes a customer is present, allowing for the progression through the COVID-19 disease states. This procedure is triggered daily for any infected staff, beginning the process by increasing the disease incubation period. This then triggers the movement from the Exposed to Infectious disease states as well as the onset of symptoms for symptomatic cases at time points described in *Section 4.5* below. Any staff that develop symptoms are required to self-Isolate alongside any staff that receive a positive COVID-19 test with the implementation of *Staff COVID-19 Testing*.

When a staff member goes into *Self-Isolation* shown in **Pink**, the staff member will move to their assigned home location. If there are any available staff at home that are not self-isolating they will substitute themselves to work at the station of the staff member that began isolation. If no staff are available, the till station is set as unavailable and is left vacant until a staff member recovers at the associated incubation period in the Progress Disease procedure, thereby allowing them to return to any vacant till station to return as Working Staff.

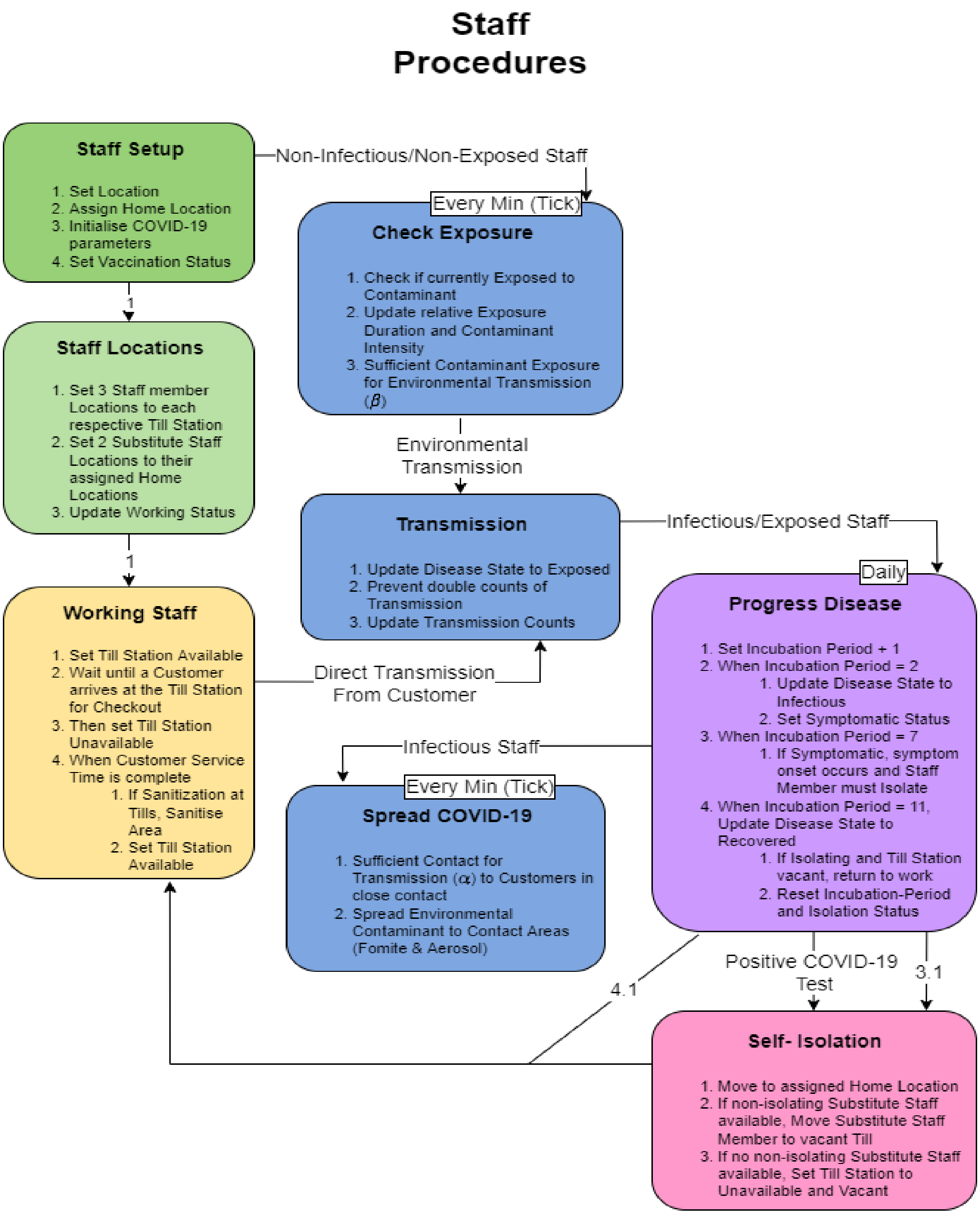

Figure 4.4: Flow Diagram showing the Sequence of Procedures for the Model Staff

4.5 Parameters of Interest

This section provides a description of the different parameters used in the Agent-Based model developed, along with the values for each parameter that are used in the Base Model specifications of the model in *Model Fitting* and *Analysis* procedures. Where possible, the sources for selected values are provided alongside the assigned values. The parameters for the model are grouped into two collections of parameters; Parameters relating to Transmission Dynamics in the model, and Parameters relating to Customer Dynamics in the model. The parameters presented in these corresponding sections are given in table format as seen in the sections below. In the interest of allowing model flexibility to changes in these parameters, the parameters for the model are made user-adjustable where possible in order for potential model users to adjust parameters to better represent the environment they aim to replicate. This can be seen as seen in *Figure 8.1* in *Appendix B, Section 8.*

4.5.1 Transmission-Related Parameters

The first group of parameters presented are the parameters relating to Transmission Dynamics in the model, these include all parameters relating to disease-state allocations, transitions between disease-states, immunity and vaccinations, and transmission chances. The presentation of the transmission-related parameters begins with the disease-state transmission durations seen in *Table 4.1* below, followed by the remaining parameters regarding disease-state allocations, immunity and vaccinations, and transmission chances in *Table 4.2* on the next page.

Parameter	Parameter Description	Base Value	Sources
Time to Infectiousness	This parameter shows the viral incubation period from Exposure at the onset of COVID-19 transmission until the infected individuals become Infectious.	2	[45]
Time to Symptom Onset	This parameter shows the viral incubation period from Exposure at the onset of COVID-19 transmission until the infected individuals become start to become symptomatic.	7	[45]
Time to Recovery	This parameter shows the viral incubation period from Exposure at the onset of COVID-19 transmission until the infected individuals recover from COVID-19 and are no longer Infectious.	11	[45]

Table 4.1: Table showing Parameter Descriptions and Values for Disease-State Transition Times in the Base Model.

Parameter	**Parameter Description**	**Base Value**	**Sources**
Partial Vaccination Coverage	This parameter represents the percentage of individuals having received at least a partial vaccination. The parameter dictates the chance of receiving at least a partial vaccination, and thus includes those who are fully vaccinated, as defined by the South African Vaccination Monitoring Dashboard.	49.0	[55]
Full Vaccination Coverage	This parameter represents the percentage of individuals having received a full vaccination.	39.8	[55]
Partial Vaccination Efficacy	This parameter represents the efficacy of having partial vaccination. The parameter dictates the chance of infection for partially vaccinated individuals given that conditions for transmission take place.	52	[43][39][53][60]
Full Vaccination Efficacy	This parameter represents the efficacy of having full vaccination. The parameter dictates the chance of infection for fully vaccinated individuals given that conditions for transmission take place.	95	[43][39][53][60]
Acquired Immunity	This parameter describes the chance of a person who has recovered from having COVID-19, preventing re-infection with the virus due to acquired immunity from COVID-19 antibodies developed.	99	[22]
Prevalence	Representative of the prevalence of COVID-19 in the system. This dictates the percentage of customers that arrive as Infectious. Values are given as a percentage.	5	Varied
Proportion Asymptomatic	This parameter dictates the proportion of arrivals and transmissions that are infectious but asymptomatic. Infected staff that are Asymptomatic do not take leave at the timepoint of symptom onset.	75	[45]
Relative Infectiousness of Asymptomatic Cases	This parameter indicates the relative infectiousness of Asymptomatic cases compared to a Symptomatic case. This parameter acts as a multiplier to reduce the chance of direct transmission as well as the infectiousness of Environmental Contamination.	80	[45]
Chance of Direct Transmission	This parameter dictates the chance of direct transmission when an Infectious individual comes into direct contact with a Susceptible individual.	5	[35]
Chance of Environmental Transmission	This parameter dictates the chance of transmission as a result of coming into contact with an area that an Infectious individual has been in contact with. It is representative of the transmission that occurs due to fomites or airborne particles.	1.5+-0.2	[46]
Dissipation Rate	This parameter dictates the rate of exponential decay for environmental contaminants. The contaminant count for an area decreases exponentially at the given rates with rates indicating the decay per minute. Rates are given as a percentage.	1.5	[82]
Super-Spreader Distribution	This parameter dictates the relative proportions of individuals classified into five degrees of intensity of Super-Spreader behaviour. Individuals with a higher degree of Super-Spreader intensity are likely to have more daily contacts and less likely to comply with intervention protocols.	(50, 30, 10, 5, 5)	[40]
Super-Spreader likelihood of Infectiousness	This parameter dictates the relative chance of being Infectious for each Super-Spreader intensity level. Individuals with higher Super-Spreader intensity are more likely to be infectious due to higher contact rates. These parameter levels are calculated with respect to the given prevalence level to ensure system prevalence remains constant.	Prevalence * (SS-level*0.5405)	Calculated

Table 4.2: Table showing Parameter Descriptions and Values for all Disease-Related Parameters in the Base Model

4.5.2 Customer Dynamics Related Parameters

The second group of parameters presented are the parameters relating to Customer Dynamics in the model, these include all parameters relating to processing times, consumer behaviours, customer arrivals, and shopper proportions. Some of the values presented were derived from surveys on customer dynamics in the COVID-19 pandemic which were filled out by store managers for small urban supermarket chain stores in Kenilworth, Cape Town, South Africa. These surveys can be found in *Figures 7.35 and 7.36* in *Appendix A, Section 7.*

Parameter	**Parameter Description**	**Base Value**	**Sources**
Till Service Speed	The speed at which customers are processed at one of till service points. Service speeds vary according to the shop-size of the customer. Service speeds are drawn from a poison distribution with a mean of (shop-size x value).	3	[62]
Step Size	The customer step size governs the movement speed of the customer in the shop. Smaller steps result in slower customer movement, and hence longer shop times.	35	Fitting
Shop Size Ratio	This parameter set dictates the ratio of customers allocated to the small, medium, and large shop-size groups respectively. This may also indicate how applicable the model may be to different shopping environments. Given as percentages (S, M, L).	(70, 20, 10)	[62]
Shop Points of Interest Visited	This parameter set dictates the number of points of interest visited/items collected in the shop products sections for the customers allocated to the small, medium, and large shop-size groups respectively. This may also indicate how applicable the model may be to different shopping environments.	(1, 2, 4)	Fitting
Shopping Periods	This parameter dictates the five time periods during the day that correspond to marked changes in the number of customers that visit the shop in a given period.	07:00-12:00, 12:00-14:00, 14:00-17:00, 17:00-19:00, 19:00-20:00	[62]
Inter-Arrival Times	This parameter indicates the inter-arrival time between each customer's arrival at each of the five time periods indicated above. The inter-arrival time is drawn from a poison distribution with a mean of the value indicated with values given in minutes.	4, 2, 3, 1, ∞	Fitting

Table 4.3: Table showing Parameter Descriptions and Values for Parameters Relating to Customer Dynamics in the Base Model.

4.6 Model Verification and Validation

The process of model fitting for simulation based modelling techniques is focused on the use of:

- **Model Verification**: to assess the associated rules and behaviours of the simulation, ensuring that model dynamics are executed as expected.
- **Model Validation**: to assess the macro-level simulation dynamics, ensuring that model processes perform with outcomes at realistic levels.

The combination of model verification and validation is used to ensure that the simulation can effectively replicate an approximation of the dynamics present in the system it aims to represent.

4.6.1 Simulation Verification

The process of model verification is aimed at assessing the specified micro-level rules and behaviours in the simulation. Model verification is performed by first, observing agent behaviour in the simulated environment as the agent progresses through each stage of the system; this is then extended in the model validation, by adjusting model parameters and comparing changes in macro-level behaviour to the expected system changes in the real-world environment.

Observed System Dynamics

System dynamics are assessed by following a single agent at different stages of a running simulation to ensure specified behaviours are executed as expected. The behaviours verified are described in *Tables 4.4 and 4.5* below.

Simulation Element	**Specified Behaviour**	**Verified**
Shop Queue	Upon arrival, when an agent reaches the shop queue, the agent will join the queue behind the last agent in the queue. The agent at the front of the queue will enter the shop after a specified wait time as long as the store has not reached maximum capacity. Thereafter, other agents in the queue will move forward by one position. An agent will Balk from the system if the queues are longer than a specified length.	Yes
Shop Movement	Upon entering the shop, each agent will visit the specified number of points in the shop depending on their assigned shop size. After visiting the assigned number of points, the agent moves to the shop tills to join the till queue.	Yes
Till Queue	Upon arrival at the till queue, the agent will join the queue behind the last agent in the queue. If one of the till service points is unoccupied, the agent at the front of the queue will move to one of the available service points. Thereafter, other agents in the queue will move forward by one position. If all service points are occupied, the agents in the queue will wait until one becomes available.	Yes
Till Service	On arrival at a till service point, the agent will wait for a servicing time, dependent on the agent's shop size. Thereafter, the agent moves to the shop exit and is removed from the simulation.	Yes
Environmental Contamination	Any infectious agents in the system leave an area of viral contamination around each point of contact as they move through the environment. The environmental contamination then begins to decay at a specified exponential rate until there is no longer a risk of transmission at that point.	Yes
Environmental Transmission	When a receptive agent comes into contact with a contaminated area, the agent becomes exposed according to a specified transmission chance. The chance of transmission increases according to both the level of contamination in the area, as well as the duration of contact with the area.	Yes
Contact Transmission	When a receptive agent comes into direct contact with an infectious agent, they become exposed according to the specified chance of direct transmission, accounting for immunity.	Yes

Table 4.4: Table showing the Verification and Demonstration of Assigned Behaviors

Simulation Element	**Specified Behaviour**	**Verified**
Asymptomatic Transmission	The relative infectiousness of an asymptomatic infectious individual is around 80% of that shown for symptomatic infectious individuals. Around three-quarters of the infectious individuals show noticeably lower levels of environmental contaminant distributed at each point of contact in the environment.	Yes
Staff Self-Isolation	When a staff member becomes infected with COVID-19, about one-quarter of these individuals move to their assigned homes at an incubation period of 7 days. These individuals are replaced by one of the substitute staff members that was positioned at their home. If no substitute staff members are available, the till station remains unoccupied and customers no longer make use of the station.	Yes
COVID-19 Recovery	When 11 days have passed since a staff member is infected with COVID-19, they transition to the Recovered disease-state and turn grey in colour. If there are any unoccupied till stations in the shop, the recovered staff member moves to that till station and customers begin using it for checkouts.	Yes

Table 4.5: Table showing the Verification and Demonstration of Assigned Behaviors Cont.

4.6.2 Simulation Validation

The process of model validation is aimed at assessing the specified macro-level outcomes and behaviours in the simulation. Model validation is performed by simulating for a period of time and comparing system dynamic outcomes to the expected dynamic values in the real-world environment. The process begins by expanding on the observed verification behaviours, evaluating the presence of expected system changes resulting from changes in model parameters.

Observed Changes in System Dynamics

Changes in the system dynamics are assessed by varying model parameters and comparing the resulting changes in simulation dynamics to changes that would be expected in a real-world environment. The effects of changes in dynamics are assessed with respect to the changes in behaviour dynamics, as well as transmission dynamics. Behaviour dynamics are assessed with respect to the following outcomes:

Customer Behaviour Dynamics Outcomes

Behaviour dynamics are assessed with respect to the following outcomes:

The number of customers:

- Average No. of customers per day
- Average No. of customers per day doing a small sized, quick shop
- Average No. of customers per day doing a medium sized shop
- Average No. of customers per day doing a large shop
- Total No. of customers lost due to balking

The customer times:

- Average total shop time per customer: Overall average time for all customers and averages for customers grouped by each shop-size. Measured from entry into the shop until exit.
- Average shop queue time per customer: Overall average time for all customers and averages for customers grouped by each shop-size.
- Average till queue time per customer: Overall average time for all customers and averages for customers grouped by each shop-size.

Transmission Dynamics Outcomes

Transmission dynamics are assessed with respect to the following outcomes: Transmission counts

- Total number of transmissions that take place in the supermarket environment
- Total number of environmental transmissions, through surface-to-person (fomite) and aerosol transmission
- Total number of direct contact transmissions
- Total number of staff transmissions
- Total number of transmissions at each store location: shop queue, shop aisles, till queue, and tills
- Total number of infectious customers that arrive to the shop
- Total number of susceptible customers that arrive to the shop
- Total number of (receptive) arrivals that can become exposed: susceptible and vaccinated customers

Transmission Ratios

- Total Transmissions : Infectious Arrivals
- Total Transmissions : Susceptible Arrivals
- Total Transmissions : Receptive Arrivals

The initial assessment of model validation procedures is be seen by the validation of expected changes in model outcomes resulting from changes in parameter values seen in *Table 4.6.2* on the next page.

Simulation Change	**Expected Customer Dynamic Change**	**Verified**	**Expected Transmission Dynamic Change**	**Verified**
Increased Movement Speed (Step-Size)	Decreased Shop Time Similar Shop Queue Times Longer Till Queue Time	Yes	Decreased Shopping Trans. Increased Till Queue Trans.	Yes
Increased Shop Queue Wait Time	Increased Shop Queue Time Decreased Till Queue Time Increased balking	Yes	Increased Shop Queue Trans. Decreased Other Trans.	Yes
Increased Till Service Time	Increased Till Queue Time Increased Shop Time Increased balking	Yes	Increased Till Queue Trans. Increased Total Trans.	Yes
Increased Proportion of smaller shop size	Increased Till Queue Time for larger shop sizes. Decreased Till Queue Time for smaller shop sizes Increased Shop Time for larger shop sizes Decreased Shop Time for small shop sizes Decreased balking	Yes	Decreased Total Trans.	Yes
Increased Inter-arrival Times	Fewer Total Shoppers per day Decreased Till Queue Time Decreased Shop Time Decreased balking	Yes	Decreased Total Trans. Decreased Till Queue Trans. Decreased Shop Queue Trans.	Yes
Increased Prevalence	No change	Yes	Increased Total Trans. Decreased Trans.: Infectious	Yes
Increased Transmission Chance	No change	Yes	Increased Total Trans. Increased Trans.:Infectious	Yes
Increased Vaccine Coverage	No change	Yes	Decreased Total Trans. Decreased Trans.:Infectious	Yes
Prevent Staff Infection	No change	Yes	Decreased Total Trans. Decreased Trans.:Infectious	Yes

Table 4.6: Table showing the Relative Changes in Simulation Model Outcomes Resulting from Adjustments in Model Inputs

Further means of validation are provided by observing whether the model outcomes, relating to information gathered in the Shop Surveys conducted at local urban supermarkets, fall within the expected ranges provided by store managers. Copies of these surveys can be seen in *Figures 7.35 and 7.36* in *Appendix A, Section 7.3.*

The two main outcomes that can be validated are the Average Proportions of Customers with each associated shop-size that visited the shop, and the average customer shopping times observed (which can also be viewed with customers grouped by shop-size. These can be seen along with the **values indicated by managers given as vertical lines** in *Figures 4.5 and 4.6* below.

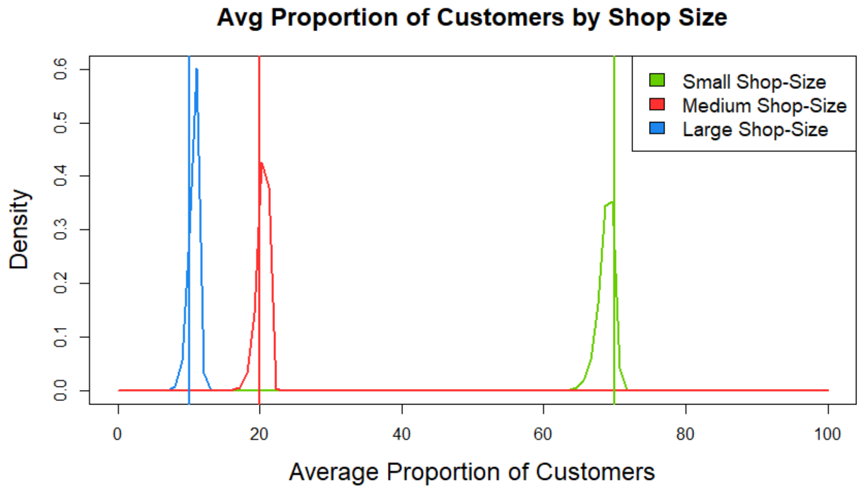

Figure 4.5: Fitted Distributions representing Distributions of the Proportion of Customers Assigned to each Shop-Size Group

Looking at *Figure 4.5* above, there appears to be a slight skewness in shop-size groups towards a central mean when looking at the relative proportions of customers in each shop-size group. However, the values indicated by store managers fall comfortably within each distribution shown.

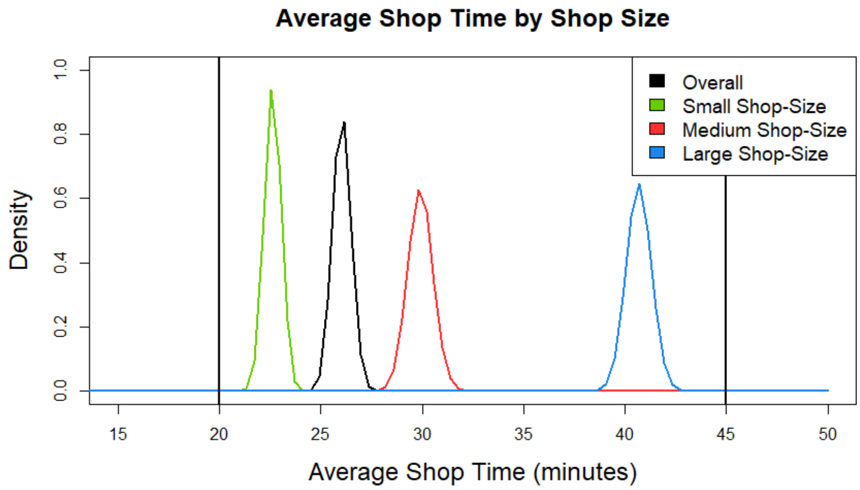

Figure 4.6: Fitted Distributions of the Average Shopping Times Shown by Customers in each Shop-Size Group

Looking at *Figure 4.6* above, the average shopping time per customer falls comfortably and entirely within the range specified by managers. This can be seen not only for the overall customer average (shown in black) but for all of the customer shop-size groups as well. These figures indicate further positive validation of model performance.

4.6.3 Simulation Sensitivity Analysis

Another fundamental component in the model fitting procedures used for simulation-based modelling techniques is the use of a Sensitivity analysis conducted on the model. The interpretation of model outcomes and the corresponding reliability one can place on the outcomes observed is largely dependent on the validity of the model's assumptions, methods, and parameter selection

The credibility or interpretation of the results of clinical trials relies on the validity of the methods of analysis or models used and their corresponding assumptions about the parameter selections for the model[80]. The purpose of conducting a sensitivity analysis on the developed model is primarily to ensure that the results and outcomes produced by the model do not depend heavily on parameter values with low confidence.

The sensitivity analysis for the Agent-Based model developed in this analysis involves a two-part implementation strategy. The first part constitutes of an initial **Univariate Sensitivity Analysis** in which each of the model's parameter inputs are independently varied across the range of their respective 95% confidence intervals reported in the sources from which they originate with all other parameter values staying fixed at their assigned *Base Values*. Each combination of input values is simulated for a period of two weeks (14 days) 30 times each and recording the values for model outcome metrics for each of these runs. This enables the model to produce, not only an estimate for the value of the outcome metric under each combination of parameters, but also a measure of the uncertainty around the outcome value observed by seeing the distribution of the values it takes over each run. This allows interpretation of results to factor for the inclusion of random effects.

The isolated univariate sensitivity of the observed model outcomes and effects can then be assessed with respect to their sensitivity to changes in each of the model parameters in order to determine the model parameters that the model outcomes are the most sensitive to. The identification of the model's most sensitive parameters is then used for the second part of the sensitivity analysis strategy, which constitutes of a **Multivariate Sensitivity Analysis** of the model's most sensitive parameters. The Multivariate Sensitivity Analysis is similar to the Univariate Sensitivity Analysis in the way that each combination of input values is simulated for a period of two weeks (14 days) 30 times each and recording the values for model outcome metrics for each of these runs provides a distribution of values that the outcome metric can take. The difference between the two approaches is that the Multivariate approach allows each selected parameter to have its values varied against every single combination of the values for all the other parameters considered.

Computational Considerations

With this in mind, it becomes important to take note of the computational processing requirements that conducting this analysis will require. As each combination of values is simulated 30 times for a simulation period of 14 days, the required number of runs that needs to be simulated will be thirty times the number of possible value combinations. A single run of the Base Model at maximum speed for this period takes around 15 minutes using the personal computer used for this analysis, which has 8 intel i7 processing cores and 20 gigabits of RAM. Fortunately, NetLogo has a Behaviourspace Tool to conduct simulation runs in parallel to one another, the number of which is limited to the number of processing cores available. Unfortunately due to access restrictions imposed due to COVID-19, access could not be granted for the use of Faculty labs computers for simulation leaving the sole use of the available personal computer to conduct analysis.

Provided the perspective of processing resources available, it is important to limit both the number of parameters as well as the range of values tested for the Multivariate Sensitivity Analysis, as the number of required runs increases by a factor of the number of values tested with the inclusion of each new parameter.

Due to the number of combinations that will be compared, the comparison of each combination with respect to model sensitivity is confined to the use of the following outcome measures:

Transmission Dynamics are measured using:

- Total No. of Transmissions that take place in the environment
- The Ratio of the Total No. of Transmissions : No. of Infectious Customers that Arrive at the shop

Customer Dynamics are measured using:

- Average No. of Customers that visit the shop per day
- Average Total Shopping Time per customer (min)
- The Ratio of Total No. of Customers Lost : Total No. of Customers Processed

Univariate Sensitivity Analysis

The parameters that are varied for the initial Univariate Sensitivity Analysis, along with their respective descriptions and the range of values assessed for each parameter is shown in *Table 4.7* on the page below.

Parameter	Parameter Description	Values Used	Base Value
Till Service Speed	The speed at which customers are processed at one of till service points. Service speeds vary according to the shop-size of the customer. Service speeds are drawn from a poison distribution with a mean of (shop-size x value).	2, 3, 4	3
Step Size	The customer step size governs the movement speed of the customer in the shop. Smaller steps result in slower customer movement, and hence longer shop times.	20, 35, 50	35
Shop Size Ratio	This parameter set dictates the ratio of customers allocated to the small, medium, and large shop-size groups respectively. This may also indicate how applicable the model may be to different shopping environments. Given as percentages (S, M, L).	(50, 20, 30), (70, 20, 10), (85, 10, 5)	(70, 20, 10)
Prevalence	Representative of the prevalence of COVID-19 in the system. This dictates the percentage of customers that arrive as Infectious. Values are given as a percentage. Note that target population prevalence may frequently exceed observed national prevalence levels.	2, 5, 10	5
Proportion Asymptomatic	This parameter dictates the proportion of arrivals and transmissions that are infectious but asymptomatic. Infected staff that are Asymptomatic do not take leave at the timepoint of symptom onset.	70, 75, 80	75
Relative Infectiousness of Asymptomatic Cases	This parameter indicates the relative infectiousness of Asymptomatic cases compared to a Symptomatic case. This parameter acts as a multiplier to reduce the chance of direct transmission as well as the infectiousness of Environmental Contamination dispersed.	77.5, 80, 82.5	80
Chance of Direct Transmission	This parameter dictates the chance of direct transmission when an Infectious individual comes into direct contact with a Susceptible individual.	2, 5, 10	5
Chance of Environmental Transmission	This parameter dictates the chance of transmission as a result of coming into contact with an area that an Infectious individual has been in contact with. It is representative of the transmission that occurs due to fomites or airborne particles.	1.3, 1.5, 1.7	1.5
Dissipation Rate	This parameter dictates the rate of exponential decay for environmental contaminants. The contaminant count for an area decreases exponentially at the given rates with rates indicating the decay per minute. Rates are given as a percentage.	0.5, 1.5, 2.5	1.5
Partial Vaccination Efficacy	This parameter represents the efficacy of having partial vaccination. The parameter dictates the chance of infection for partially vaccinated individuals given that conditions for transmission take place.	30, 52, 67	52
Full Vaccination Efficacy	This parameter represents the efficacy of having full vaccination. The parameter dictates the chance of infection for fully vaccinated individuals given that conditions for transmission take place.	90, 95, 98	95

Table 4.7: Table showing the Parameters Varied for Conducting the Univariate Sensitivity Analysis of the Base Model

Due to the large quantity of data that is observed in a sensitivity analysis procedure, it has been suggested by the Cochrane Training Handbook that sensitivity analysis outcomes should be interpreted through the use of key bullet points or summary tables[14]. Therefore the approach of providing a few key summary points for each metric will be used. The plots shown in this section will consist of two sets of box-plots with the left-hand set representing outcome measure values with the varied parameter set to its lower bounded value and the right-hand set of plots representing the outcome values with parameters set to their respective upper bound values. These can be compared to the Base Model outcome values with the parameter set to its Base Value by comparing to the first box-plot in each/either set, both of which should be the same distribution of values. Beginning by assessing the total number of transmissions sensitivity to changes in model parameters seen in *Figure 4.7* below.

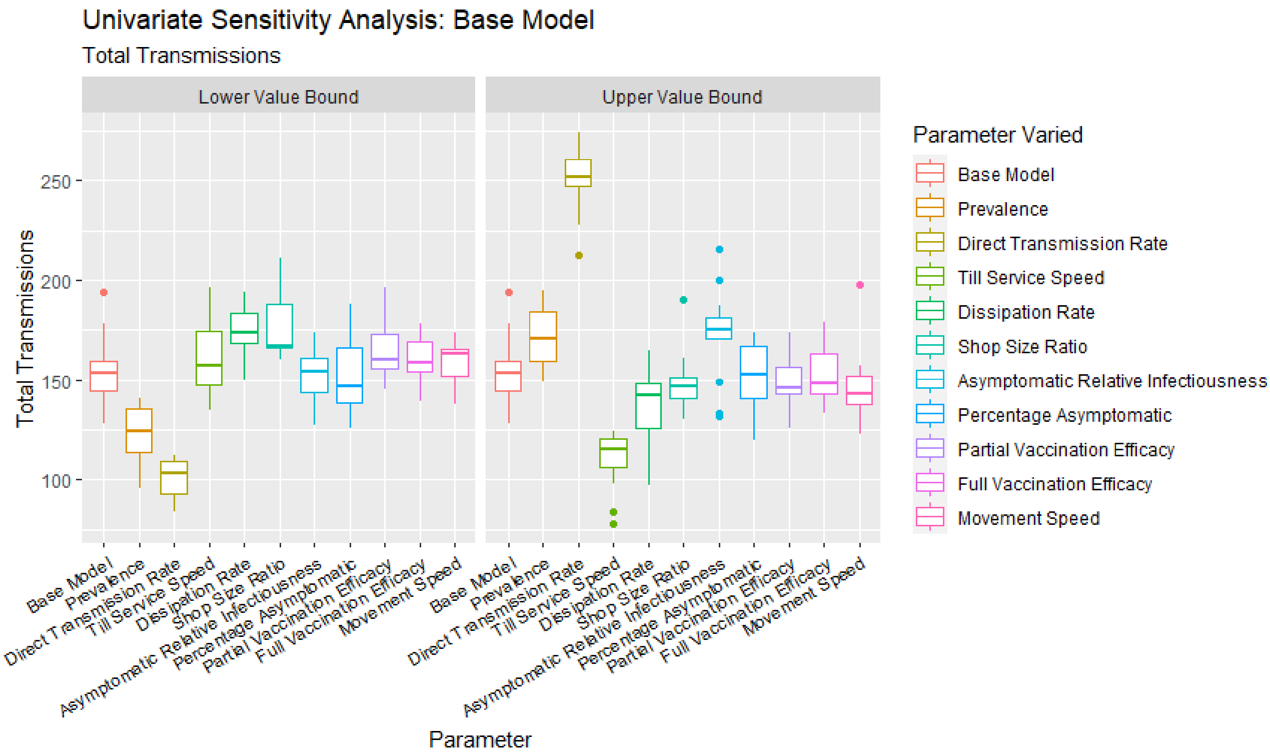

Figure 4.7: Box-plots showing the Change in the Total Number of Transmissions resulting from Changes in Model Parameters

The total number of transmissions observed showed the following in respect to its sensitivity to changes in model parameters:

- The outcome appears to be most sensitive to the changes in the chance of Direct Transmission, followed by prevalence, till service speed(time), dissipation rate, and shop-size ratios.
- Does not appear to be sensitive to changes in the relative infectiousness of asymptomatic cases, the percentage of asymptomatic cases, vaccine efficacy levels, or movement speed (step size)
- Total transmission counts are positively correlated with prevalence and Direct Transmission Chance, and negatively correlated with till service speed(time), dissipation rate, and shop-size ratios (value as proportion of small shop size).
- Important to note prevalence change also allows for more infectious individuals and therefore more opportunities for transmission, should compare to the plots of the ratio of transmission to the number of infectious customers.

Changes in the distribution of total transmission with respect to changes in model parameters can be seen more clearly for more sensitive and less sensitive parameters in *Figures 9.1 and 9.2* in *Appendix C, Section 9.*

The analysis of Transmission Dynamics measuring sensitivity to univariate changes in model parameters continues by assessing the ratio of total number of transmissions to infectious customer arrivals and its sensitivity to changes in model parameters seen in *Figure 4.8* below.

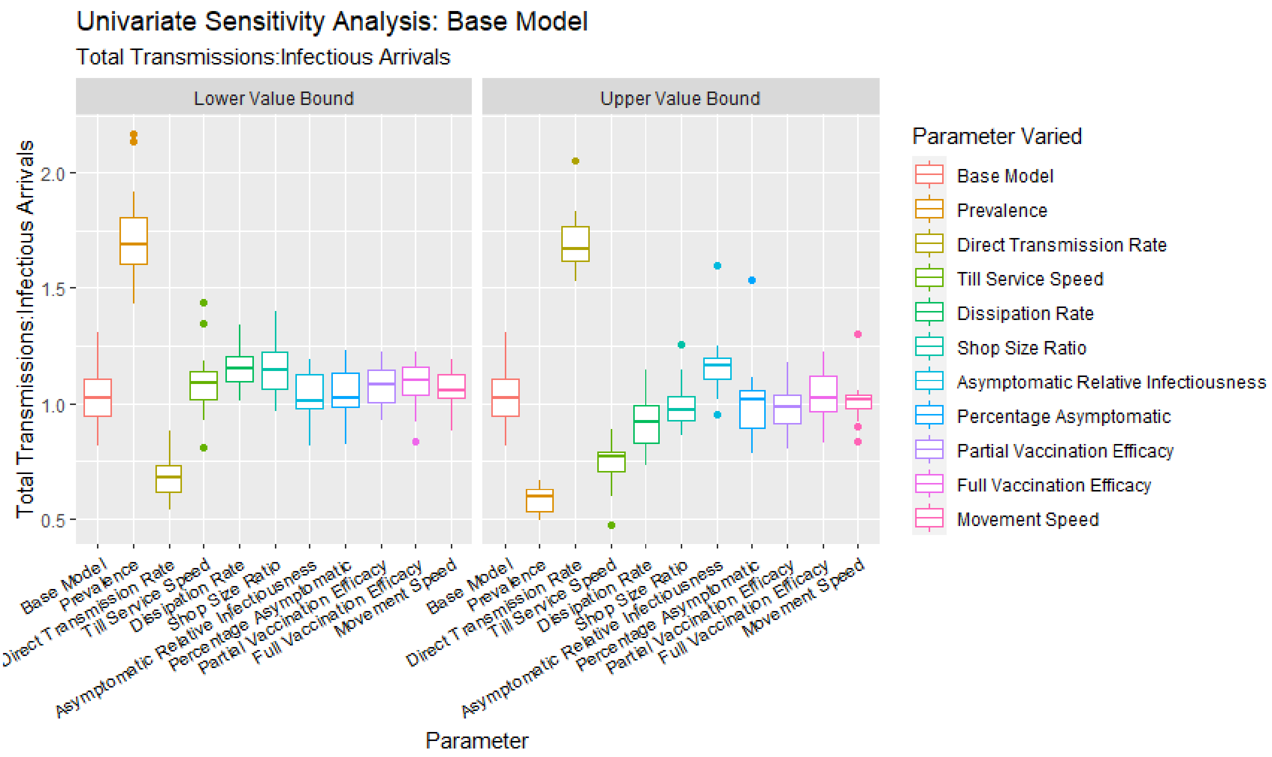

Figure 4.8: Box-plots showing the Change in the Ratio of Total Transmissions to Infectious Customer Arrivals resulting from Changes in Model Parameters

The Ratio of Total Transmissions to Infectious Customer Arrivals observed showed the following in respect to its sensitivity to changes in model parameters:

- The outcome appears to be most sensitive to the changes in the prevalence as opposed to the chance of Direct Transmission as seen above, this is followed by till service speed(time) with no other considerably sensitive parameters shown.
- Prevalence now appears to show a negative correlation, indicating an increase in transmissions, but not as large at the proportional increase in Infectious arrivals.

Changes in the distribution of the Ratio of Total Transmissions : Infectious Customer Arrivals with respect to changes in model parameters can be seen more clearly for more sensitive and less sensitive parameters in Distribution plots in *Figures 9.3 and 9.4* in *Appendix C, Section 9.*

The sensitivity analysis now looks at changes in customer dynamics, through measuring sensitivity to univariate changes in model parameters starting by assessing the sensitivity of the Average number of Customers per Day to changes in model parameters seen in *Figure 4.9* below.

The Average number of Customers per Day observed showed the following in respect to its sensitivity to changes in model parameters:

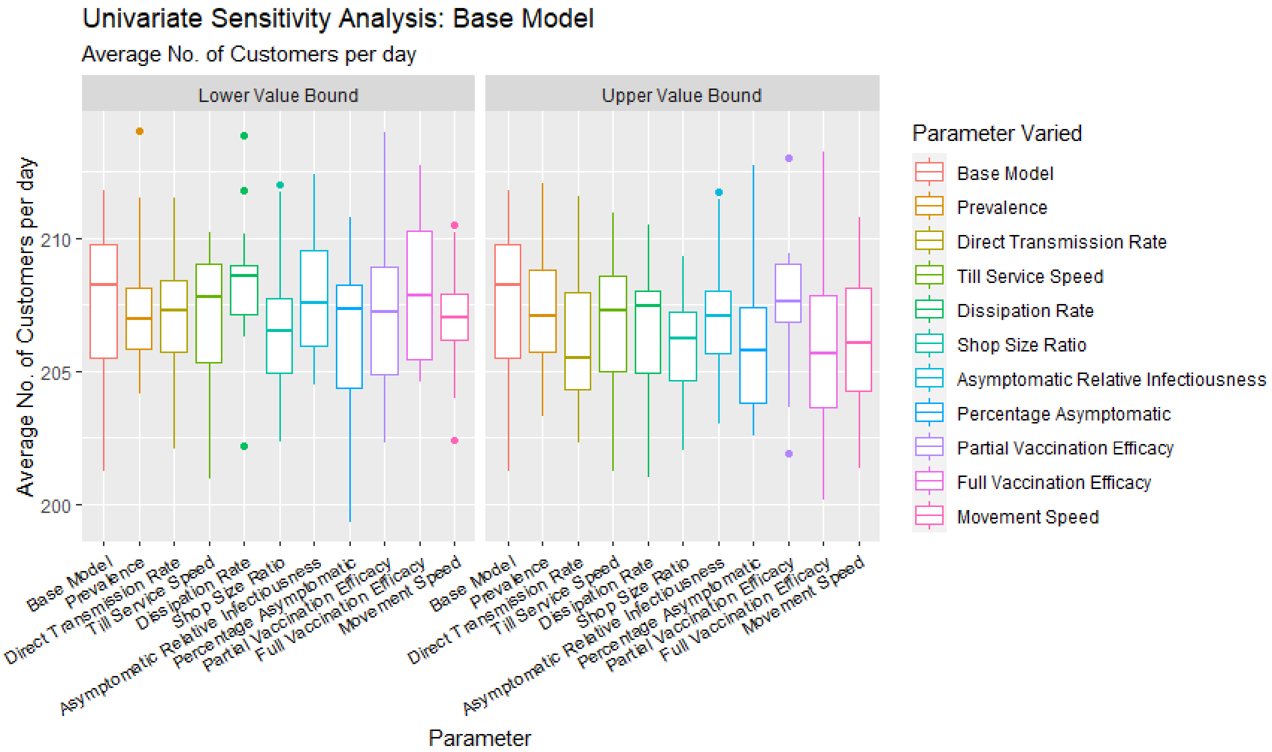

Figure 4.9: Box-plots showing the Change in the Average number of Customers per Day resulting from Changes in Model Parameters

- The Average number of Customers per Day does not appear to be sensitive to any of the given model parameters.

This is seen again in the Distribution plots in *Figures 9.7 and 9.8* in *Appendix C, Section 9.*

The next model outcome measure that is an important evaluation of customer dynamics in the model is the Average Customer Shopping Time. The sensitivity of this measure to changes in model parameters can be seen in *Figure 4.10* below.

The Average Customer Shopping Time (min) observed showed the following with respect to its sensitivity to changes in model parameters:

- The Average Customer Shopping Time appears to be most sensitive to changes in Customer movement speed, governed by changes in step-size, this is followed by a similar level of sensitivity to the proportion of customers assigned to each shop-size group and till service speed (time). The measure appears to be negatively correlated with all three of these parameter values.
- The Average Customer Shopping Time does not appear sensitive to any other model parameters.

This can be seen clearly in the Distribution plots in *Figures 9.5 and 9.6* in *Appendix C, Section 9.*

The final important model outcome measure for the evaluation of customer dynamics in the model is the ratio of Customers Lost:Customers Processed. The sensitivity of this measure to changes in model parameters can be seen in *Figure 4.11* below.

The ratio of Customers Lost:Customers Processed observed showed the following with respect to its sensitivity to changes in model parameters:

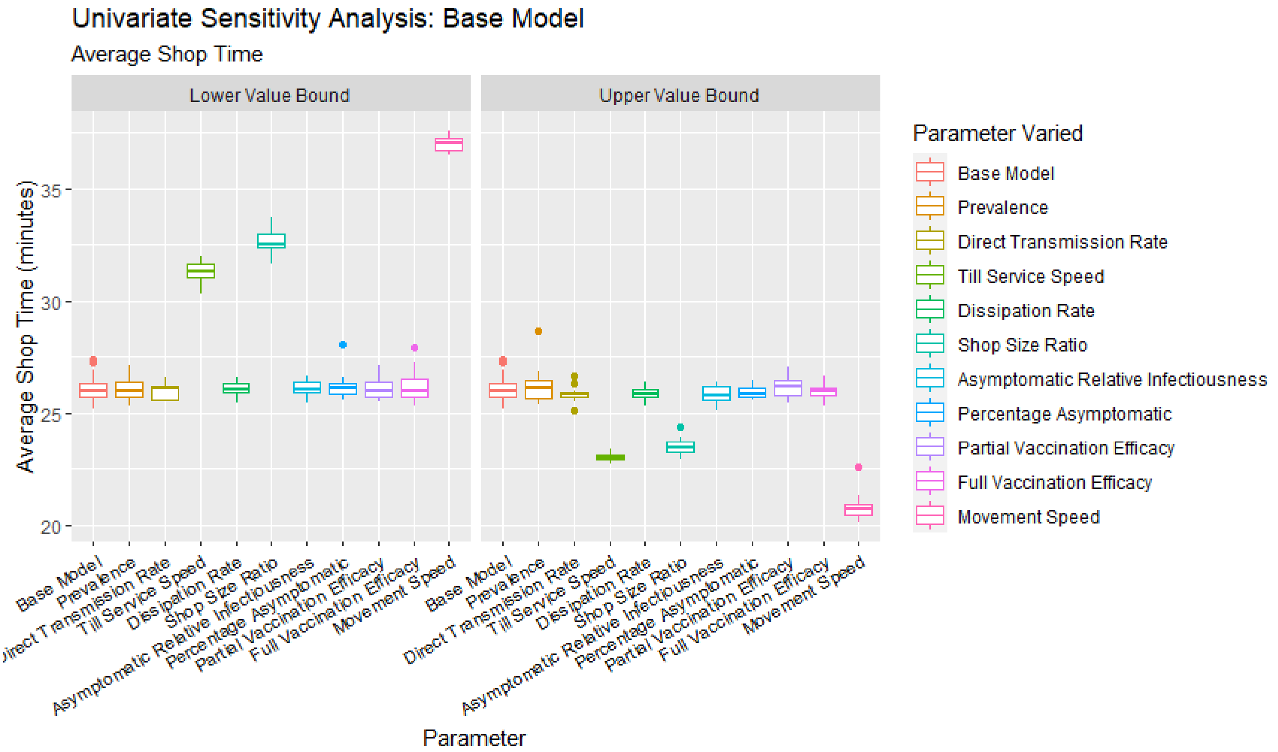

Figure 4.10: Box-plots showing the Change in the Average Customer Shopping Time (min) resulting from Changes in Model Parameters

- The ratio of Customers Lost:Customers Processed appears to be most sensitive to changes in Customer till service speed (time), this is followed by a lesser level of sensitivity to the proportion of customers assigned to each shop-size group and till service speed (time). The measure appears to be negatively correlated with both of these parameter values and only appears sensitive at lower parameter values.
- The ratio of Customers Lost:Customers Processed does not appear sensitive to any other model parameters.

This lack of sensitivity can be seen clearly in the Distribution plots in *Figures 9.9 and 9.10* in *Appendix C, Section 9*.

After looking at the various levels of model outcomes to variation of each of the model parameters in the figures above, the four parameters that the model is most sensitive to are:

- Prevalence
- Direct Transmission Chance
- Till Service Speed (Customer service times)
- Contaminant dissipation rate

These four parameters are retained for use and implementation of the Multivariate Sensitivity Analysis below, they are varied over the same three values seen in the Univariate Sensitivity Analysis with an allowance for varying parameters against differing values for the remaining three parameters.

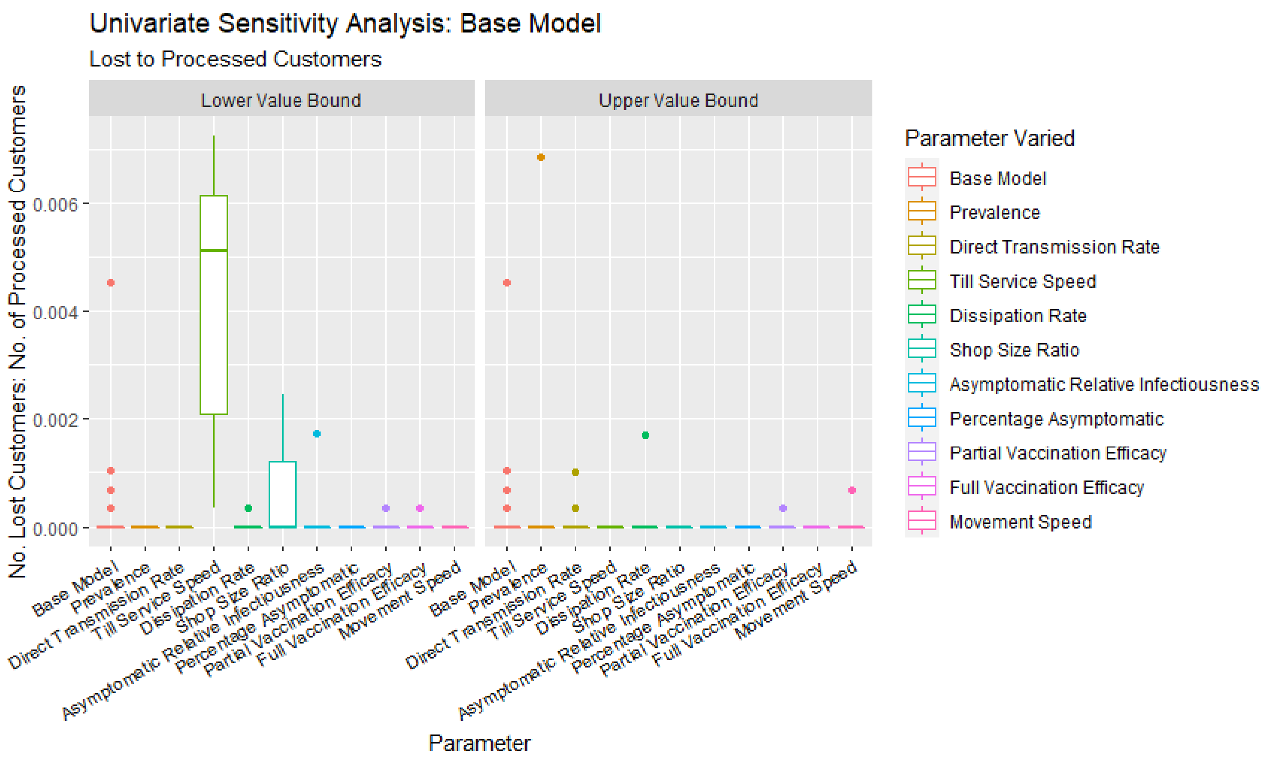

Figure 4.11: Box-plots showing the Change in the ratio of Customers Lost:Customers Processed resulting from Changes in Model Parameters

Multivariate Sensitivity Analysis

As described above, the second part of the sensitivity analysis involves the measurement of outcome measures for the model at every possible combination of the three value levels for the four model parameters selected in the univariate sensitivity analysis above.

The measurement of model outcomes with combined variations in model parameters allows for more significant variation in the outcome measures changes experienced. This is as a result of the interaction effects that take place between the proposed parameters. For example, the parameters regarding the proportion of cases that are asymptomatic and the relative infectiousness of asymptomatic cases would exhibit high levels of interaction effects. Following the example, an increase in the proportion of cases that are asymptomatic combined with a large decrease in the relative infectiousness of asymptomatic cases would result in considerable decreases in the transmission dynamics of the system.

The plots produced in this section are interpreted as follows:

- The time it takes for staff to process customers (Till Service Speed) is indicated by the colour of the box in the plot.
- The dissipation rate of environmental contaminant is given by plot groupings along the x-axis for each plot facet displayed.
- The varied levels of prevalence are indicated by the facet rows, with the lowest prevalence in the top row.
- The varied chances of Direct Transmission are indicated by the facet columns, with the lowest transmission chance seen in the left-most column.

Following the cochrane proposed presentation of sensitivity analysis results used for the Univariate Sensitivity Analysis Above, the presentation of results for model transmission dynamics sensitivity begins by looking at the sensitivity of the total number of transmissions to changes in model parameters seen in *Figure 4.12* below.

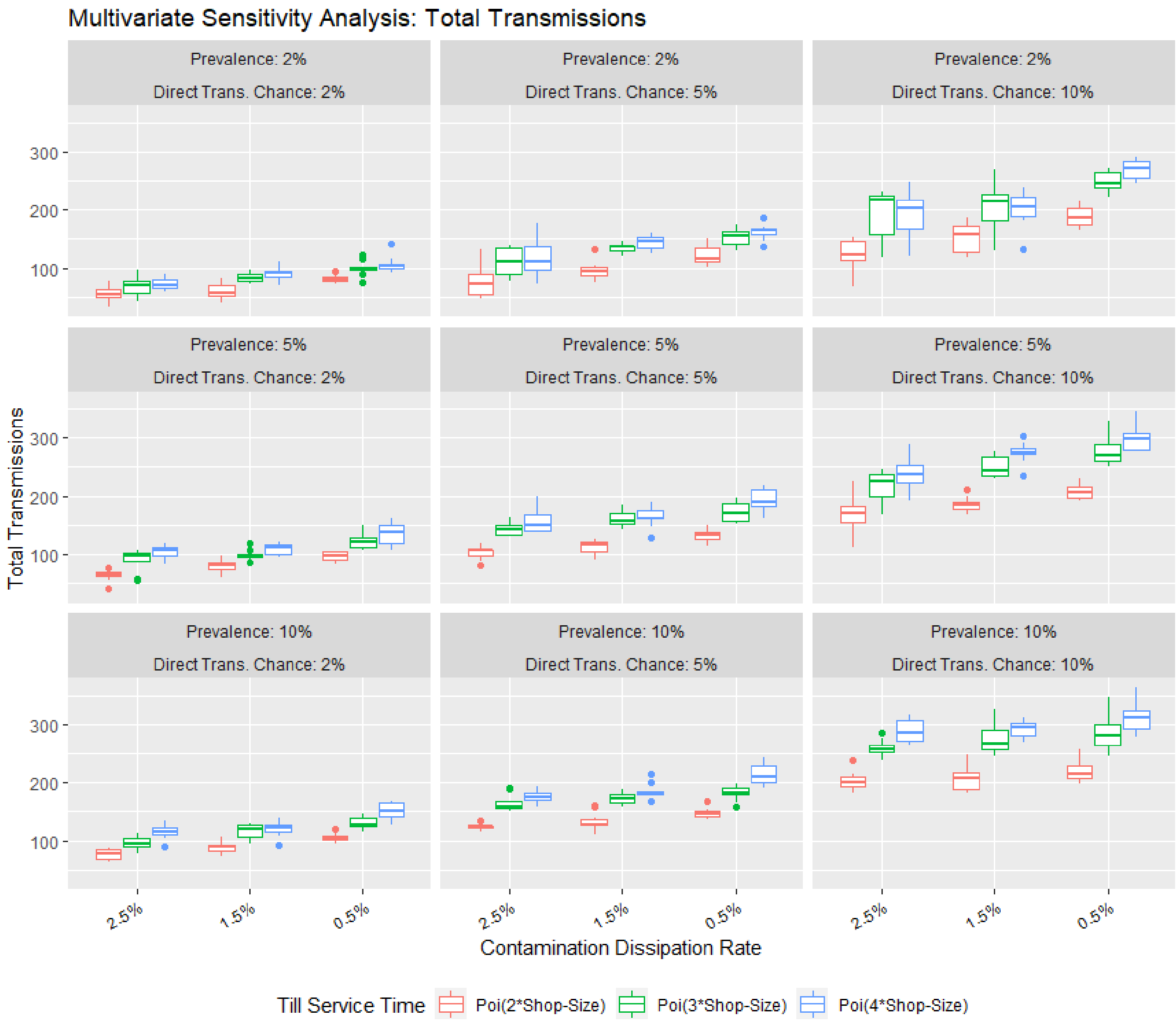

Figure 4.12: Box-plots showing the Change in the Total Number of Transmissions resulting from Multivariate Changes in Model Parameters

The total number of transmissions observed showed the following in respect to its sensitivity to the multivariate changes in model parameters considered:

- The number of transmissions with respect to changes in dissipation rate appears to have little interaction effects with other selected parameters, showing similar transmission count increases among the different groupings.
- Although changes of prevalence correlate with changes in the total number of transmissions, this increase is not close to the increases in total transmissions shown by the change in the chances of direct transmission.

- Total transmission counts appear to show the highest sensitivity to changes in chances of direct transmission as seen by the univariate analysis above.
- Most interactions and effects regarding variation of parameters appear to be additive, with no clear multiplicative effects shown.
- Some evidence of a mildly multiplicative interaction can be seen between the till service speed and chances of direct transmission. This is indicated by the increasing changes between box-plots for varied till service time as the chance of direct transmission increases.
- There is a large variation in the possible range of values for the total transmissions count that could be observed across the possible ranges of the selected parameters, ranging from lows of around 50 transmissions given a 2% prevalence and direct transmission chance, 2.5% dissipation rate, and Poi(2*x) till service speed (time); to a transmission count over 300 given a 10% prevalence and direct transmission chance, 0.5% dissipation rate, and Poi(4*x) till service speed (time) on the other end of the value ranges.

To gain better insight into the way prevalence interactions occur, transmission dynamics are examined further by assessing the sensitivity of the ratio of total number of transmissions to infectious customer arrivals to changes in model parameters seen in *Figure 4.13* below.

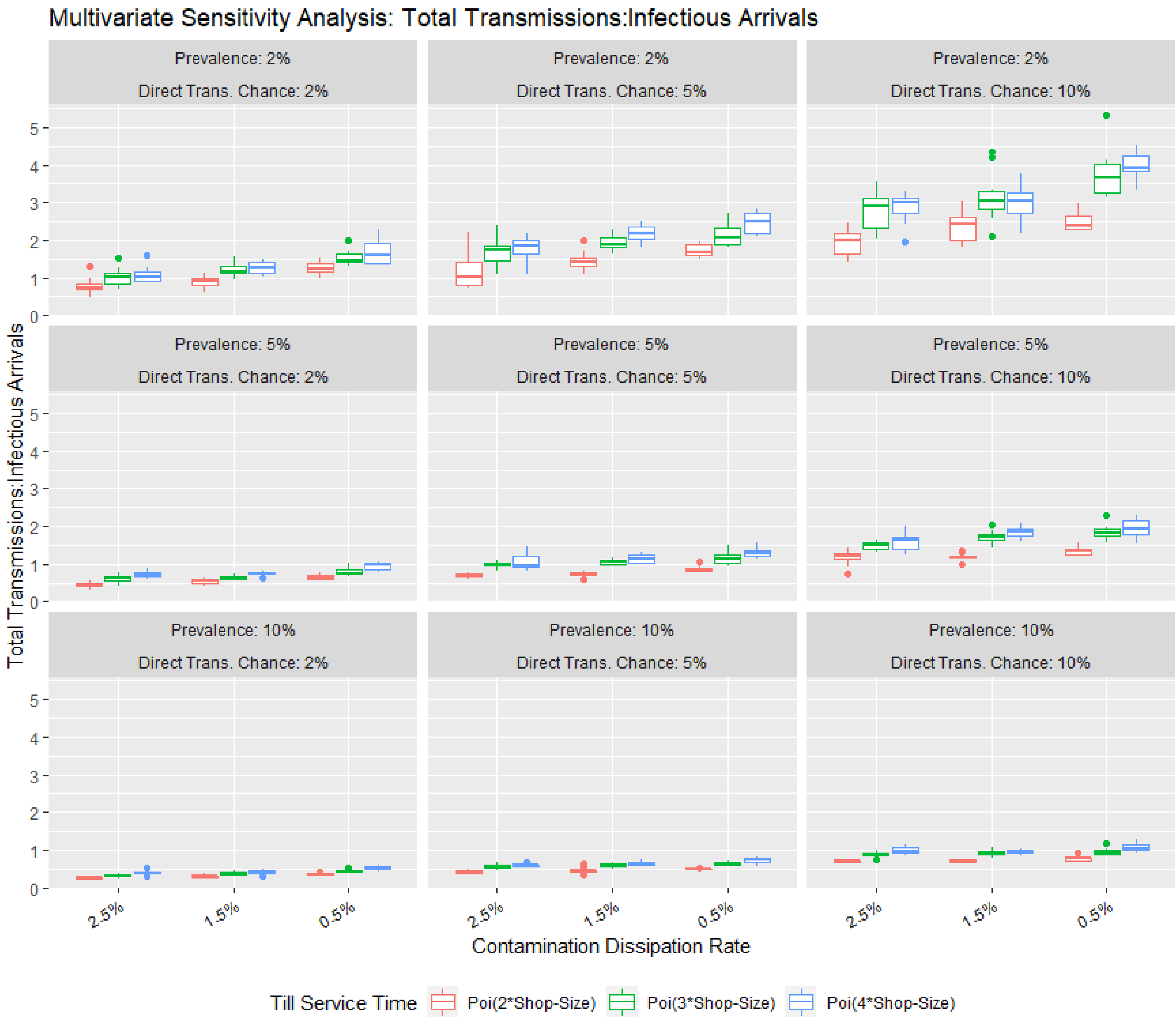

Figure 4.13: Box-plots showing the Change in the Ratio of Total Transmissions to Infectious Customer Arrivals resulting from Multivariate Changes in Model Parameters

The Ratio of Total Transmissions to Infectious Customer Arrivals observed showed the following variation with multivariate changes in model parameters:

- The outcome appears to be most sensitive to the changes in the prevalence as opposed to the chance of Direct Transmission as seen above, this is followed by till service speed(time) with no other considerably sensitive parameters shown.
- Prevalence now appears to show a negative correlation, indicating an increase in transmissions, but not as large at the proportional increase in Infectious arrivals. This reflex what was seen in the Univariate analysis

- sensitivity to prevalence appears to greatly overshadow other sensitivities, further demonstrated with the addition of changes in direct transmission chances.
- There is a large variation in the possible range of values for the total transmissions:Infectious Arrivals ratio that could be observed across the possible ranges of the selected parameters, ranging from lows of around 0.3:1 given a 10% prevalence, 2% direct transmission chance, 2.5% dissipation rate, and Poi(2*x) till service speed (time); to a ratio over 4:1 given a 2% prevalence, 10% direct transmission chance, 0.5% dissipation rate, and Poi(4*x) till service speed (time) on the other end of the value ranges.

The multivariate sensitivity analysis now looks at changes in customer dynamics, through measuring sensitivity to multivariate changes in model parameters starting by assessing the sensitivity of the Average number of Customers per Day to changes in model parameters seen in *Figure 4.14* below.

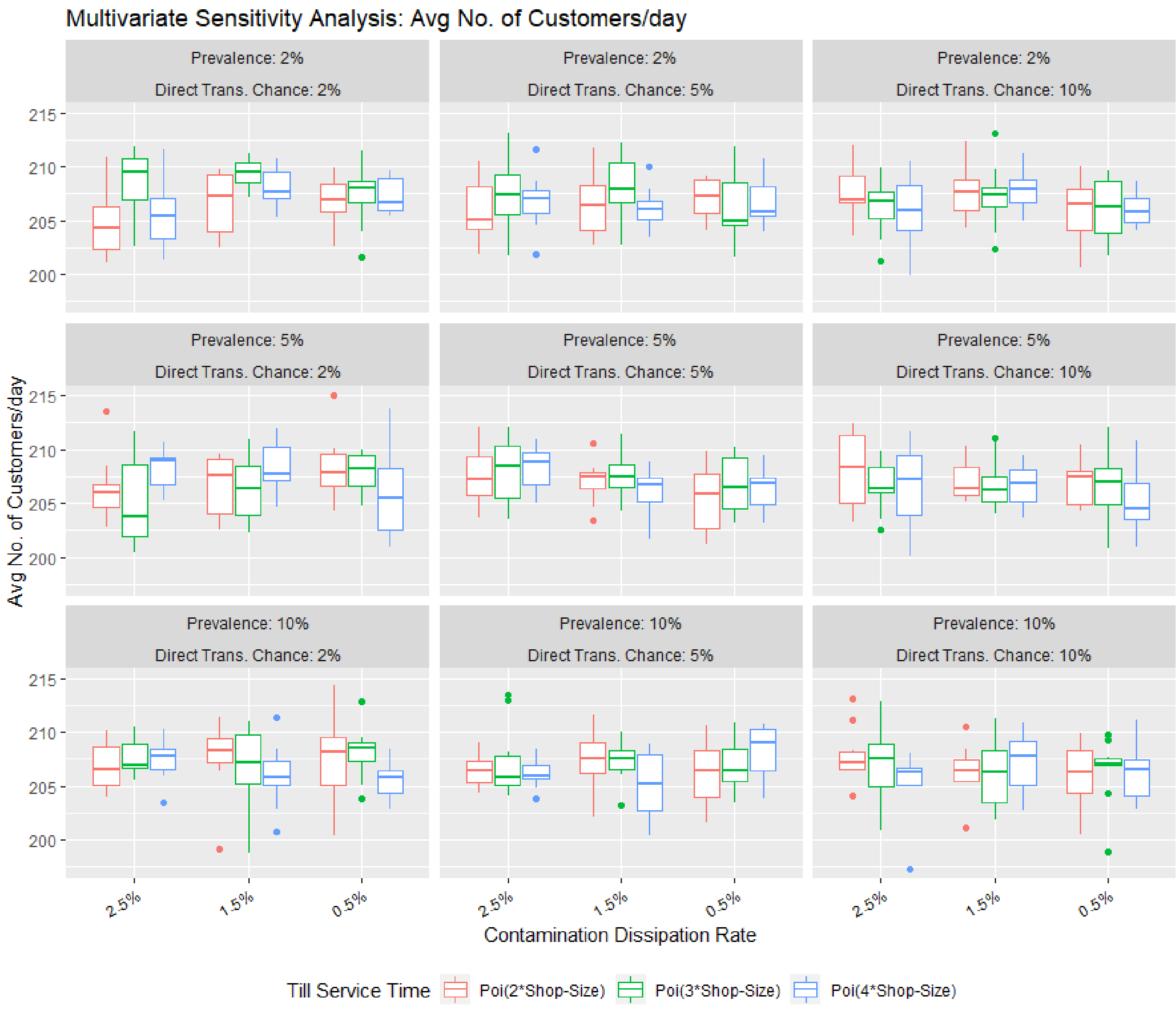

Figure 4.14: Box-plots showing the Change in the Average number of Customers per Day resulting from Multivariate Changes in Model Parameters

The Average number of Customers per Day observed showed the following in respect to its sensitivity to changes in model parameters:

- The Average number of Customers per Day does not appear to be sensitive to any of the given model parameters, or combinations thereof.

The next model outcome measure that is an important evaluation of customer dynamics in the model is the Average Customer Shopping Time. The sensitivity of this measure to changes in model parameters can be seen in *Figure 4.15* below.

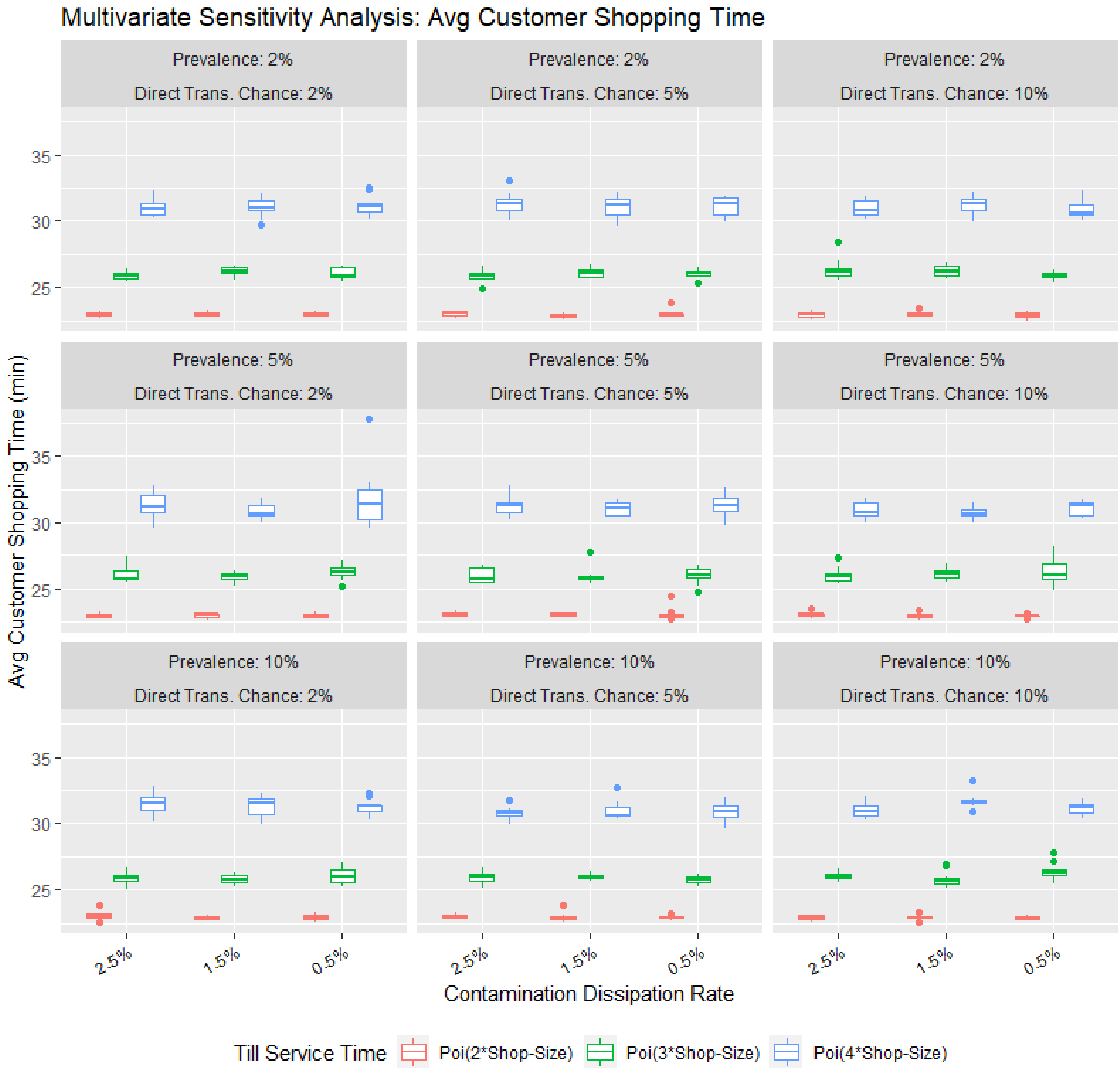

Figure 4.15: Box-plots showing the Change in the Average Customer Shopping Time (min) resulting from Multivariate Changes in Model Parameters

The Average Customer Shopping Time (min) observed showed the following with respect to its sensitivity to changes in model parameters:

- The Average Customer Shopping Time appears to only show sensitivity with respect to changes in till service speed (time), with shop time increasing as service time increases. No other changes appear to take place with any other selected parameter changes.

The final, important model outcome measure for the evaluation of customer dynamics in the model is the ratio of Customers Lost:Customers Processed. The sensitivity of this measure to changes in model parameters can be seen in *Figure 4.16* below.

Figure 4.16: Box-plots showing the Change in the ratio of Customers Lost:Customers Processed resulting from Multivariate Changes in Model Parameters

The ratio of Customers Lost:Customers Processed observed showed the following with respect to its sensitivity to changes in model parameters:

- Just as was seen for the Average Customer Shopping Time in the figure above, the ratio of Customers

Lost:Customers Processed appears to only show sensitivity with respect to changes in till service speed (time), with the number of customers lost increasing as service time increases. No other changes appear to take place with any other selected parameter changes.

In interpreting the use of information gathered by conducting the sensitivity analysis procedure, one of the primary objective is the identification of the model's most sensitive parameters. A major benefit of the modelling structure developed is the ease with which model parameters can be adjusted using the model interface. This flexibility aids the ability the model has to adapt to changing information regarding COVID-19 disease parameters. The most sensitive transmission parameters of prevalence and chance of direct transmission are subject to frequent change in real world environments, so a model with results that are robust to this changes would be ideal. However, the nature of these parameters and their role in transmission makes this difficult.

Future models might allow for improvement in customer dynamics with the collection of better data-sourcing with respect to till service times. Unfortunately this data in the environment setting described is not currently freely available, which limits the accuracy of its assignment in the model.

4.7 Model Scalability

An investigation of the model's scalability serves to indicate whether or not the model would be able to scale the customer-load it receives, in an attempt to replicate shopping environments that serve a considerably higher number of customers. Models that present high levels of scalability are able to extensively increase their simulation load/traffic, without any significant variation in the operational performance of the model as assessed by its response outcomes.

The limitations on the developed model's structural rigidity, may not allow for sufficient flexibility in its processing capabilities to withstand considerable increases in customer arrivals without baseline customer dynamics becoming unrealistic in their representation of real-world processes. The scalability of the model is assessed by increasing the number of customers that arrive at the shop and simulating these scenarios of increased customer load repeatedly for a simulation period of 14 days, as described in *Section 4.6.3*. Model outcomes are recorded for each of these repeated simulations to provide measures of estimated value and associated variability for each measure. These measures are then compared to their counterparts in the validated base model, with a focus on Customer Dynamics outcomes, to determine whether or not the model is able to produce realistic customer dynamics measures with the increased customer-load. The model's scalability was tested with an increase in customer arrivals by a factor of 2 and 3, or a 100% and 200% increase, in customer load respectively. The assessment begins by looking at the average number of customers processed per day, seen in *Figure 4.17* below.

Figure 4.17: Box-plots showing the Average No. of Customers Processed per Day under Increased Customer-Loads

Looking at the average number of customers processed per day in the figure above, the disproportionate increases in the average number of customers processed provides an initial indication of problems in the model's ability to accurately represent the customer dynamics of shops with similar structural layouts and considerably higher customer arrivals. Looking at the average number of customers processed for a 200% increase in customer arrivals compared to those under the base level of arrivals, the average number of customers processed is just over 400 customers per day. This reflects an increase of less than 100% in the average number of customers processed per day despite a 200% increase in the average number of customers arriving. This indicates that the difference in the number of customers processed compared to those arriving must reflect substantial increases in the number of customers lost. Looking at the Ratio of the number of customers lost against the number of customers processed in *Figure 4.18* below confirms this assumption.

Figure 4.18: Box-plots showing the Ratio of Customers Lost to Customers Processed under Increased Customer-Loads

Looking at the box-plots of ratio values shown in the figure above, the model went from a ratio of 0 with no customers lost due to balking to an average ratio of just under 0.5 in the scenarios reflecting a 200% increase in customer arrivals. This indicates that for almost every two customers served by the shop, a potential customer is lost. The majority of supermarket environments would consider this an unacceptable inability to serve customer demand, showing that the model is unable to accurately represent real-world situations at this level of customer demand. Looking further at the model's performance with respect to the customers it is able to process, box-plots of the average customer shopping times for each customer-arrival scenario are seen in *Figure 4.19* on the next page below.

Figure 4.19: Box-plots showing the Average Customer Shopping Time under Increased Customer-Loads

Looking at the average customer shopping times in *Figure 4.19*, the shopping times under the 200% increased customer-load appear to average around 52 minutes, compared to the 27 min averages seen with the base customer-load. Although this is a substantial increase, and the times fall outside of the expected ranges provided by real-world supermarket managers, the average shopping times are not extreme enough to invalidate their potential to represent real-world estimates. However, it's important to recall the increased number of customers lost due to balking as this would indicate excessively long customer queues. Shifting focus to further investigate the average shop queuing times seen in *Figure 4.20*

Figure 4.20: Box-plots showing the Average Customer Shopping Time under Increased Customer-Loads

Looking at the average shop queuing times seen in *Figure 4.20* on the following page, the average shop queuing times for the scenario representative of a 200% increase in customer arrivals are averaged at just over 20 minutes. This reflects an increase of over 1000% from the 2 minute average queuing time under the baseline customer load. Although the average queuing time of around 20 minutes may not appear to be completely unrealistic, they present two major issues in the models reflected ability to withstand this level of customer arrivals. Firstly the wait times of over 20 minutes before entering the shop are not representative of any realistic standard, everyday shop operation in real-world observation. Secondly, waiting times of this extent under standard shop operation would only be considerably worsened by control measure implementations that affect the shop's operating capabilities and processing speeds.

Ultimately the Customer Dynamics for the model show considerable changes in baseline operation with increases in customer arrivals, which reflects an inability for model analysis to be robust to increases in customer load. The most concerning outcome is the considerable increase in the number of customers lost. This inability to withstand increased customer loads is primarily due to the fixed nature of the shop environment's processing availability. All additional customer arrivals will still be processed by the same number of till stations and will still adhere to the same queuing structures as those defined under baseline conditions. The inability to increase till stations or change queuing structures ultimately imposes limitations on the model's ability to be scaled. It is important to factor in these limitations of interpreting model outcomes and finding for supermarket environments that would not be representative of the considered model structure or any structure with proportionally scaled processing capabilities such as till stations.

4.8 Transmission Control Measures

The control measures described in this section are implemented in the shop environment in an attempt to reduce the number of COVID-19 transmissions that take place. Several strategies for the reduction of COVID-19 transmission have arisen since the onset of the COVID-19 pandemic, as described in *Section 2.1.3*. Five of the more commonly implemented control measures are considered for implementation at a variety of implementation-levels in the simulation model described. The control measures considered are the use of the following:

- Vaccines and Vaccine Mandates
- Social Distancing
- Capacity Limiting
- Staff COVID Testing
- Sanitization

These transmission control measures may be implemented independently in isolation to one another, or as a combination of any or all of the control measures. The selection of control measures should be conducted before model setup and the initialisation of the simulation. Thus the use-level of each control measure may not change throughout the simulation period.

This section describes each transmission control measure, followed by a description of the way its implementation is reflected in the model behaviours and procedures. This is followed by the specification of all control measure related parameters.

4.8.1 Vaccines and Vaccine Mandates

Description

Vaccines have been a fundamental tool in fighting the spread of a number of infectious diseases over the past century. Their development has been a critical tool in combating the spread of COVID-19, and the global effort aimed at the development of a COVID-19 resulted in the fastest vaccine developments seen to date[33]. Vaccines as a transmission control measure aim to increase an individual's immunity to COVID-19 through the production of antibodies. Individuals who have been vaccinated thereby have a higher level of immunity to COVID-19 and a correspondingly lower chance of infection when in contact with an infectious individual. Several vaccines for COVID-19 have been developed globally, in the context of South Africa the majority of vaccines distributed have been either the *Pfizer adenovirus vector-based vaccine* or the *Johnson & Johnson mRNA-based vaccine*. At the time of model development, the *Pfizer* vaccine required two separate doses for an individual to be considered **Fully Vaccinated**, where individuals who have received a single dose considered to be **Partially Vaccinated**. The *Johnson & Johnson* vaccine requires only a single dose for an individual to be considered **Fully Vaccinated**. The use and development of COVID-19 vaccines is described in more detail in *Section 2.1.4*

The coverage of the vaccines describes the percentage of the population that has received the respective dosage level. The coverage for *Fully Vaccinated* individuals is defined as a subset of the individuals who are *Partially Vaccinated*, as described by the Department of Health for the Republic of South Africa for use in the national COVID-19 Vaccine Statistics Dashboard. As the number of vaccinated individuals changes on a daily basis, the COVID-19 vaccine coverage levels are subject to change and may be adjusted in the simulation model developed. However, for the purpose of analysis, the coverage levels used and described for the *Standard Vaccination Schedule* are fixed at the national coverage levels as seen on Dec 01 2021.

Implementation

Each person in the simulation environment has an assigned `immunity` level between 0 and 100, representative of their independent chance of becoming infected provided the conditions are met for transmission to take place.

As this is a proportional percentage, the vaccine efficacy levels form a sufficient measure of individual immunity. The same idea is applied with respect to the chance of reinfection and the acquired immunity level assigned to staff who have *Recovered* from COVID-19 infection.

There are four possible use-levels for the **Vaccines** transmission control measure, which are as follows:

- **No Vaccines**: At initialisation, all staff are *Susceptible* and Customer arrivals will either be *Susceptible* or *Infectious* proportional to the set prevalence level.
- **Standard Vaccine Schedule**: At initialisation, all staff are *Susceptible* and Customer arrivals will be *Fully Vaccinated* proportional the Full Vaccination coverage level, *Partially Vaccinated* proportional the Partial Vaccination coverage level less the Full Vaccination coverage level (as per coverage definition), *Susceptible*, or *Infectious* proportional to the set prevalence level.
- **Staff Vaccine Mandate**: At initialisation, all staff are *Fully Vaccinated* and Customer arrivals will be *Fully Vaccinated* proportional the Full Vaccination coverage level, *Partially Vaccinated* proportional the Partial Vaccination coverage level less the Full Vaccination coverage level (as per coverage definition), *Susceptible*, or *Infectious* proportional to the set prevalence level. The real-world implementation of a Staff Vaccine Mandate would likely either be enforced by the store management as a requirement for staff to be vaccinated in order to come to work, or my government as a requirement for essential service workers.
- **Full Vaccine Mandate**: At initialisation, all staff are *Fully Vaccinated* and Customer arrivals will be *Fully Vaccinated*, or *Infectious* proportional to the set prevalence level. The real-world implementation of a Full Vaccine Mandate would likely need to be enforced at a government level, requiring individuals to produce a vaccine card indicating administered vaccines in order to access highly trafficked spaces, such that all customers arriving to the shop would be fully vaccinated.

These effects take place for Customers and Staff in the *Customer Arrival* and *Staff Setup* procedures shown in *Sections 4.4.2 and 4.4.3* respectively.

The input parameters associated with the implementation of this control measure are:

- Partial Vaccination coverage
- Partial Vaccination efficacy
- Full Vaccination coverage
- Full Vaccination efficacy

4.8.2 Social Distancing

Description

The main means of direct transmission for COVID-19 takes place through large respiratory droplets and particles expelled by an infectious individual, and these droplets are breathed in or ingested by another individual. These large droplets usually settle gravitationally quite close to the infectious individual[83], which has lead to the implementation of **Social Distancing** measures in order to control and reduce transmissions. The underlying principle is that individuals are required to keep at least 1 meter apart from one another. This serves to reduce the number of direct-contacts each individual is likely to have, thereby reducing the number of chances for transmission to take place.

An important component to consider is that there are many individuals that fail to comply with the implementation of these social-distancing measures[5][13][68]. This non-compliance behaviour is heterogeneous in nature and likely to vary between individuals, even between those with super-spreader behaviours.

Implementation

Each customer in the simulation environment has an assigned `personal-space`, representative of the independent amount of space they would leave between themselves and other customers. This amount of space is a fixed number when no Social Distancing is implemented, this amount of space is considered a standard personal-space level that all individuals are likely to keep in the shop environment in a standard shopping situation. When Social Distancing is implemented, this personal-space distance is doubled. However, individuals that exhibit high levels of super-spreader behaviour are likely to exhibit non-compliance to the required social distance to varying degrees. Individuals with the highest super-spreader behaviour level exhibit between 0 and 100% compliance with the extra Social Distancing on a uniform distribution, and individuals with the second highest super-spreader behaviour level exhibit between 30 and 100% compliance with the extra Social Distancing on a uniform distribution.

There are only two possible use-levels for the **Social Distancing** transmission control measure, as it is a binary control that is either in effect or it isn't.

These effects take place for Customers in the *Join Shop Queue*, *Shop Queue Movement*, *Join Till Queue* and *Till Queue Movement* procedures shown in *Section 4.4.2*.

The input parameters associated with the implementation of this control measure are:

- Super-Spreader Distribution

4.8.3 Capacity Limiting

Description

The use of **Capacity Limiting** involves placing a limit on the number of people that are permitted to be in a shared space or environment. These limits of the allowed venue capacity have been widely implemented globally in an attempt to control COVID-19 transmissions. In the setting of South Africa, the limits placed on venue capacity were given as fixed person-counts in the initial stages of the pandemic. These fixed limits were later appended to percentage reductions in the capacity limits of each venue in order to account for the variation in venue standard capacities that depend on the physical venue. [56]

The implementation of the use of Capacity Limiting was a familiar and noticeable experience in supermarket environments. Individuals that arrived at the shop would frequently be required to wait in a queue for customers in the shop to finish their shopping and leave the store before they would be allowed to enter the store due to there being a limit on how many customers were permitted to be in the shop at a given point in time. This limit on capacity varied over the course of the pandemic, ranging from limiting to 50% up to 75% capacity.[12]

Implementation

The implementation of the **Capacity Limiting** control measure in the simulation model involved setting a level for the global `capacity-limit` parameter. When a customer arrives at the Shop and joins the Shop Queue, the customer at the front of the queue will only progress to the procedure of entering the shop if the number of customers in the shop environment is less than the set capacity limit. If the shop has reached limited capacity, the customer will wait until a customer leaves the shop and some capacity becomes available. The levels for the `capacity-limit` parameter were selected by simulating the baseline environment 60 times for a period of 2 weeks (14 days) and recording the maximum number of customers in the shop environment for each of the 60 simulation runs. Limits were then calculated as percentages of the mean maximum observed capacities recorded.

There are three possible use-levels for the **Capacity Limiting** transmission control measure, which are as follows:

- **No Limit on Capacity**
- **75% Capacity Limit** which limited the maximum number of customers in the shop to 75% of the mean maximum observed capacity described above.
- **50% Capacity Limit** which limited the maximum number of customers in the shop to 50% of the mean maximum observed capacity described above.

These effects take place for Customers in the *Shop Queue Movement* procedure shown in *Section 4.4.2*.

As compliance for this measure is enforced by the shop, compliance does not vary between individual customers and thus is not dependant on the distribution of super-spreader levels between customers. There are no additional input parameters that affect the implementation of this transmission control measure.

4.8.4 Staff COVID Testing

Description

The use of testing for COVID-19 has been around since the onset of the COVID-19 pandemic in order to identify positive cases of COVID-19 infections. In the initial stages of the pandemic, cases had to be positively identified through the use of reverse transcription polymerase chain reaction RT-PCR tests. RT-PCR tests utilise technology by which viral RNA molecules are converted into their complementary DNA (cDNA) sequences by reverse transcriptases[84]. These tests can identify positive cases with high sensitivity, but are relatively time expensive. The high demand for tests to be conducted as the number of COVID-19 cases grew resulted in extensive backlogs of results for many facilities world-wide. This lead to a need for the development of a more rapid test for COVID-19. The developed rapid diagnostics tests developed rely on the detection of antigens in the body developed by the immune response to the presence of COVID-19 in the body[59][47]. These tests have become widely favoured over the use of PCR testing due to their considerably lower turn-around times and testing costs. This does however come at the cost of test sensitivity with lower test sensitivity observed for the rapid antigen (RA) tests compared to the RT-PCR test. Tests also rely on the seroprevalence or antibody counts, resulting in a variation in sensitivity over time from the moment of exposure[87]. The reported diagnostic test sensitivity levels for the RT-PCR test, as well as all FDA EUA-approved RA tests (As of June 2021), for each day of viral incubation from exposure is shown in *Figure 7.1* in *Appendix A, Section 7* from a comparative study by Wells et al. (2021).

The implementation of testing and isolation strategies became a widely used transmission control strategy globally and is the idea underpinning the use of **Staff COVID-19 Testing** in the model. This idea aims to reduce the number of contacts an infectious individual has by requiring them to self-isolate.

Implementation

The implementation of the **Staff COVID-19 Testing** control measure in the simulation model involves testing all staff for COVID-19 at the set *Weekly* or *Daily* intervals. Exposed or Infectious staff members report a positive test result at the test sensitivity levels corresponding to their `incubation-period` and assigned relative `test-sensitivity`. Upon receiving a positive test result, the staff member will be required to isolate until their recovery from COVID-19.

There are three possible use-levels for the **Staff COVID-19 Testing** transmission control measure that relate to the frequency of testing, which are as follows:

- **No Staff COVID-19 Testing**
- **Weekly** Staff COVID-19 Testing which implemented a COVID-19 test once per week in the middle of the week, this allows time for antigens to develop if infected early on to increase chances of a positive result in the first test and allows for time effects of isolation to be shown by allowing observation of the days following the second test.
- **Daily** Staff COVID-19 Testing which implemented a COVID-19 test each day of the simulation period.

These effects take place for Staff members in the *Progress Disease* and *Test Staff* procedures shown in *Sections 4.4.3 and 4.4.1* respectively.

The input parameters associated with the implementation of this control measure are:

- Test Sensitivity, with sensitivity levels selected as an Average (Base Level) sensitivity, Maximum sensitivity, or Minimum sensitivity from the sensitivity levels shown by the 6 tests in the study by Wells et al. described above.

4.8.5 Sanitization

Description

Beyond the direct transmission of COVID-19 through large respiratory droplets and particles expelled by an infectious individual, there is evidence to suggest Environmental transmission through the inhalation of smaller aerosol droplets or exposure to fomites[83][71]. Fomite transmission describes the transmission that takes place when an individual comes into contact with a virus by exposure to contaminants/particles (fomites) on surfaces that they touch followed by touching a fluid barrier to the body such as the eyes, nose, or mouth[30][46][82].

The implementation of **Sanitization** strategies became a widely used transmission control strategy globally in use for personal hygiene and surface sanitization[83]. This idea aims to reduce the exposure individuals have to the COVID-19 virus by reducing the tranmissibility of surface transmissions by rendering COVID-19 particles inactive with sanitizer.

Implementation

The implementation of the **Sanitization** control measure in the simulation model involves the use of sanitizer for personal hygiene, by sanitizing hands at the shop *Entrance*, and surface sanitization, by sanitizing surfaces at the *Tills*. With sanitizer use at the shop *Entrance*, Infectious Customers entering the shop have a reduced contaminant level that is left behind at each area they come into contact with. This reduction describes the reduction in the spread of fomites due to the inactivation of particles that would have been on the customer's hands. However, this has no effect on the spread of aerosols. The reduction in the level of environmental contaminant spread is shown as a proportion of the full contaminant level and indicated by the `sanitizer-disinfection` parameter. The use of sanitizer as a surface disinfectant at the Till Stations is implemented by clearing surface fomites between each customer processed.

The implementation of Sanitization also results in added processing times with an extra minute (smallest available time step) added to entering the shop, as well as an added minute to sanitize Till Station surfaces between customers. As the added time to process shop entrance is longer than would be seen in real-world implementation, it may be analogous to other time consuming entry processes such as filling out contact tracing details. Thus we will define the implementation of sanitization in conjunction with the implementation of such measures.

As this control measure requires adherence by Customers themselves in many instances, the issue of non-compliance may arise. This is implemented in the model by having individuals with the highest level of super-spreader behaviour skip the use of sanitizer at the entrance.

There are three possible use-levels for the **Sanitization** transmission control measure, which are as follows:

- **No Sanitization**.
- **Entrance** Sanitization which describes the use of hand sanitization for customers entering the shop.
- **Entrance and Tills** Sanitization which describes the use of hand sanitization for customers entering the shop as above, as well as the use of sanitizer as a surface disinfectant at the Till Stations.

These effects take place for Staff members in the *Working Staff* procedure shown in *Section 4.4.3* with implementation at the level including sanitization at the Tills. These effects also take place for Customers in the *Shop Queue Movement* procedure shown in *Section 4.4.2* with implementation at the levels including sanitization at the Entrance.

The input parameters associated with the implementation of this control measure are:

- Sanitizer Reduction Capabilities, selected as a proportion of the contaminant level post sanitization such that a lower proportion corresponds with an increase in the sanitizer reduction capabilities..

- Super-Spreader Distribution, with non-compliance to the use of hand sanitizer shown by individuals with a very high super-spreader level.

4.8.6 Transmission Control Measure Parameters

The tables presented in this section provide a contextual description of the parameters relating to the implementation of the transmission control measures described, along with the baseline values they are set to. As research around COVID-19 develops or mutations occur, the levels and values selected are likely to vary and change. The parameters presented are all adjustable in the simulation environment developed as seen in *Figure 8.2* in *Appendix B, Section 8*, allowing for its future use and development alongside changes in disease parameters.

Parameter	**Parameter Description**	**Values Used**	**Sources**
Super-Spreader Distribution	This parameter dictates the relative proportions of individuals classified into five degrees of intensity of Super-Spreader behaviour. Individuals with a higher degree of Super-Spreader intensity are likely to have more daily contacts with a higher resulting chance of infectiousness and less likely to comply with intervention protocols. Defined by 5 levels of super-spreader intensity, with varied proportions of the population assigned to each.	Fewer Contacts, Base Level, More Contacts See *Table 4.9*	[40][64]
Test Sensitivity	The diagnostic sensitivity of COVID-19 tests conducted on Staff members for Staff COVID-19 Testing. Sensitivity is based on a variety of Rapid Antigen tests and the RT-PCR test, with sensitivity varying according to the viral incubation period.	Less Sensitive, Base Level, More Sensitive See *Table 4.10*	[87][59]
Sanitizer Disinfection	This parameter describes the relative amount of environmental contaminant distributed by an Infectious Customer/Staff Member at each location visited. Amount selected as a percentage.	70	[63][32]
Partial Vaccination Coverage	This parameter represents the percentage of individuals having received at least a partial vaccination. The parameter dictates the chance of having received at least a partial vaccination and thus includes those fully vaccinated, as defined by the South African Vaccination Monitor platform.	49	[55]
Full Vaccination Coverage	This parameter represents the percentage of individuals having received a full vaccination.	39.8	[55]
Partial Vaccination Efficacy	This parameter represents the efficacy of having partial vaccination. The parameter dictates the chance of infection for partially vaccinated individuals given that conditions for transmission take place.	52	[43][39][53][60]
Full Vaccination Efficacy	This parameter represents the efficacy of having full vaccination. The parameter dictates the chance of infection for fully vaccinated individuals given that conditions for transmission take place.	95	[43][39][53][60]

Table 4.8: Table showing the Control Measure related Parameter Description and Values

Table 4.9 below outlines the proportions of customers assigned to each super-spreader level. The assignment to each super-spreader level is based on the proportions of populations that fall into similarly defined levels regarding the number of contacts they have. These values are based on values provided by the study of the regarding social contact patterns relevant to the spread of respiratory infectious diseases by Leung et al. (2017)[40], which draws from samples taken globally. Values are based on *Figure 7.2* in *Appendix A, Section 7.*

	Super-Spreader Level (No. of Contacts) Proportions				
Parameter Value	Minimal	Low	Average	High	Very High
Fewer Contacts	60	25	8	5	2
Base Level	50	30	10	5	5
More Contacts	40	30	15	10	5

Table 4.9: Table showing the relative Proportions of Customers Assigned to each Super-Spreader Level[40]

Table 4.10 below outlines the diagnostic sensitivity of COVID-19 tests conducted on Staff members for Staff COVID-19 Testing. Sensitivity is based on a variety of Rapid Antigen tests and the RT-PCR test, with sensitivity varying according to the viral incubation period or days since infection. Values are based on the comparative study comparing diagnostic sensitivity for COVID-19 tests by Wells et al. (2017)[87], which draws from samples taken globally. Values are based on *Figure 7.1* in *Appendix A, Section 7.*

Test Sensitivity	**No. of Days Since Infection**													
Parameter Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Less Sensitive	0	0	1	25	61	80	87	85	77	65	55	40	30	22
Base Level	0	0	10	35	67	85	92	90	82	70	60	50	40	30
More Sensitive	0	0	27	45	75	97	100	98	90	77	68	58	47	40

Table 4.10: Table showing the Diagnostic COVID-19 Test Sensitivity at varied Test Sensitivity Parameter Values for each Day Since Infection [87]

4.8.7 Transmission Control Measure Verification

As the behaviours and processes associated with the control measures implemented act as an extension to those described for the base model, the simulation model-fitting process of verification and validation, as well as the sensitivity analysis on related parameters, must be extended to the transmission control measure extensions. Although the verification outcomes are described within this section in the Agent-Based Model chapter, the validation and sensitivity analysis outcomes are presented in *Sections 5.3 and 5.4* in the Synthesis and Analysis of Results chapter below. This is due to the necessary presentation of resulting outcomes and outcome assessments required for these processes, making it necessary for their discussion to follow from an initial presentation of the model's outcomes.

As shown in *Section 4.6.1*, the verification process is aimed at assessing the specified micro-level rules and behaviours in the simulation to ensure that model dynamics are executed as expected. Model verification is performed by observing agent behaviour in the simulated environment as the agent progresses through each stage of the system, assessing the presence of the behavioural changes expected from the implementation of the different transmission control measure procedures. The verified associated behaviours are described in *Table 4.8.7* on the following page.

Simulation Element	**Specified Behaviour**	**Verified**
Customer Vaccinations	The proportion of customers that arrive at the shop in each vaccine-related disease state, exhibit changes representative of the selected Vaccine Scenario. Showing all non-infectious arrivals seen as Susceptible (Green) in the "No Vaccines" scenario, all non-infectious arrivals seen as Fully Vaccinated (Dark Blue) in the "Full Vaccine Mandate" scenario, and non-infectious arrivals as Fully Vaccinated (Dark Blue) at the proportion indicated by the Full Vaccine Coverage rate, Partially Vaccinated (Light Blue) at a proportion of the difference between the Partial and Full Vaccine Coverage rates for the "Standard Vaccine Schedule" and "Staff Vaccine Mandate" scenarios. Infectious customers arrive at the selected prevalence level.	Yes
Staff Vaccinations	The vaccine-related disease states of staff members exhibit changes representative of the selected Vaccine Scenario. With all staff seen as Susceptible (Green) in the "No Vaccines" scenario, and Fully Vaccinated (Dark Blue) in the "Full Vaccine Mandate" and "Staff Vaccine Mandate" scenarios.	Yes
Social Distancing	When the Social Distancing control measure is set to be active, the distances between each customer in the shop and till queues is visibly increased.	Yes
Capacity Limiting	When the Capacity Limiting control measure is implemented, customers that arrive at the shop will wait in the shop queue if the number of people inside the shop is at the corresponding limit level. When a customer inside the shop has been processed and leaves the shopping area, the number of customers inside the shop will drop below the set capacity limit and the next customer in the shop queue will be able to enter the shop.	Yes
Staff COVID-19 Testing	When the Staff Covid-19 Testing control is implemented, the staff members will get tested at the beginning of each day at the Daily testing level and on days 3 and 10 at the Weekly testing level. Infected staff receive a positive test result with a probability that varies according to their disease incubation period. If an infected staff member receives a positive result, they will perform the Self-Isolation behaviour described in *Table 4.5*	Yes
Hand Sanitization	When the Sanitization control measure is in use, each customer experiences a slight increase in wait-time in the shop queue corresponding to an increase in processing. Thereafter, Infectious customers will deposit a reduced amount of viral contamination as they move through the shop environment.	Yes
Till Surface Sanitization	When the Sanitization control measure is in use at the "Entrance and Tills" level, there is an increased wait time between each customer arrival to the till stations from the queue. Between each customer arrival at the till station, the amount of viral contamination is reduced by surface sanitization.	Yes

Table 4.11: Table showing the Verification and Demonstration of Assigned Control Measure Behaviors.

4.9 Monitoring the Simulation in Netlogo

This section describes the tools, features, and values that form part of the developed simulation model and can be used to monitor the epidemiological changes and effects that arise in the simulation environment for each simulated period. The description of the monitoring aspects of the simulation model begins with a description of the use of the **Simulated Shop Environment** as a monitoring tool. This is followed by a description of the use of the **Transmission Dynamics** and **Customer Dynamics** Tabs respectively.

These varied monitoring features combine to show the full simulation model environment seen in *Figure 4.21* below.

Figure 4.21: Complete Display of the Simulation Model Application Environment developed

4.9.1 Simulated Shop Environment

The central simulated shop environment view is the core observation and monitoring component of the Agent-Based model developed. The view features both 2-Dimensional and 3-Dimensional viewing capabilities of the shop environment, which can be seen in *Figure 4.1* in *Section 4.2* and *Figure 4.22* below respectively. The monitoring environment can be used to observe the arrival, movement, and interactions of Customers through the environment. The visual representation of the underlying simulation processes allows the user to visualise transmission dynamics as Customers and Staff progress through different epidemiological disease states, with disease states indicated by a person's colour as follows:

- Susceptible (Green)
- Exposed (Yellow)
- Infectious (Red)
- Recovered (Grey)
- Partially Vaccinated (Light Blue)
- Fully Vaccinated (Dark Blue)

At a glance, the user can see the state of the environment in terms of any customer dynamics issues, staff infections and self-isolations, and areas of concentrated transmission at any given point in time. The extent of environmental contamination can also be seen using the related switch under the Transmission Dynamics Tab seen in *Figure 4.24* in *Section 4.9.2* below. Environmental Contaminant levels are shown in *Yellow*, with darker shades indicating a higher contamination level.

Figure 4.22: 3-Dimensional Representation of the Simulated Shop Environment

The simulation day is shown by a collection of time-viewing monitors above the view, and the simulation speed can also be varied using the speed adjustment slider indicated. These can be seen in *Figure 4.23* below.

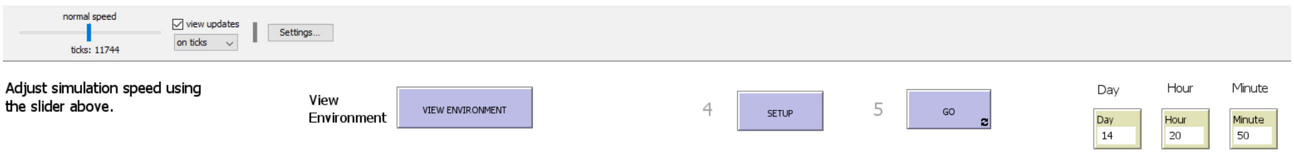

Figure 4.23: Simulation Time Monitors and Speed Control Slider

4.9.2 Transmission Dynamics Tab

The Transmission Dynamics Tab is found in the top-right section of the application window, just to the right of the Shop Environment View. This simulation monitoring tab is the section of the environment containing all the Transmission Dynamics related value monitors. Looking at the image of the Transmission Dynamics Tab seen in *Figure 4.24* below, the first item in the tab is the switch that enables viewing of the extent of environmental contamination in the environment as seen in *Figure 8.3* in *Appendix B, Section 8.* Below that, is a list of Transmission Counts in two columns. The left-hand column shows the transmission counts in each section of the shop environment and the right-hand column shows the transmission counts of total direct, environmental, and staff transmissions respectively. This is accompanied by the plot to the right of these monitors showing the change in all of these transmission counts over the entire simulated period.

Below these is a collection of the Transmission Ratios of interest, namely those of Total Transmission to Total Infectious Customer Arrivals, Total Susceptible Customer Arrivals, and Total Infectious Receptive Arrivals (All Customers other than those who are Infectious) respectively. All of these monitors and the plot are updated constantly for every minute of the simulation.

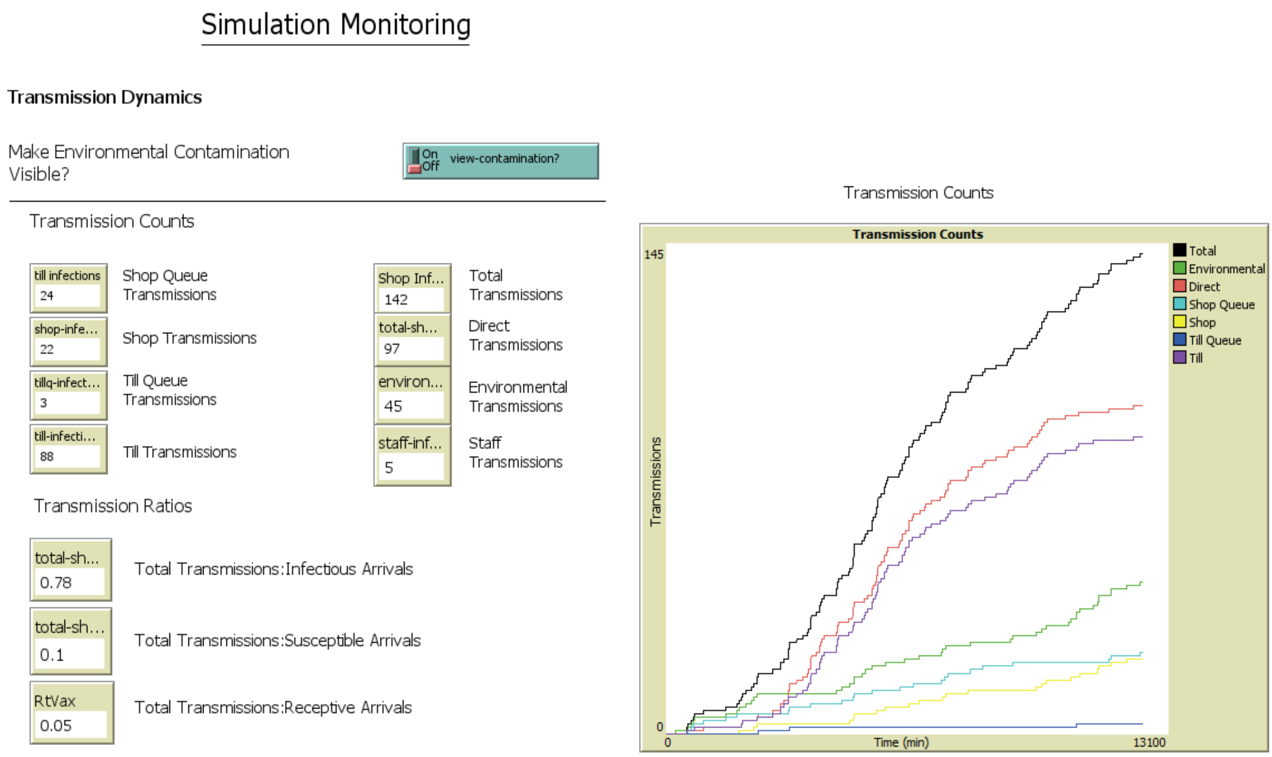

Figure 4.24: Simulation Transmission Dynamics Monitoring Tab

4.9.3 Customer Dynamics Tab

The Customer Dynamics Tab is found in the bottom-right section of the application window, just to the right of the Shop Environment View. This simulation monitoring tab is the section of the environment containing all the Customer Dynamics related value monitors. Looking at the image of the Customer Dynamics Tab seen in *Figure 4.25* below, the first section is a collection of monitors indicating mean values for the number of customers processed per day, along with the mean times for customer shop queuing, shopping, and till queuing respectively. The first row of monitors shows the values for these means for all customers, followed by three more rows indicating these mean values for customers grouped according to the size of the shop they conducted in the environment. This is accompanied by the plot to the right of these monitors showing the change in the number of customers in each of the shop environment sections, as well as the total number of customers present, for each time point over the entire simulated period.

Below these are three Customer Dynamics monitors for values of interest, namely those of the maximum queuing times for the shop and till queues, followed by the total number of customers lost due to balking on the left and right respectively. Just as seen for the Transmission Dynamics Tab, all of these monitors and the plot are updated constantly for every minute of the simulation.

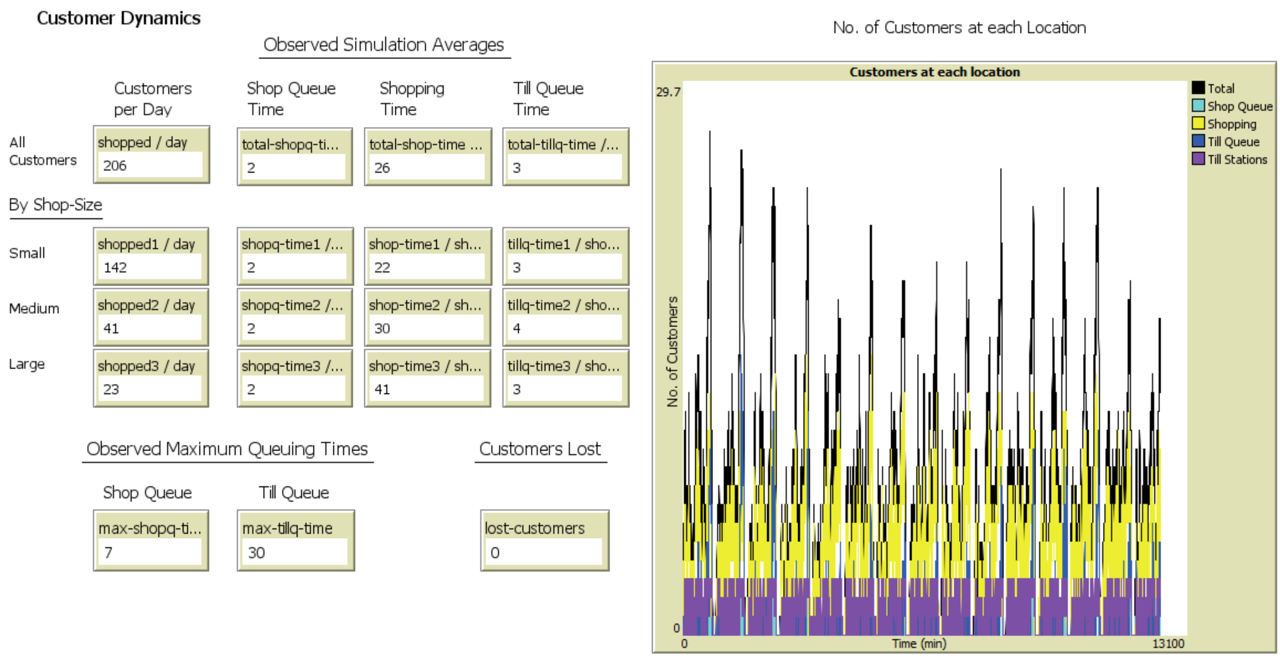

Figure 4.25: Simulation Time Monitors and Speed Control Slider

Chapter 5

Synthesis and Analysis of Results

This chapter describes the process followed to generate meaningful response outcomes, as well as the steps used to further process and analyse the response outcomes generated, in order to provide a comprehensive comparison and evaluation of the transmission control measures implemented.

The chapter begins by describing the utilisation of the simulation tool developed, to generate response outcomes for assessing transmission and customer dynamics in the environment. This is followed by a description of the data processing and preparation performed on the response measures collected, outlining the statistical tools used in these steps. Thereafter, the transmission control measures implemented in the simulation environment are evaluated and compared according to the processed response outcomes measured. This is done by an initial evaluation and comparison of each control measure in isolation, simulating the environment with one transmission control measure at a time and recording environment responses. The initial evaluation is followed by a repeated evaluation of isolated control measures at varied levels of disease prevalence. This secondary evaluation is followed by a final evaluation of the transmission control measures in combination with the other control measures, simulating the environment with all of the available combinations of the control measures active in unison.

The effectiveness of the transmission control measures implemented is evaluated and described according to the resulting changes in response measures associated with transmission and customer dynamics in the shop environment. The initial assessment serves to estimate the isolated effects of each transmission control measure without the effects of other control measures confusing the ability to attribute changes in dynamics to a single control measure. This is followed by a secondary evaluation at varied disease prevalence levels, which serves to determine the way the effectiveness of each control measure varies over the different stages of a pandemic cycle. The effects of any interaction between control measures is highlighted through the combined assessment of control measures implemented in combination with one another. This is followed by the validation and sensitivity analysis of the transmission control measure behaviours imposed and their related input parameters respectively.

5.1 Data Synthesis and Preparation

The process of data synthesis and preparation is performed through the initial genesis of response metrics through the process of simulation, followed by the subsequent preparation and transformation of the response values generated. This enables a quantitative means of comparing transmission control measures, alongside an associated measure of the response uncertainty that follows from randomisation in simulation procedures.

5.1.1 Simulation Process

The synthesis of response data is conducted using the simulation model built using the Netlogo software described in *Section 3.4.1*[89]. In order to compare and evaluate each of the transmission control measures described for the simulation model, response measures for the environment were synthesised in a two-part process. The first part involved simulating the shop environment with each control measure independently successively activated, in isolation, at each of their respective intensity levels. We define each simulated period with fixed input parameters and defined active/inactive transmission control measures as a scenario. The simulation period was conducted for a **duration of 14 days** (two weeks) for each scenario, with every control measure scenario run for **30 iterations each**. Response measures are calculated continuously at every minute throughout the simulation period to be seen by the observer. Response measure data are collected at the end of the simulation period for each run and saved for further processing and analysis. The second part of the data synthesis process followed the same procedure as the first, with the key difference being an allowance for multiple transmission control measures to be implemented simultaneously. Each distinct combination of control measures and control measure intensity is therefore an individual scenario for analysis.

Simulation runs were conducted through the use of Netlogo's BehaviourSpace tool, described in *Section 3.4.2*, enabling the ability to run several simulation iterations simultaneously in parallel to one another. The maximum number of iterations that can be run simultaneously is limited by the number of processing cores available on the device used, with a maximum of one iteration per available core. Response metrics were collected and saved at the end of each iteration and compiled into a single `csv (Comma Separated Value)` file containing response measure data for the defined session.

The same computational considerations as were described in *Section 4.6.3* must be made for the analysis of the model results that follow.

5.1.2 Analysis of Simulation Outcomes

The data synthesised through the simulation process described above is further analysed through the use of statistical programming software. The chosen statistical programming software for further analysis is `R` and `RStudio`[65].

The data synthesised is loaded into the R environment and separated into response measure information from each respective scenario. The comparison metrics for each run are then calculated from response measure data to be used for scenario comparison. The separated data allows for the calculation of variability and a measure of uncertainty of the values for each comparison metric. Thus comparisons between scenarios are performed through a comparison of metric distributions, rather than single values through an individual simulated run.

Distribution Fitting for The Additional Illustration of Metric Distributions

Although comparative assessments of the metric distributions found can be done directly on histograms of metric values, plotting several histograms on a single plot can quickly become difficult to interpret. For this reason, parsimonious approximate descriptions of the data can be used in exchange to represent the data when viewing the distribution of the values an outcome may take, providing plots that are easier to interpret.

Different distributions can be fit against the data and compared using goodness-of-fit measures such as Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) to determine which of the distributions provides the best approximation of the data.

Parameters for the distributions of choice are found through the `fitdist` function from the `fitdistrplus` package[19] in R. As an example *Figure 5.1* below shows the approximations of the data for the ratio of Total Transmissions to the No. of Infectious Customers who arrive at the shop. The plot illustrates approximations from the Normal, Gamma, Log-Normal, Inverse Gamma, and Weibull Distributions over the histogram of values for the response metric in the Base Model.

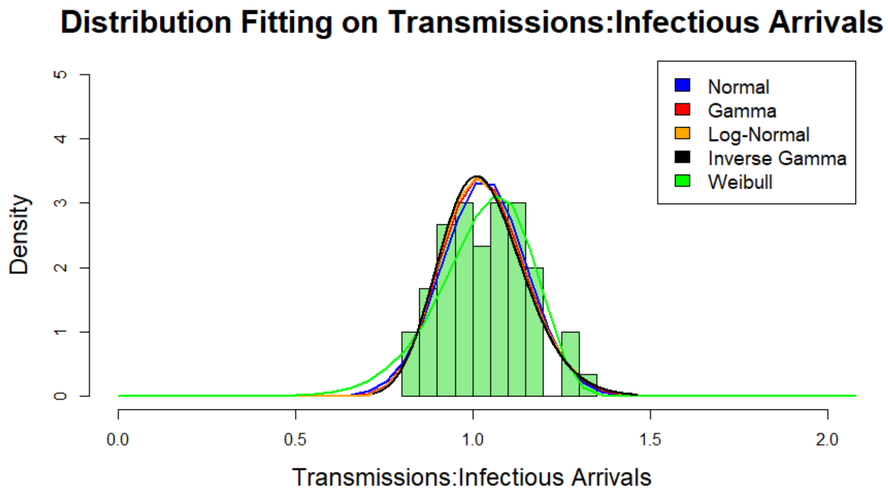

Figure 5.1: Continuous Response Distribution Fitting

The `fitDist` function from the `gamlss` package[67] in R, uses this idea to fit several different distributions against the data provided and determines the selected distribution with the lowest AIC. The `fitDist` function is used on each of the different response comparison metrics, testing the appropriate count or continuous distributions, and the best fitting distribution is selected to approximate a range for possible metric values under each scenario. In comparison plots, seen in *Appendix C, Section 9*, this parsimonious approximate description is used to make visual comparison easier to interpret.

Comparison Metrics

The response metrics for each simulated run are calculated in `R` prior to grouping data according to each scenario. A more direct comparison is made between comparison metrics in the assessment of model results using the raw data provided by the model, rather than through the distributional approximations described in the section above. The direct comparison of raw data, in place of an approximated distribution, provides a more definitive interpretation of differences between metrics. Whereas the use of approximations may allow the lost accuracy in distribution fitting to provide evidence of differences that aren't explicitly present in the raw data generated. For this reason, the distributional approximations in *Appendix C, Section 9* serve as tools for simplified communication of results to audiences without an academic background, or reduced levels of data literacy. The comparison metrics are split according to their use on comparing changes in either *Transmission*

Dynamics or *Customer Dynamics*. The metrics available for model comparison follow from those described in the description of the simulation validation, *Section 4.6.2*. However, as many of these metrics provide similar measures in model dynamics, a greater focus is placed on the following comparison metrics.

The comparison metrics used in assessing and comparing *Transmission Dynamics* have a focus on the following outcomes:

- Total number of transmissions in the supermarket environment
- Total number of transmissions at each location in the shop: shop queue, shop aisles, till queue, and tills
- Total number of environmental transmissions, made up of a combination of aerosol and surface to person(fomite) transmissions
- Total number of direct contact, person-to-person, respiratory transmissions

The comparison metrics used in assessing and comparing *Customer Dynamics* have a focus on the following outcomes:

- Average total shop time per customer: Overall average time for all customers and averages for customers grouped by each shop-size. Measured from entry into the shop until exit.
- Average shop queue time per customer: Overall average time for all customers and averages for customers grouped by each shop-size.
- Average till queue time per customer: Overall average time for all customers and averages for customers grouped by each shop-size.
- Ratio of customers lost due to balking to the number of customers process by the shop.

Although the comparison of model scenarios draws from a focus on the comparison metrics described above, the comparison of transmission control measure scenarios is not limited to the above metrics.

5.2 Transmission Control Measure Scenarios

The effectiveness of the different transmission control measures described in *Section 4.8* is evaluated through a three-part process. The process of evaluation and comparison begins by comparing control measure scenarios, using the comparison metrics described above, according to the isolated, independent implementation of each control measure. The evaluation continues by comparing the changes in dynamics seen in the initial evaluation to the changes in dynamics using the same control measure implementation scenarios at varied disease prevalence levels. This serves to assess whether the effectiveness of each transmission control measure is dependent on the stage of the pandemic at the time. The final step of control measure evaluation assesses the effectiveness of the combinations of each considered control measure. This serves to evaluate control measure effectiveness, allowing for the effects of interactions between each control measure.

The **Base Model**, which serves as a baseline comparison level for the evaluation of changes in comparison metrics for each respective control measure scenario, refers to the model scenario with a *Standard Vaccine Schedule* and no other active transmission control measures in place.

5.2.1 Individual Control Measure Evaluation and Comparison

As the primary objective of any transmission control measure is to reduce the number of viral transmissions in the system, the evaluation of the control measures considered begins with a focus on resulting changes in *Transmission Dynamics.* A secondary key objective for any measures put in place is to ensure that the measure does not result in major changes in the functionality of the environment. Looking at the changes in *Customer Dynamics* serves not only to evaluate the impact of control measure implementation on shop functionality, but also provides insight into any changes in transmission that may result from differences in customer dynamics.

Changes in Transmission Dynamics

Looking at the number of **Total Transmissions** that take place in the shop environment over the simulation period for each control measure scenario compared to the Base Model Transmission count, provides an initial evaluation of how effective each isolated control measure is at reducing COVID-19 transmissions in the shop environment. The plot in *Figure 5.2* below, shows box-plots of the range of Total Transmission values that are observed for each control measure scenario. The colour of the box-plot serves to indicate the transmission control measure used, with the use-level shown on the x-axis.

Looking at the plot in *Figure 5.2*, the transmission control measure with most considerable effect on the resulting number of COVID-19 transmissions in the shop environment is the use of **Vaccines**. As the use-level scenario with a *Standard Vaccine Schedule* forms part of the *Base Model* definition, there appears to be no considerable difference in the number of total transmissions between these scenarios with a mean of 153 transmissions taking place. The scenario of *No Vaccines* serves to demonstrate an estimation of the number of further transmissions that would take place if no COVID-19 vaccines had been developed or administered to the population. As can be seen in the figure, there is a considerably large increase (of around 70%) in the number of total transmissions that occur in the scenario of *No Vaccines* when compared to the Base Model with a mean of 265.3 transmissions occurring. The next use-level of the vaccination scenario control measure is the use of a *Staff Vaccine Mandate*, in which all shop staff are required to be fully vaccinated against COVID-19. As can be seen by the corresponding bar-plot in the figure, there is a considerably large decrease (of around 40-60%) in the total number of transmissions that occur in the *Staff Vaccine Mandate* scenario when compared to the Base Model with a mean of 70.9 transmissions taking place. The large reduction in the number of transmissions that occur in the shop environment due solely to the change in staff vaccination status, provides evidence of the roles that shop staff play as Super-Spreaders in the system. The final vaccine scenario use-level is that of a *Full Vaccine Mandate*, in which all staff and customers are required to be fully vaccinated against COVID-19. The corresponding range of values for the total transmissions in this scenario indicates the most considerable effect on the number of total transmissions in the shop environment, with a decrease of around 90% in the number of total transmissions when compared to the Base Model, resulting in a mean of 8.8 transmissions taking place.

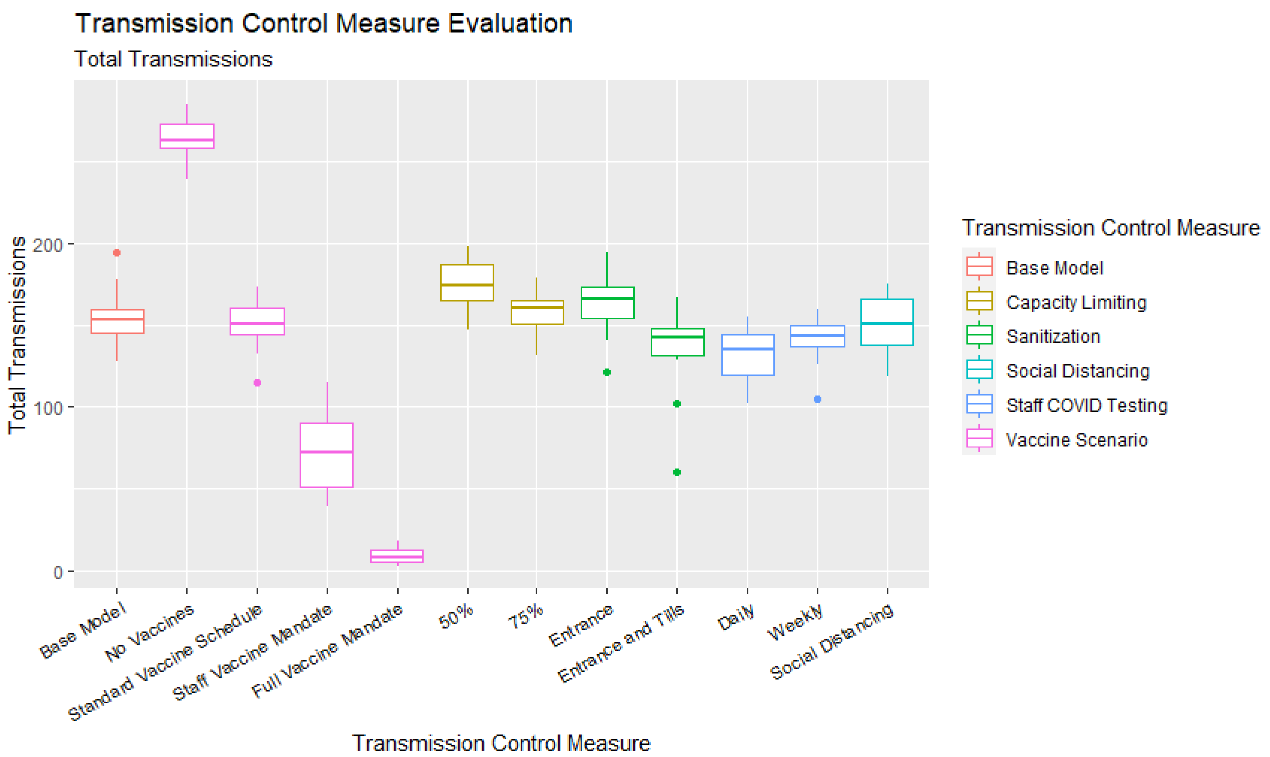

Figure 5.2: Box-plots showing the Total Transmission Count under each Isolated Control Measure Scenario

The next most notable transmission control measure with respect to reducing the number of total transmissions in the shop environment is that of **Staff COVID-19 Testing**. The use-level of *Daily Staff Testing* is the level that results in the greatest reduction in total transmissions, resulting in a mean of 133 total transmissions as a decrease of around 15% when compared to the Base Model. A lesser reduction in the number of total transmissions is seen at a use-level of *Weekly Staff Testing*, with a resulting decrease of around 8% in total transmissions in the shop environment to a mean of 141.3 transmissions. This gives evidence that a more frequent testing schedule results in a greater reduction in transmissions in the environment. Looking further at the total number of transmissions for the remaining control measure scenarios, there appears to be no considerable change in the number of total transmissions for the scenario in which **Social Distancing** is implemented. Most notably, there appears to be an unexpected increase in the number of total transmissions that take place in the shop environment for both use-levels of the **Capacity Limiting** control measure as well as for the **Sanitization** control measure with a use-level of sanitising at the shop *Entrance* only. While the Sanitization use-level of sanitising at the shop *Entrance and Tills* results in a decrease of about 13% in the number of total transmissions to a mean of 135.6 transmissions when compared to the Base Model, there is an increase of about 7% in the number of total transmissions to a mean of 163.7 transmissions with sanitising at the *Entrance*. This indicates that the additional use of sanitiser at the shop tills results in a considerable improvement in the effectiveness of using sanitiser to reduce COVID-19 transmission in the shop environment.

Looking at the changes in the number of total transmissions that result from the implementation of **Capacity Limiting**, the implementation of Capacity Limiting under either use-level resulted in an unexpected increase in the total number of transmissions that took place when compared to the Base Model. The scenario with a Capacity Limiting use-level of *50%* of maximum customer capacity resulted in an increase of about 15% in total transmissions compared to the Base Model, with a mean of 173.5 COVID-19 transmissions taking place. With a use-level of *75%* of maximum customer capacity, there was a marginal increase of about 2% in the total number of transmissions to a mean of 157.6 transmissions. The larger increase in transmissions at the 50%

use-level indicates a greater number of transmissions resulting from increasingly strict capacity limiting. The increases in the total number of transmissions that correspond to the implementation of Capacity Limiting and Sanitization at the shop Entrance indicate that there may be a negative impact with respect to transmission dynamics that is due to changes in shop customer dynamics, and that this impact is outweighing any positive change from the implementation of the control measures. For example, an increase in customer queuing times resulting from the implementation of a control measure may result in increased transmission due to interactions that take place in the queue.

To ensure that the changes in the number of transmissions in the system are not as a result of changes in the number of infectious customers that are arriving at the shop, the results from *Figure 5.2* are compared to *Figure 7.3* in *Appendix A, Section 7*. Looking at the two figures, there are no considerable differences in the changes in transmission dynamics indicated by the two figures. The same affirmations are made with respect to ensuring changes in transmission counts are not as a result of changes in receptive/susceptible populations, by comparing the results from *Figure 5.2* to those in *Figure 7.4* in *Appendix A, Section 7*. In comparing the figures, there appears to be no considerable changes in the indicated transmission dynamics other than for the vaccine-related scenarios. However, these differences are to be expected due to the inherent nature of the way an inclusion of vaccinated populations changes the receptive and susceptible populations in the environment.

In order to gain further insight into the ways in which each transmission control measure affects the transmission dynamics in the shop environment, one can look at the changes in transmission dynamics that take place in each section of the shopping process as a result of implementing each control measure. The group of plots in *Figure 5.3* below, shows box-plots of the range of Total Transmission values that are observed for each control measure scenario at each of the shop locations; the shop queue (A), within the shop product areas (B), the till queue (C), and at the tills (D). As shown in the previous figure and for all figures in this chapter, the colour of the box-plot serves to indicate the transmission control measure used, with the use-level shown on the x-axis.

Looking at the plots in *Figure 5.3*, the changes in transmission dynamics resulting from the implementation of each isolated control measure appear to vary more considerably than was seen in the previous figure of total transmissions above. Looking at the changes in disease dynamics at each shop location provides a more focused understanding of the way in which transmission dynamics are affected by each transmission control measure, providing insight into how the changes in total transmissions came about. Starting by looking at changes in the number of transmissions in each shop location resulting from the **Vaccine Scenario** control measures, compared to the Base Model. As inferred by the previous plot, the scenario with *No Vaccines* resulted in a considerable increase in the number of transmissions that took place in all locations in the shop. This provides further evidence of the impact reduced population immunity has on transmission throughout the environment. As established in the discussion of the previous figure, the scenario of the *Standard Vaccination Schedule* is that which is used in the Base Model, resulting in no considerable differences in transmission counts for any of the plots in the figure. Looking at the transmission counts in each shop location under the scenario for the *Staff Vaccine Mandate*, there appears to be no considerable difference between the transmission counts in both the shop queue (A) as well as the till queue (C) when compared to the Base Model. This is to be expected as customers in these locations in the shop have no interaction with the shop staff. There is a slight decrease in the number of transmissions that take place in the product sections of the shop (B), and a considerable decrease in the number of transmissions that occur at the tills (D). This large decrease is to be expected due to the greatly reduced chance of vaccinated staff becoming infectious and thereby infecting customers. The most considerable reduction in transmission counts overall is seen by the *Full Vaccine Mandate* scenario, in which the high levels of immunity throughout the population of both customers, and staff, corresponds to a considerable reduction in the number of transmissions that take place throughout the shop.

In looking at the number of transmissions that take place in each location in the shop for scenarios relating to the implementation of **Capacity Limiting**, the most notable changes in transmission dynamics in comparison to the Base Model are seen in the number of transmissions that occur in the shop queue (A). There appears to be a considerable increase in the number of transmissions that take place in the shop queue for both use-levels of the capacity limiting control measure when compared to the Base Model. The increase in the number of shop queue transmissions for the *50%* capacity limit, of around 150%, is considerably higher than the increase in shop queue transmissions for the *75%* use-level of around 75% when compared to the Base Model.

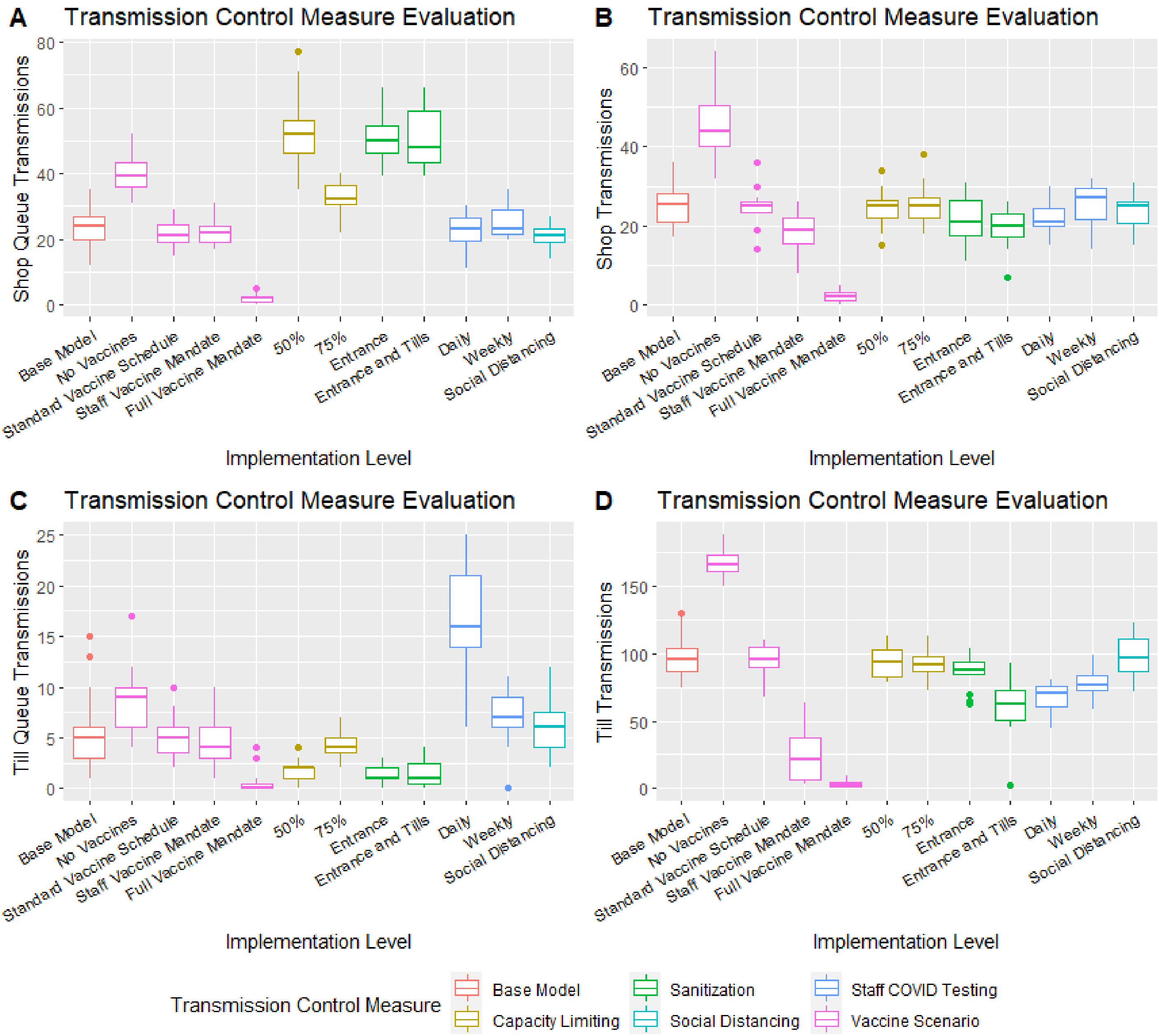

Figure 5.3: Box-plots showing the Total Transmission Count at each Location in the Shop under each Isolated Control Measure Scenario

These increases provide further indication that the implementation of the capacity limit in the shop results in an increase in time and customer interactions in the shop queue while customers wait to enter, allowing for more transmissions to take place. In looking at the number of transmissions that occur in the remaining shop locations for the capacity limiting scenarios, there appears to be a slight reduction in the number of transmissions that take place in the till queue (C). This is likely due to the reduced till queue size and queuing duration with fewer in-store customers. The remaining locations of the shop products sections (B) and tills (D) indicate no considerable change in the number of transmissions with the implementation of capacity limiting when compared to the Base-Model.

Shifting focus to the number of transmissions that take place in each location in the shop for scenarios relating to the implementation of the **Sanitization** control measure. Both use-levels, of sanitization at the *Entrance* and at the *Entrance and Tills*, show slight decreases in the number of transmissions that take place in the shop products sections (B) and till queue (C). This is likely due to the reduction in the amount of viral environmental contamination that COVID-positive customers produce. The use-level including sanitization at the tills has a considerable reduction in the number of transmissions that take place at the tills, with no considerable change in the total number of till transmissions (D) for the use-level of sanitization at the shop entrance alone, when compared to the Base Model. This indicates that sanitiser use at the tills is considerably effective at reducing transmissions at the tills. Looking at the plot showing the number of transmissions in the shop queue (A), there is a substantial increase in the number of transmissions that take place for both sanitiser scenarios when compared to the Base Model. This is likely due to the increase in shop queue processing time that occurs when customers are required to sanitise at the entrance of the shop, resulting in longer queues and more customer interactions for transmission to take place. It is important to note that due to the limitation of 1 min minimum time steps in the model, the shortest amount of time for a customer to sanitise is 1 min, which may be considerably shorter in real-world application, which may result in an unrealistic increase in the shop queue processing speed. However, this may still serve as an analogous representation of any process to entry that increases entrance time, such as filling in an entrance form with customer details for contact tracing.

Looking at the final two transmission control measures implemented, the isolated implementation of the **Social Distancing** control measure appears to have no considerable change in the number of transmissions at any of the shop locations when compared to the Base Model. The final control measure considered is the implementation of **Staff COVID-19 Testing**. Both use-levels show no considerable change in the total number of transmissions that occur in either the shop queue (A) or in the shop products sections (B) when compared to the Base Model. As customers move to the till queue (C), there is a considerable change in the number of transmissions that occur due to the implementation of staff COVID-19 testing. Both use levels indicate an increase in transmissions in the till queue, with a respectively smaller increase at a use-level of *Weekly* staff testing and a substantially large increase of around 300% in the number of till queue transmissions compared to the Base Model with a use-level of *Daily* staff testing. These increases are very likely to be as a result of the cases in which staff testing positive for COVID-19 results in fewer staff working. This results in a considerable reduction in processing speed for the till queue, leading to a substantial increase in till queue times and allowing for more transmissions to take place. These cases become more frequent when daily testing is adhered to, providing more time points in which exposed staff will be required to isolate.

Further insight to be drawn from the plots in *Figure 5.3* is the indication of the proportions of the total transmissions that are attributed to each shop location, shown by looking at the number of transmissions indicated on the y-axis of each respective plot. Looking at the plots in the figure for the Base Model, around two thirds of the transmissions in the shop environment take place at the tills (D). With less than 5% of the transmissions occurring in the till queue (C) and the remaining transmissions taking place roughly equally between the shop queue (A) and shop products sections (B). This adds some insight into why the control measures, such as staff vaccination or till sanitization, that are able to reduce transmissions at the shop tills appear to be more effective at reducing the total number of transmissions in the environment. The high number of till transmissions also serves to provide further indication of the roles that the shop staff play as Super-Spreaders in the system.

Before looking at the way in which the implementation of each of the considered transmission control measures affects customer dynamics in the shop, some final insight into their effects on transmission dynamics can be drawn from developing understanding around the way each control measure affects transmission with respect to Direct and Environmental Transmissions. The plots in *Figure 5.4* below, show box-plots of the range of Total Transmission values that are observed for each control measure scenario resulting from either Direct Transmission (A) or Environmental Transmission (B).

In order to develop further understanding of the effectiveness of implementing each transmission control measure ahead of the insight gained from the figures above; looking for differences in the effects a control measure has on direct transmissions and environmental transmissions, provides insight beyond the effect on transmission as a whole established in the previous figures.

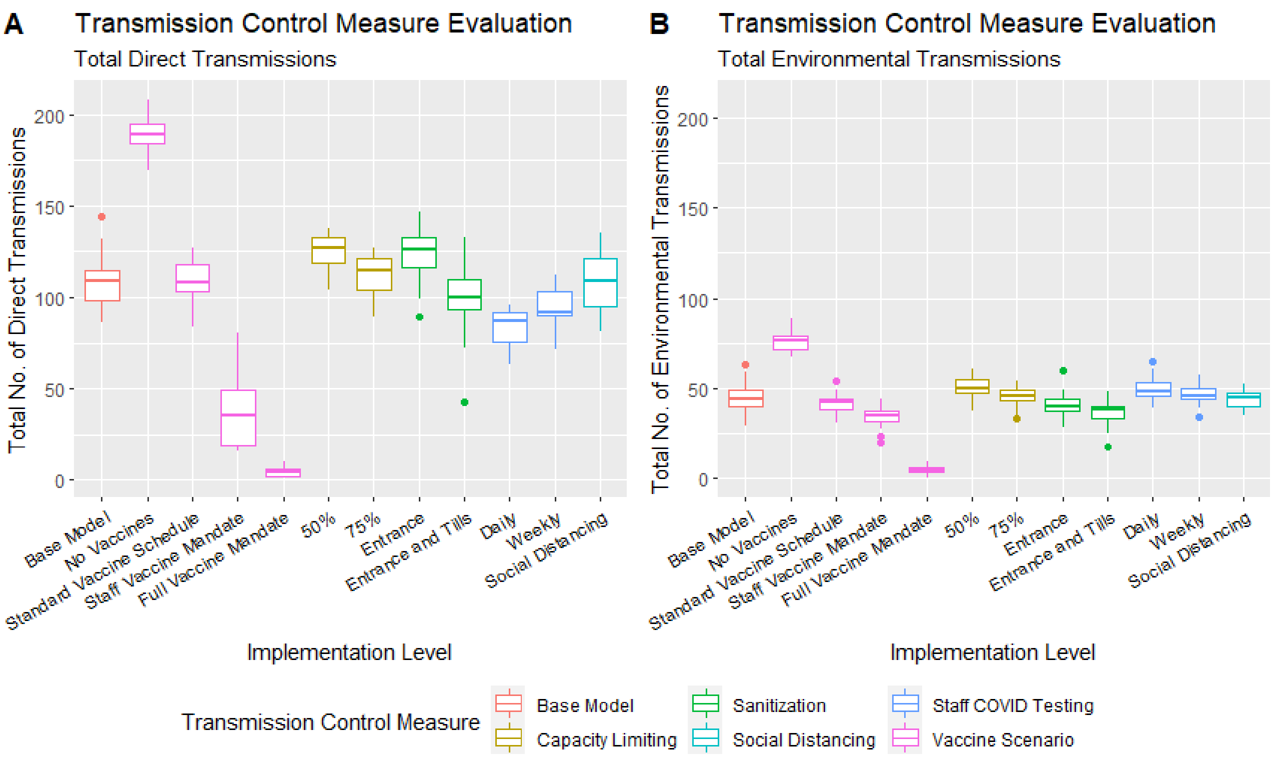

Figure 5.4: Box-plots showing the Total Direct Transmissions (A) and Total Environmental Transmissions (B) under each Isolated Control Measure Scenario

Looking at the plots in *Figure 5.4*, the transmission control measures that show a variation in the ways in which they affect direct and environmental transmission are those of *Sanitization*, and **Staff COVID-19 Testing**. The scenarios relating to the implementation of **Sanitization** show a decrease in the number of environmental transmissions, with a simultaneous increase in the number of direct transmissions compared to the Base Model for the *Entrance* sanitization use-level and a slight decrease at the *Entrance and Tills* sanitization use-level. This can be attributed to the reduction in environmental contamination that is attributed to hand and surface sanitization, while the increase in direct transmissions can be attributed to the increase in shop queue transmissions seen in *Figure 5.3*. The slight decrease in direct transmissions for the *Entrance and Tills* sanitization use-level, despite increased shop queue transmissions, may be as a result of reduced staff transmission leading to fewer staff to customer direct transmissions. Looking at the scenarios relating to the implementation of **Staff COVID-19 Testing**, there appears to be no considerable change in the number of environmental transmissions compared to the Base Model. However, there is a considerable reduction in the number of direct transmissions. This is likely due to a reduction in direct transmission from infectious staff, as these staff would be more likely to isolate. The smaller reduction in environmental transmissions resulting from the implementation of a *Staff Vaccine Mandate* compared to the reduction in the number of direct transmissions, gives further evidence of transmissions between staff and customers at the tills being mostly direct transmissions. This would make sense due to the person-to-person contact nature of the till transaction between customers and staff.

Further insight gained from the plots in *Figure 5.4* is the indication of the proportions of the total transmissions that are attributed to direct and environmental transmission respectively. This is shown by looking at the number of transmissions indicated on the y-axis of each respective plot. Looking at the plots in the figure for the Base Model, around two thirds of the transmissions in the shop environment are attributed to Direct transmission with the remaining third attributed to Environmental transmission. This indication, that a transmission is around twice as likely to result from direct contact transmission compared to environmental transmission, serves to illustrate that control measures affecting direct transmission may be more likely to have greater effectiveness at reducing the total transmissions that take place. However, as a considerable proportion of transmission is attributed to environmental exposure, this highlights a need to consider transmission control measures that reduce exposure to viral contaminants in the environment and not give sole focus to those reducing person-to-person contact transmission.

Changes in Customer Dynamics

The importance of assessing the changes in customer dynamics that result from the implementation of each transmission control measure is two-fold. Firstly the implementation of a control measure should not result in a considerably negative impact on the customer shopping experience. If control measures result in intolerable increases in shopping and queuing times, this would likely result in customers seeking shopping alternatives leading to losses in shop revenue and unhappy customers. Secondly, observing the changes in customer dynamics that result from each control measure implementation provides valuable insight into the indirect effects that the implementation might have on transmission dynamics, allowing for informed measures to be taken to reduce these impacts.

As the area in the shop environment with the most considerable unexpected changes in transmission dynamics indicated by *Figure 5.3* was the shop queue area (A), the assessment of changes in customer dynamics resulting from the control measure implementations begins by looking at the average amount of time (minutes) spent by each customer in the shop queue under each control measure scenario. The box-plots in *Figure 5.5* below, show the range of values for the average amount of time in minutes spent by each customer in the shop queue for each of the isolated transmission control measure implementation scenarios.

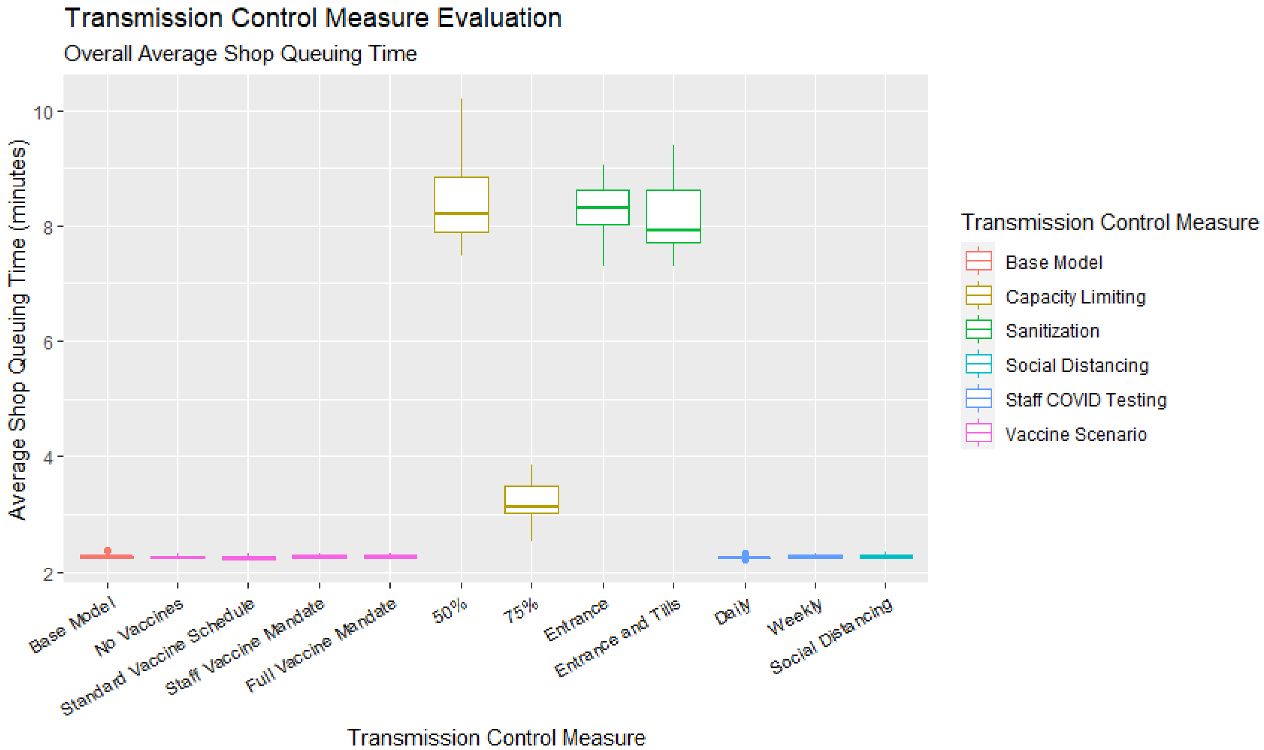

Figure 5.5: Box-plots showing the Average Shop Queuing Time per Customer under each Control Measure Scenario

Looking at the box-plots in *Figure 5.5*, the only transmission control measure scenarios that appear to show a considerable difference in the customer shop queuing time when compared to the Base Model are those relating to the implementation of **Capacity Limiting** or **Sanitization**. The *75%* capacity limit use-level scenarios appear to show an increase of around 50% in the average customer queuing time, while the *50%* use-level as well as both Sanitization use-levels with shop entrance sanitising appear to show increases of around 300% in the average customer shop queuing time when compared to the Base Model. In comparing to plot (A) in *Figure 5.3*, the same four control measure scenarios show considerable increases in the number of transmissions that took place in the shop queue when compared to the Base Model. This strong correlation between the average customer shop queuing time and the number of shop queue transmissions provides evidence that the increased time in the shop queue is likely to be the cause of the increase in transmissions seen for these control measure scenarios. Although these increases are substantial in proportion to the average queue times without the implementation of these control measures, the largest average shop queuing time for these scenarios is under 10 minutes. An average shop queuing time at this level would likely be seen as still within an acceptable range to warrant considering the use of these control measures, solely with respect to the resulting change in customer dynamics.

The next area in the shop that indicated considerable changes in transmission dynamics with control measure implementations is the till queue area. Similarly to the shop queue, looking at changes in the average customer till queuing time may provide further insight into any changes in customer dynamics that are driving these changes in transmission dynamics. The box-plots in *Figure 5.6* below, show the range of values for the average amount of time in minutes spent by each customer in the till queue for each of the isolated transmission control measure implementation scenarios.

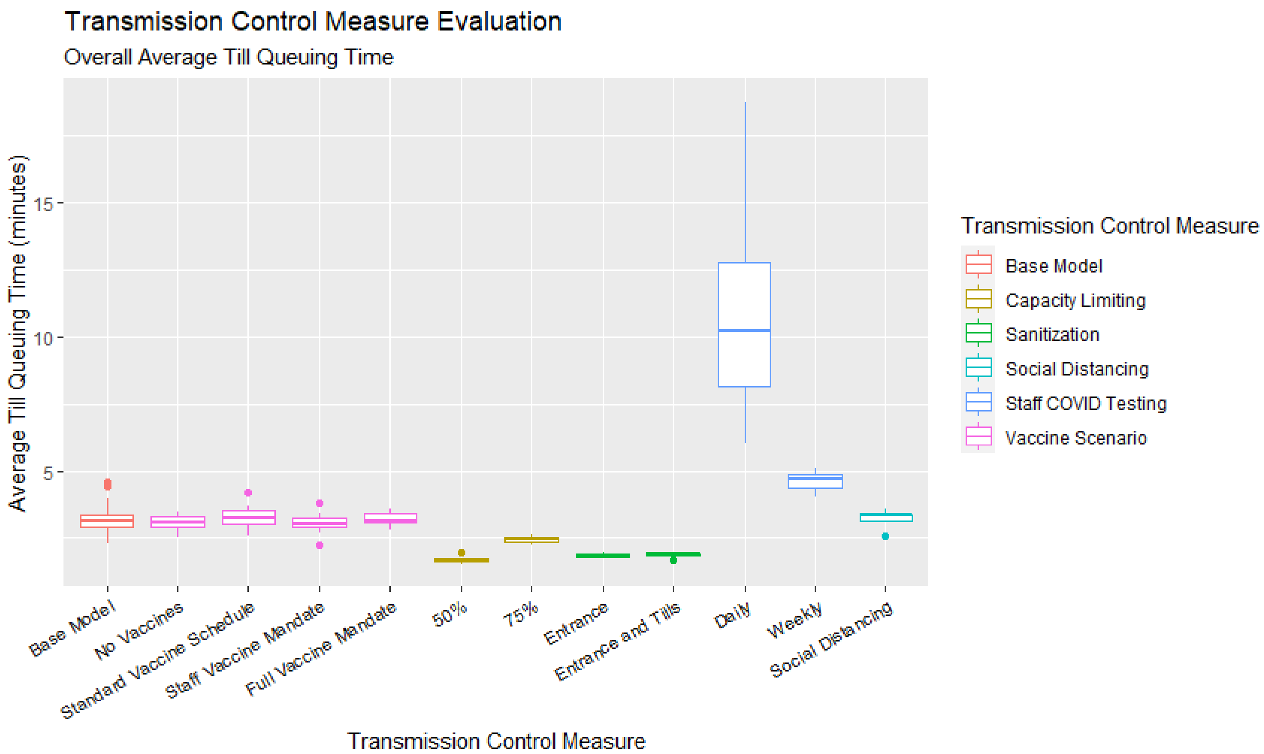

Figure 5.6: Box-plots showing the Average Till Queuing Time per Customer under each Control Measure Scenario

Looking at the average till queuing times shown in *Figure 5.6*, the four scenarios that displayed considerable increases in average customer shop queuing times appear to have corresponding decreases in average till queuing times. These scenarios, relating to the implementation of **Capacity Limiting** or **Sanitization**, show decreases in the average till queuing time due to the entrance delay for customers entering the shop. This delay in customer entry allows for more time to pass between a customer entering the system and their arrival at the till queue. This additional time allows for staff to process more preceding customers, resulting in a shorter till queue upon arrival. The only other control measure scenarios that result in considerable changes in the average customer till queuing time are those relating to the implementation of **Staff COVID-19 Testing**. The *Weekly%* staff testing use-level scenarios appear to show an increase of around 60% in the average customer queuing time, while the *Daily* staff testing use-level appears to show increases of around 200% in the average customer till queuing time when compared to the Base Model. In comparing to plot (C) in *Figure 5.3*, the same two control measure scenarios show considerable increases in the number of transmissions that took place in the till queue when compared to the Base Model. This strong correlation between the average customer till queuing time and the number of till queue transmissions provides evidence that the increased time in the till queue is likely to be the cause of the increase in transmissions seen for these control measure scenarios, just as was seen for scenarios relating to the shop queue increases.

Comparing the changes in average shop and till queuing times for each customer shop-size group can be done to establish whether the changes in average queuing time is dependent on the number of items a customer purchases. This is done by looking at the box-plots for the average customer queue times for each customer shop-size under each control measure scenario for the shop and till queues in *Figures 7.6 and 7.7* in *Appendix A, Section 7* respectively. Looking at the figures, there appears to be no difference in the changes in customer queue time dynamics resulting from control measure implementations with respect to each customer shop-size. The last comparison metric relating to average customer dynamics times is that of the average shopping time per customer. Looking at the box-plots in *Figure 7.5* in *Appendix A, Section 7*, the changes in average customer shopping times with each control measure implemented in comparison to the Base Model values show a very similar structure to that seen by *Figure 5.6.* As the shopping time encompasses the time spent shopping, queuing for the tills, and checking out at the tills; the similar structures in customer dynamics between these two figures indicates not considerable changes in the average customer shopping and check-out times as should be expected.

Looking at the box-plots showing the maximum customer queue times for the shop (A) and till (B) queues under each control measure scenario *Figure 5.7* below, the structural changes in customer dynamics appear to lead to the same conclusions as those drawn from average queue time plots. Beyond structural changes in customer dynamics for these queues, the values shown for the maximum shop and till queuing times in the scenarios resulting in increases compared to the Base Model show considerably high queuing times. The scenarios relating to the implementation of **Sanitization** and the *75%* **Capacity Limiting** use-level show a maximum shop queue waiting time of over 50 minutes, which may be considered as unacceptably long. This may indicate that alternative measures might need to be put in place in order to reduce these queuing times. Looking at the maximum till queuing times (B), the scenarios relating to the implementation of **Staff COVID-19 Testing** show till queue wait times of over an hour for both use-levels. With maximum waiting times of over two hours seen under the *Daily* staff testing use-level scenarios, these waiting times would definitely be considered unacceptable to shop customers. These long waiting times are as a result of instances in which there are minimal staff available to process customers at the tills, so the consideration of adding additional substitute staff or reducing customers when most staff are in isolation would be necessary to consider these control measure uses.

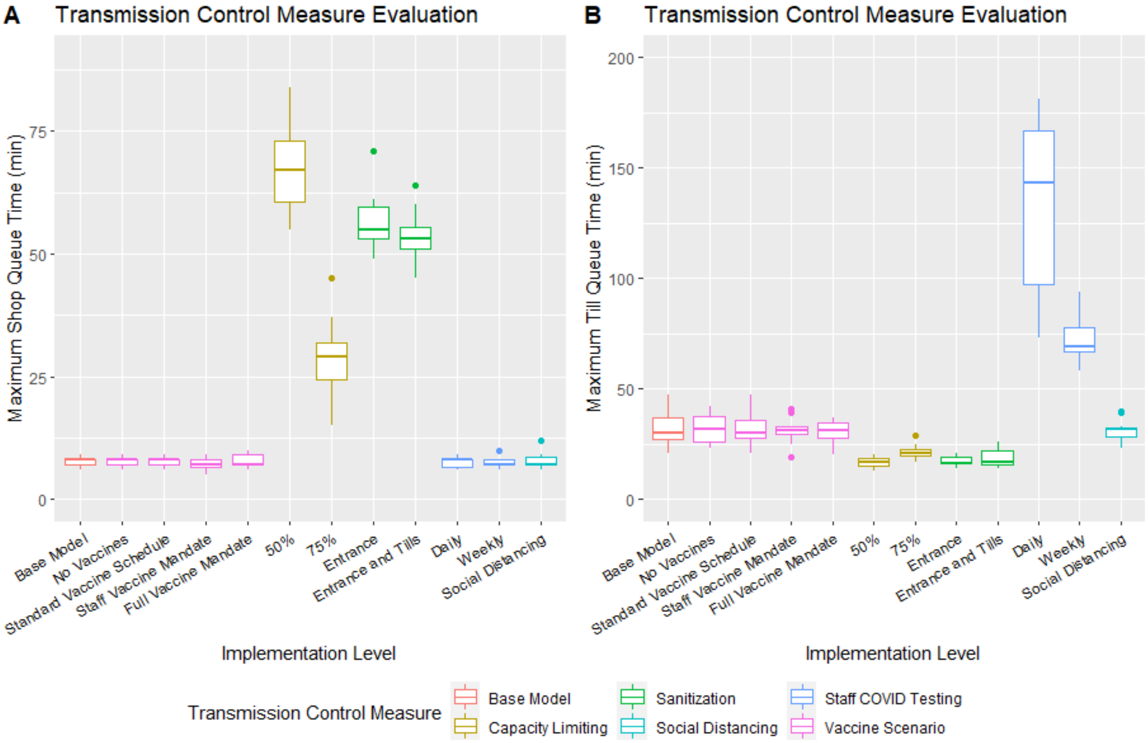

Figure 5.7: Box-plots showing the Maximum Shop (A) and Till (B) Queuing Time under each Control Measure Scenario

Another important comparison metric in assessing the effectiveness of each control measure is the ratio of customers lost to the number of customers processed by the shop. This metric serves to evaluate the number of customers that would avoid using the shop due to unacceptably long queues upon their arrival while ensuring any change in the number of lost customers is not due to changes in the number of customers visiting the shop. This ensures that the change follows as a result of the control measure implemented. Looking at the box-plots showing the changes in this ratio under each control measure scenario *Figure 5.8* below, the only control measure scenarios indicating considerable changes in the number of customers lost are those relating to the implementation of **Staff COVID-19 Testing**. This is further confirmed by looking at the Average number of customers processed by the shop per day seen in *Figures 7.8 and 7.9* in *Appendix A, Section 7*. As seen by these figures the scenarios relating to the implementation of **Staff COVID-19 Testing** appear to result in a decrease in customers across all customer shop-sizes. As implied by *Figure 5.7* the increase in till queue size and duration is likely the result of these customers lost to balking, further indicating a need for alternative measures to be put in place in order to consider the use of these measures.

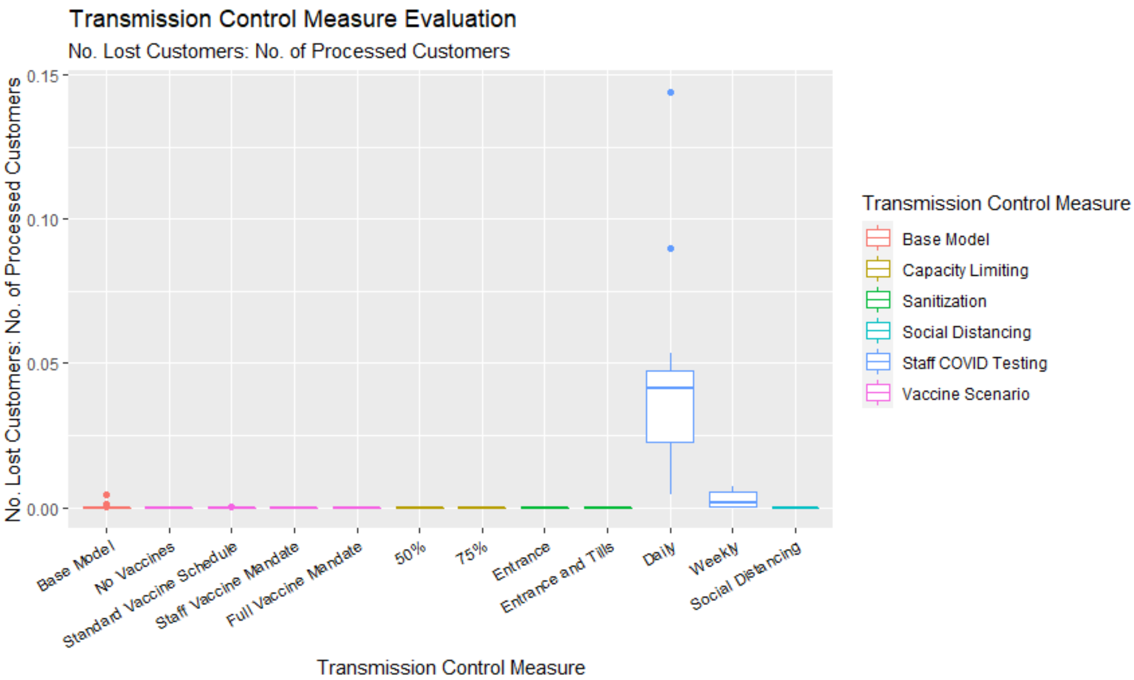

Figure 5.8: Box-plots showing the Ratio of Total Customers Lost: Total Customers Processed under each Control Measure Scenario

Relative Control Measure Effectiveness at Varied COVID-19 Prevalence

As the level of COVID-19 prevalence varies constantly throughout the pandemic, an important factor to consider regarding the choice of which transmission control measure to implement in the shop environment is whether or not the effectiveness of the control measures considered varies with changes in prevalence through transmission cycles in the pandemic. If there appear to be considerable levels of dependence between the prevalence of COVID-19 in the population and which transmission control measure is the most effective at reducing transmission, then the choice of which control measure(s) to implement would vary through the stages of the pandemic.

In order to establish the sensitivity of the control measure effectiveness to changes in COVID-19 prevalence, the assessment of the comparison metrics evaluated in *Sections 5.2.1 and 5.2.1* above is repeated at varied levels of prevalence. Following this procedure, the assessment begins by looking at the number of **Total Transmissions** that take place in the shop environment over the simulation period for each control measure scenario at prevalence levels of **2%, 5%**, and **10%** in *Figure 5.9* below. Comparing the relative ranges of Total Transmissions under each control measure scenario at each of the specified prevalence levels, the changes in transmission dynamics for each control measure scenario relative to the Base Model appear very similar. Although the number of Total Transmissions recorded appears to increase with a relative increase in prevalence, the changes in these counts for each control measure scenario relative to their respective Base Model values appears consistent across the range of prevalence levels. It is worth noting that the increase in the total number of transmissions is not proportional to the increase in the number of infectious customers arriving at the shop, as seen by *Figure 7.10* in *Appendix A, Section 7*. This follows the same pattern as was seen in the sensitivity analysis in *Section 4.6.3*. The only control measure that appears to show changes in relative effectiveness with changes in prevalence is the *Entrance and Tills* use-level of the **Sanitization** control measure. The use of Sanitization at the Entrance and Tills appears to result in a larger reduction in the number of Total Transmissions relative to the Base Model at lower levels of COVID-19 prevalence, with relative decreases in the effective reduction in transmissions as the level of prevalence increases. All other transmission control measure scenarios appear to show no considerable changes in effectiveness, with respect to transmission reduction, at varied levels of COVID-19 prevalence.

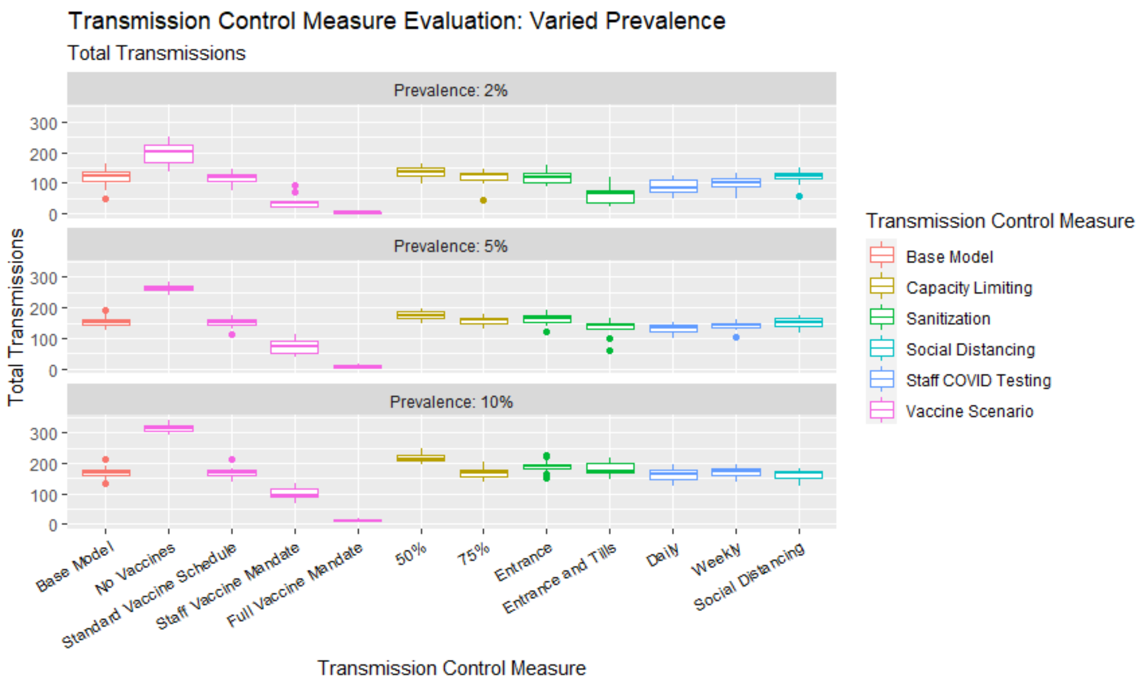

Figure 5.9: Box-plots showing the Total Transmission Count under each Isolated Control Measure Scenario with Varied Levels of Prevalence

Looking further other the other key comparison metrics for Transmission Dynamics, of the Total Transmissions at each Shop Location and the Total Direct (A) and Environmental (B) Transmissions in *Figures 7.11 and 7.12* in *Appendix A, Section 7*, the same similarities are seen for transmission dynamics between each control measure across the prevalence levels. Again, the *Entrance and Tills* use-level of the **Sanitization** control measure is the only scenario that shows any considerable change across prevalence levels. The difference appears to result from higher effectiveness at low prevalence until the prevalence reaches a point high enough to result in staff becoming exposed early in the simulated period. Thereafter, the resulting increase in staff to customer transmissions outweighs the reduced transmissions from the use of sanitizer.

Looking at the key comparison metrics relating to changes in Customer Dynamics with varied prevalence, the changes in average shop and till queuing times for each control measure scenario relative to the Base Model appear to be consistent across the varied prevalence levels for all control measures. This can be seen in *Figures 7.13 and 7.14* in *Appendix A, Section 7* respectively. One key comparison metric relating to changes in Customer Dynamics that does appear to show considerable change with changes in prevalence is the ratio of customers lost to balking against the number of customers processed by the shop, which can be seen in *Figure 5.10* below. The only control measure scenario showing changes in relative Customer Dynamics with changes in prevalence is the *Daily* use-level of the **Staff COVID-19 Testing** control measure. There appears to be an increase in the number of customers lost with an increase in the prevalence of COVID-19 when this measure is in use. This is as a result of staff becoming exposed earlier in the simulation period when prevalence is high. As a result, with COVID-19 tests being done daily, these staff transmissions are detected faster and the staff are made to self-isolate. With staff in isolation, the number of staff available to work decreases, leading to increased till queue durations and therefore customers lost due to balking. In the instances where all staff are in isolation, the shop is unable to process any customers and all customer arrivals within this time are lost.

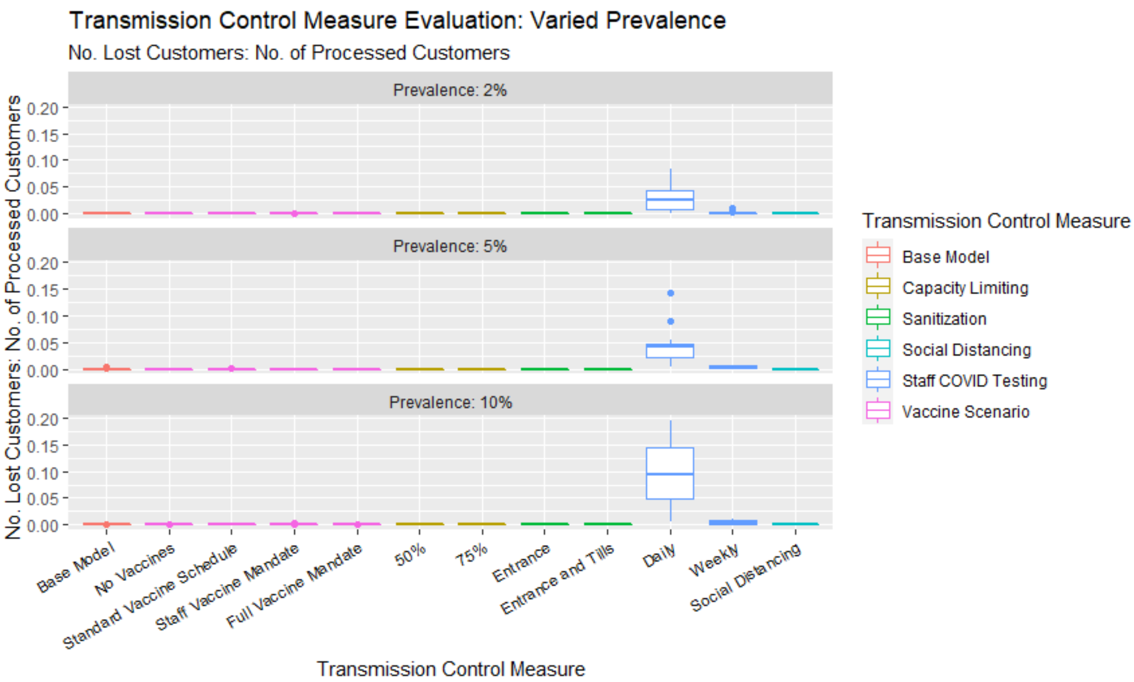

Figure 5.10: Box-plots showing the Ratio of Customers Lost to Total Customers Processed under each Isolated Control Measure Scenario with Varied Levels of Prevalence

5.2.2 Combined Control Measure Evaluation and Comparison

The real world implementation of COVID-19 transmission control measures rarely consists of a single isolated control measure. With the primary goal of maximizing the reduction in COVID-19 transmissions, the combined implementation of multiple control measures is an intuitive step in achieving this goal and has become commonplace in many environments world-wide. The implementation of more than one control measure at a time allows not only for the effects of each control measure on transmission and customer dynamics, but facilitates an interaction effect between control measures that may serve to either increase or decrease the effectiveness of the control measures put in place. The evaluation of the scenarios using the combined implementation of transmission control measures follows the same process as was seen for the isolated control measures in *Section 5.2.1* above, by starting with looking at key comparison metrics measuring changes in Transmission Dynamics followed by those relating to changes in Customer Dynamics.

As the number of possible scenarios regarding combined control measure scenarios is calculated multiplicative with the use-levels of each control measure, the number of scenarios considered is 216. In order to reduce this in the interest of model run-time as well as visualising results, the scenarios involving the *No Vaccines* use-level of the **Vaccine** control measures are not considered. This is due to the fact that much of the real-world population has already been vaccinated, making these scenarios impossible to replicate in real-world application. This reduces the number of considered scenarios to 162.

Figure Layout

The figures relating to comparison metrics for the combined implementation of transmission control measures have a similar structure to those used in the multivariate sensitivity analysis in *Section 4.6.3*. As these figures attempt to condense information from higher-dimensional space into a two-dimensional space, they can quickly become difficult to interpret.

The figures in this chapter have the following structure:

- The value for the **comparison metric** of interest is shown on the *y-axis*
- The use-levels for **Vaccine** controls are shown on the *x-axis*
- The use-levels for **Sanitization** controls are shown by the *plot rows*
- The use-levels for **Staff COVID Testing** controls are shown by the *plot columns*
- The use-levels for **Capacity Limiting** controls are shown by the *box-plot outline colours*
- The use-levels for **Social Distancing** controls are shown by the *box-plot fill colours*

Changes in Transmission and Customer Dynamics

As with the assessment of the isolated implementation of control measures, looking at the number of **Total Transmissions** that take place in the shop environment over the simulation period for each control measure scenario provides a good initial evaluation of how effective each control measure combination is at reducing COVID-19 transmissions in the shop environment. The plot in *Figure 5.11* below, shows box-plots of the range of Total Transmission values that are observed for each control measure scenario. Similar changes with respect to changes in transmission dynamics are seen by the ratio of total transmissions to the number of customers processed in *Figure 7.10* in *Appendix A, Section 7.*

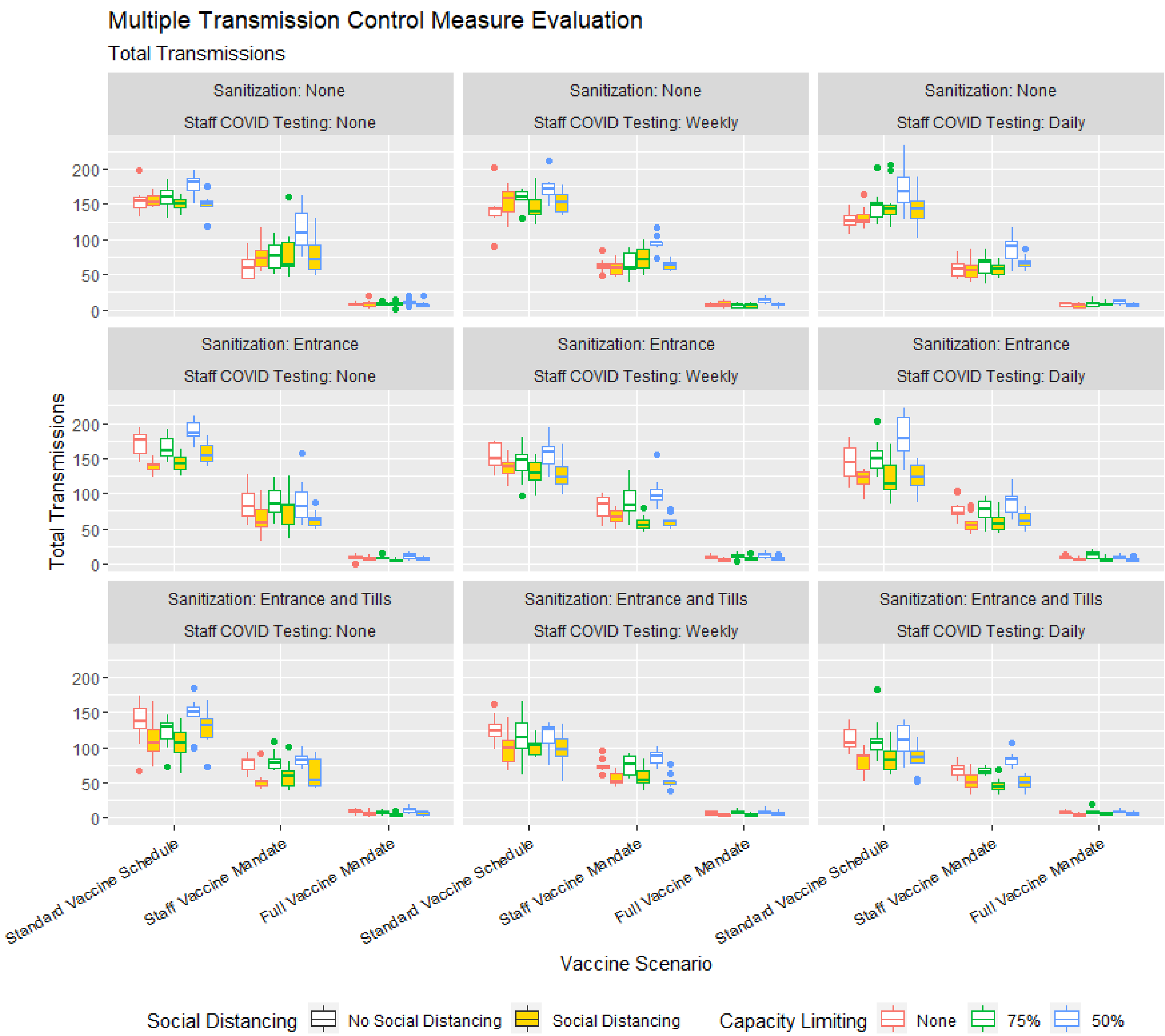

Figure 5.11: Box-plots showing the Total Transmission Count under each Combined Control Measure Scenario

Looking at the box-plots in *Figure 5.11*, the control measure that shows the most considerable change in the total number of transmissions appears to be the use of **Vaccines** across all combinations of the control measures considered. The change between each use-levels for any of the Vaccine Scenarios shows a corresponding considerable change in the number of resulting transmissions regardless of the combination of other control measures in place. The *Full Vaccine Mandate* use-level for the Vaccine control measures (rightmost grouping of box-plots in each facet) shows less than 20 total transmissions throughout the simulation period for all combinations of the other control measures. With this in mind, if a Full Vaccine Mandate were enforced for all customers and staff, there would be no benefit in the implementation of any other control measures as minimal transmissions would still take place. Without consideration for the legal and practical limitations to implementing this control measure, the use of a Full Vaccine Mandate appears to be the most effective control measure at reducing COVID-19 transmission in the shop environment.

Looking at the *Staff Vaccine Mandate* use-level for the Vaccine control measures (center grouping of box-plots in each facet), the implementation of a Staff Vaccine Mandate over the Standard Vaccination Schedule appears to result in a considerable reduction in the number of resulting transmissions regardless of the combination of other control measures in place. Apart from the Full Vaccine Mandate, the Staff Vaccine Mandate appears to be the most effective control measure at reducing transmissions in the shop environment. Looking lastly at the *Standard Vaccine Schedule* use-level for the Vaccine control measures (leftmost grouping of box-plots in each facet), although the implementation of a vaccine mandate would result in a decrease in total transmissions compared to the corresponding scenarios of control combinations; there are combinations of the remaining control measures that reduce the number of transmissions to levels that outperform some of the scenarios with a Staff Vaccine Mandate implemented.

The control measure provides the clearest evidence of an interaction effect between control measures in that of **Social Distancing**. Although the isolated implementation of Social Distancing in *Section 5.2.1* showed no considerable impact on the resulting number of transmissions in the shop environment, *Figure 5.11* shows that the combined implementation of Social Distancing as well as a form of Sanitization or Capacity Limiting results in a considerable change in the number of transmissions produced. The box-plots showing the use of Sanitization or Capacity Limiting control measures show noticeably reduced transmission counts with the simultaneous implementation of Social Distancing (box-plots with white fill) compared to when Social Distancing isn't implemented (box-plots with grey fill). With this in mind, the scenarios that have the most beneficial implementation of Social Distancing are those relating to the control measures that resulted in considerable increases in queuing times as seen by *Figure 5.5.* The control measure scenario resulting from the largest change in the number of transmissions due to the implementation of Social Distancing is the scenario with; Daily Staff COVID Testing, Sanitization at the Entrance, and a 50% Capacity Limit. This is likely due to the combined increase in shop and till queuing time as was seen by *Figures 5.5 and 5.6*, without the further implementation of Social Distancing this scenario is also the combination resulting in the highest number of transmissions. However, if Social Distancing is implemented it becomes a control measure combination with a considerable reduction in transmissions compared to the Base Model.

In looking at the effects of implementing **Capacity Limiting** in combination with the other control measures, there is evidence in many combinations that the *75%* capacity limit (green) use-level results in the lowest number of transmissions compared to the *50%* capacity limit (blue) or no limit on capacity (red). Looking at the box-plots for limits on capacity, there appear to be more combinations in which the implementation results in an increase in transmissions rather than a reduction. However, with capacity limits used simultaneously with Sanitization or Social Distancing differences in the number of transmissions between relative Capacity Limiting use-levels become considerably less pronounced.

Shifting focus to the scenarios relating to the implementation of **Staff COVID Testing**. When the use-level of the Vaccine control measures involve the implementation of a vaccine mandate, the effects of staff testing appear to show no considerable change in the number of transmissions with the use of Social Distancing. This is due to the considerably reduced chance of transmission to vaccinated staff, resulting in a reduction of positive test results. For control measure combinations with a Standard Vaccine Schedule, the implementation of Staff COVID-19 Testing appears to result in a marginal reduction in the number of resulting transmissions when testing is implemented on a *Weekly* (middle column of facets) or *Daily* (right column of facets) use-level. However, there appears to no considerable reduction in transmissions between these levels, with some combinations resulting in a relative increase in transmissions for Daily testing compared to Weekly tests.

The last control measure considered is that regarding the use of **Sanitization**. Looking at the change in the number of transmissions resulting from each level of its use, the use of sanitiser at the *Entrance* of the shop (middle row of facets) appears to result in an increase in transmissions compared to no sanitiser use whenever the use of Social Distancing is not used in combination with Sanitization. However, with the simultaneous implementation of Social Distancing there appears to be a reduction in transmission for the majority of relative control measure combinations. The use of sanitiser at the *Entrance and Tills* of the shop (bottom row of facets) appears to result in a considerable decrease in transmissions for most corresponding combinations of control measures, with more considerable reductions shown for combinations including the use of Social Distancing.

With an overall look at the figure of Total Transmissions at each combination of transmission control measures, the combinations resulting in the lowest number of transmissions with each level of Vaccine use appears as follows:

- At a Standard Vaccine Schedule: Daily Staff COVID Testing, Sanitization at the Entrance and Tills, Social Distancing, and No Capacity Limit
- With a Staff Vaccine Mandate: No Staff COVID Testing, Sanitization at the Entrance and Tills, Social Distancing, and No Capacity Limit
- With a Full Vaccine Mandate: No additional control measures necessary

Continuing with the process of assessing changes in Transmission Dynamics under each control measure combination scenario, the number of transmissions at each of the shop locations can be seen in *Figure 5.12* below and *Figures 7.16, 7.17, and 7.18* in *Appendix A, Section 7* for the Shop Queue, Shop Products Areas, Till Queue, and Tills respectively.

Looking at the shop queue transmissions for each control measure scenario in *Figure 5.12*, similar patterns emerge to those seen for the isolated control measure implementation in *Figure 5.3* (A). The scenarios associated with increased shop queue transmissions in *Figure 5.3* (A) show similar associations in their implementation combined with other control measures, with an additive effect for combinations of these control measures. Thus the increase in transmissions with the implementation of **Sanitization** at the shop *Entrance* in either use-level still shows an associated increase compared to instances with no Sanitization. Additionally implemented **Capacity Limiting** shows increases shop queue transmission in all in combinations other than those with **Social Distancing**, whereas the addition of social distancing greatly reduces the increase in transmissions for corresponding control measure combinations such that some combinations show decreased shop queue transmissions with the addition of a capacity limit. This is shown by the combinations including Sanitization at the tills. The most considerable changes in the number of till queue transmissions are seen in combinations including a *Daily* use-level of **Staff COVID Testing** and a limit on capacity, but not including the scenarios with **Sanitization** at the *Entrance and Tills*. These scenarios show notably large increases in their respective number of transmissions. This is likely due to reduced staff availability leading to longer till queue times and a correspondingly compounded increase in the shop queue time as customers waiting in the shop queue wait for customers in the till queue to be processed until the number of customers in the shop falls below capacity. This is confirmed by looking at the figures showing the Average and Maximum Shop and Till Queuing Times in *Figures 7.21, 7.22, 7.23, and 7.24* in *Appendix A, Section 7* respectively. Looking at the Queue Times for the related scenarios in these figures, both the Average and Maximum queuing times are unacceptably high. The extreme values seen for the maximum queuing times in these control measure combination scenarios appear to relate to cases of staff having to isolate with customers waiting in a queue and no substitute staff to complete the customer processing, resulting in customers waiting in the queue until a staff member returns from isolation.

Interestingly, the combinations in which **Sanitization** at the *Entrance and Tills* is included in addition to Daily staff testing and Capacity Limiting do not show these extreme values in queuing times. This provides evidence that the inclusion of till sanitization reduces transmissions to staff sufficiently enough to prevent cases of too many staff members being in isolation.

Figure 5.12: Box-plots showing the Total Transmission Count in the Shop Queue under each Combined Control Measure Scenario

Looking at *Figures 7.16 and 7.18* in *Appendix A, Section 7* the only control measures resulting in a considerable change in the number of shop and till transmission respectively are the **Vaccine** use-levels involving the introduction of vaccine mandates, just as was seen for the isolated control measure implementations in *Figure 5.3*.

The last key comparison metric to be considered is the Ratio of Customers Lost to Total Customers Processed seen in *Figure 5.13* below. Looking at the box-plots in the figure below, the only control measure combinations resulting in a change in the Ratio of Customers Lost to Total Customers Processed by the shop are all of the combinations including the *Daily* use-level of **Staff COVID Testing**, with the exception of the cases in which **Sanitization** at the *Entrance and Tills* is included in addition to Daily staff testing. This provides further indication that the inclusion of till sanitization reduces transmissions to staff sufficiently enough to prevent cases of the majority of staff members being in isolation.

Figure 5.13: Box-plots showing the Ratio of Customers Lost to Total Customers Processed under each Combined Control Measure Scenario

5.3 Transmission Control Measure Validation

As described in *Section 4.8.7* in the Agent-Based Model chapter, the validation of the model's assigned behaviours and effects relating to the implementation of transmission control measures is presented in the Synthesis and Analysis of Results chapter. This is because the process of validating these behaviours depends on an evaluation of model outcome measures relating to the transmission control measure implementations in the model. This process would serve to preemptively provide confirmation of hypothesised analysis outcomes for the elements that are successfully validated. Additionally, the discussion of any elements that were not successfully or entirely validated may require discussion of and references to analysis results. This prevents the placement of the control measure validation procedure from preceding the initial presentation of Analysis outcomes. *Table 5.1* below shows the expected changes in model outcomes relating to Customer and Transmission Dynamics outcomes alongside the successful validation of these changes in the outcome values produced.

Simulation Element	**Expected Customer Dynamic Change**	**Verified**	**Expected Transmission Dynamic Change**	**Verified**
Increased Vaccination Coverage	No change	Yes	Decreased Transmissions throughout	Yes
Social Distancing Implementation	Slightly increased queuing times	Yes	Decreased Total Trans. Decreased Shop Queue Trans. Decreased Till Queue Trans. Decreased Direct Trans.	Partially
Capacity Limiting Implementation	Increased Shop Queue Times Decreased Till Queue Times Increased balking	Partially	Increased Shop Queue Trans. Decreased Shop Trans.	Yes
Staff COVID-19 Testing Implementation	Increased Till Queue Times Increased Shopping Times Increased balking	Yes	Decreased Till Trans. Decreased Total Trans. Increased Till Queue Trans.	Yes
Hand Sanitization	Slightly Increased Shop Queue Times	Partially	Increased Shop Queue Trans. Decreased Shop Trans Decreased Environmental Trans.	Yes
Till Surface Sanitization	Increased Till Queue Times	No	Decreased Till Trans. Decreased Environmental Trans.	Yes

Table 5.1: Table showing the Validation of Macro-level changes in Customer and Transmission Dynamics Related to Control Measure Implementation.

Looking at the simulation elements which Customer and Transmission Dynamics that were not successfully validated as seen in *Table 5.1* above, the only element with a completely invalidated expected change is the *Till Surface Sanitization* element and the associated expected change in Average Till Queuing times. The specification of the behaviours relating to implementing sanitization measures at the tills involved the addition of processing time between customers serviced, in order to represent the time required to sanitize till surfaces between each customer. This additional processing time would be associated with an expected increase in till-queuing times. However, looking at the average till queuing times shown in *Figure 5.6*, the data presented shows conflict with this expectation. The reason for this is the unexpectedly large increase in shop-queuing times seen in *Figure 5.5* associated with the use of hand sanitization measures at the shop entrance. The effect of this considerable increase in shop-queuing time is a delayed entry to the shop that allows for staff to serve customers at the till stations at a rate proportionally faster than the arrival of customers to the till queue, which results in a reduced till queue time. This unexpectedly large increase in shop-queuing times also serves to account for the partial validation of expected Customer Dynamics associated with the use of Hand Sanitization measures, as the size of the increase in shop queue times was considerably larger than the increase expected.

The other simulation element relating to the implementation of transmission control measures is the implementation of Social Distancing measures. The reason that the expected transmission dynamics changes were only partially validated is that although some of the expected changes such as the decrease in Total Transmissions and Till Queue Transmissions were not present, the lack of any substantial change in these outcomes also meant the expectation wasn't invalidated. Looking at the transmission counts in *Figure 5.3* there does appear to be a small decrease in shop queue transmissions, however the change is too small to be considered as substantial evidence validating this expected change.

5.4 Sensitivity Analysis of Transmission Control Measure Parameters

As described in the sensitivity analysis procedure for the model's baseline parameters in *Section 4.6.3*, the sensitivity analysis of the model's transmission control measure related parameters serves to assess the robustness of model outcomes to changes in input parameters. The approach to assessing the model outcomes' sensitivity to changes in the values of the control measure parameters considered follows a similar process as was seen in *Section 4.6.3*. However, some adjustments to the presentation of these results will need to be made to accommodate for the fact that the parameters considered will only have a direct effect on a select few of the related control measures. As such, the sensitivity of each of the three control measure parameters is assessed and discussed independently.

As seen for the base model sensitivity analysis procedure, the process begins with a description of the parameters varied in the related sensitivity analysis, alongside the values at which they were set for the analysis.

Parameter	**Parameter Description**	**Values Used**	**Base Value**
Super-Spreader Distribution	This parameter dictates the relative proportions of individuals classified into five degrees of intensity of Super-Spreader behaviour. Individuals with a higher degree of Super-Spreader intensity are likely to have more daily contacts with a higher resulting chance of infectiousness and less likely to comply with intervention protocols. Defined by 5 levels of super-spreader intensity, with varied proportions of the population assigned to each.	Fewer Contacts, Base Level, More Contacts See *Table 4.9*, *Section 4.8.6*	Base Level
Test Sensitivity	The diagnostic sensitivity of COVID-19 tests conducted on Staff members for Staff COVID-19 Testing. Sensitivity is based on a variety of Rapid Antigen tests and the RT-PCR test, with sensitivity varying according to the viral incubation period.	Less Sensitive, Base Level, More Sensitive See *Table 4.10*, *Section 4.8.6*	Base Level
Sanitizer Disinfection	The parameter describes the relative amount of environmental contaminant distributed by an Infectious Customer/Staff Member at each location visited. Amount selected as a percentage.	(60, 70, 80)	70

Table 5.2: Table showing the Parameters Varied for Conducting the Univariate Sensitivity Analysis of Model Control Measures

As seen in the previous sensitivity analysis procedure, the comparison of each parameter scenario with respect to model sensitivity is confined to the use of the following outcome measures:

Transmission Dynamics are measured using:

- Total No. of Transmissions that take place
- The Ratio of Total Transmissions : Infectious Customers that Arrive at the shop

Customer Dynamics are measured using:

- Average No. of Customers that visit the shop per day
- Average Total Shopping Time per customer
- The Ratio of Total Customers Lost : Total Customers Processed

5.4.1 Sanitizer Disinfection

The control measure parameter sensitivity analysis begins by looking at the changes in the model outcome measures relating to varied levels of the **Sanitizer Disinfection** parameter. The only transmission control measure directly affected by the Sanitizer Disinfection parameter is the use of Sanitization measures. As such, the sensitivity of the model outcomes relating to the changes in the Sanitizer Disinfection parameter begins by looking at the total transmissions for Sanitization implementation scenarios with varied levels of Sanitizer Disinfection capabilities in *Figure 5.14* below. Looking at the differences in the observed number of transmissions between scenarios with changes in the disinfection capabilities of the sanitizer used, there appears to be a noticeable decrease in the total number of transmissions observed with an increase in the disinfection capabilities the sanitizer has (resulting in proportionally lower environmental viral contaminant), for both of the Sanitizer implementation levels. However, the number of transmissions observed does not appear to be sensitive to decreases in the relative disinfection capabilities the sanitizer has, showing no considerable difference in the number of transmissions observed with *Relative Contaminant Levels* of 70% and 80%. The same trends can be seen with respect to the observed changes in the ratio of Total Transmissions to the Total Number of Infectious Customer Arrivals seen by *Figure 7.25* in *Appendix A, Section 7.*

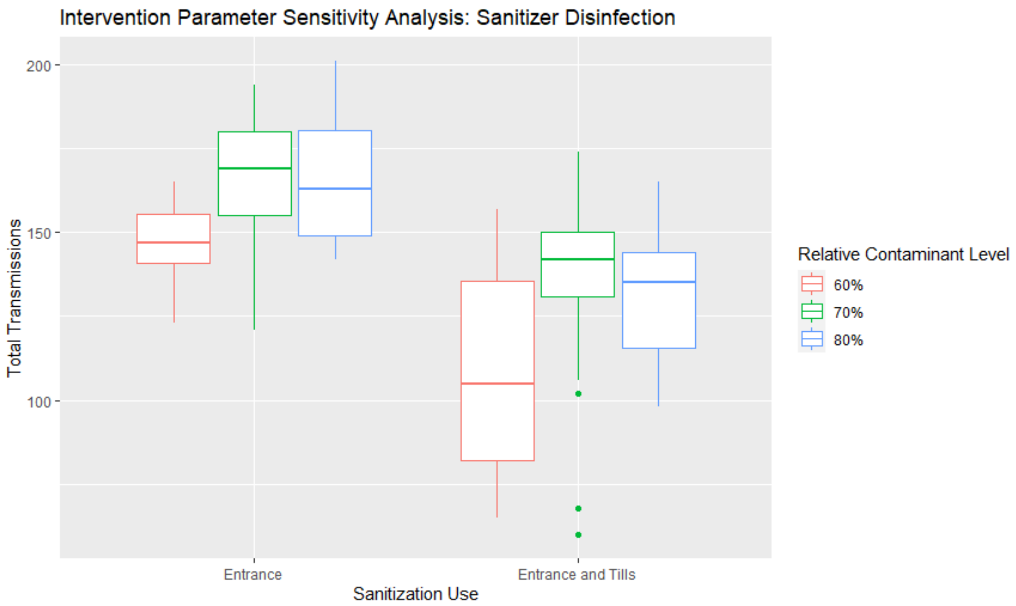

Figure 5.14: Box-plots showing the Total Transmission Counts Under the Implementation of Sanitization Measures with Varied Levels of Viral Contaminant Reduction

Looking further at the sensitivity of Customer Dynamics related model outcomes to changes in the relative disinfection capabilities of the sanitizer used. *Figure 5.15* below, shows the Average Shopping Time per Customer under the two Sanitization implementation measures with varied levels in the relative disinfection capabilities of the sanitizer. Looking at the average shopping times for the different sanitizer disinfection scenarios, the values recorded for all of the scenarios considered span across an interval of about 1 minute. This indicates no sensitivity of the average customer shopping time to changes in the relative disinfection capabilities of the sanitizer. The same can be seen for the other Customer Dynamics related model outcomes of the average number of customers processed per day and the ratio of Customers Lost to Customers Processed in *Figures 7.26 and 7.27* in *Appendix A, Section 7* respectively.

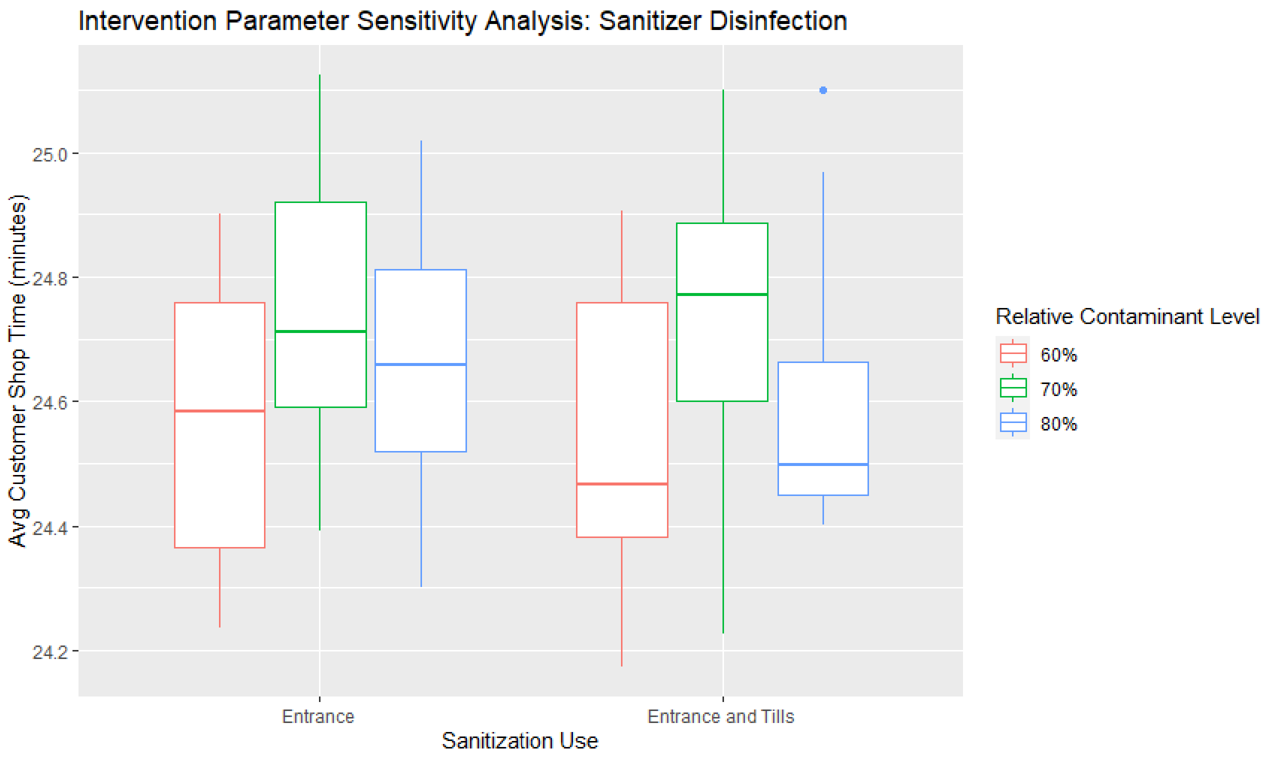

Figure 5.15: Box-plots showing the Average Shopping Time per Customer Under the Implementation of Sanitization Measures with Varied Levels of Viral Contaminant Reduction

5.4.2 Test Sensitivity

The sensitivity analysis of the transmission control measure parameters continues by looking at the changes in the model outcome measures relating to varied levels of the **Test Sensitivity** parameter. The only transmission control measure directly affected by the Test Sensitivity parameter is the use of Staff COVID-19 Testing measures. As above, one begins by looking at the total transmissions for the Staff COVID-19 Testing scenarios with varied levels in the diagnostic sensitivity of the COVID-19 tests in *Figure 5.16* below. Looking at the differences in the observed number of transmissions between the testing scenarios with changes in test sensitivity, there appears to be some slight variation in the number of transmissions observed with a marginal decrease in transmission counts in scenarios with increased test sensitivity. These effects are more pronounced with staff testing conducted in weekly intervals, however the variation between the different test sensitivity scenarios does not indicate considerable sensitivity of the observed number of transmissions to changes in test sensitivity. Similar observations are made with respect to the observed changes in the ratio of Total Transmissions to the Total Number of Infectious Customer Arrivals seen by *Figure 7.28* in *Appendix A, Section 7*.

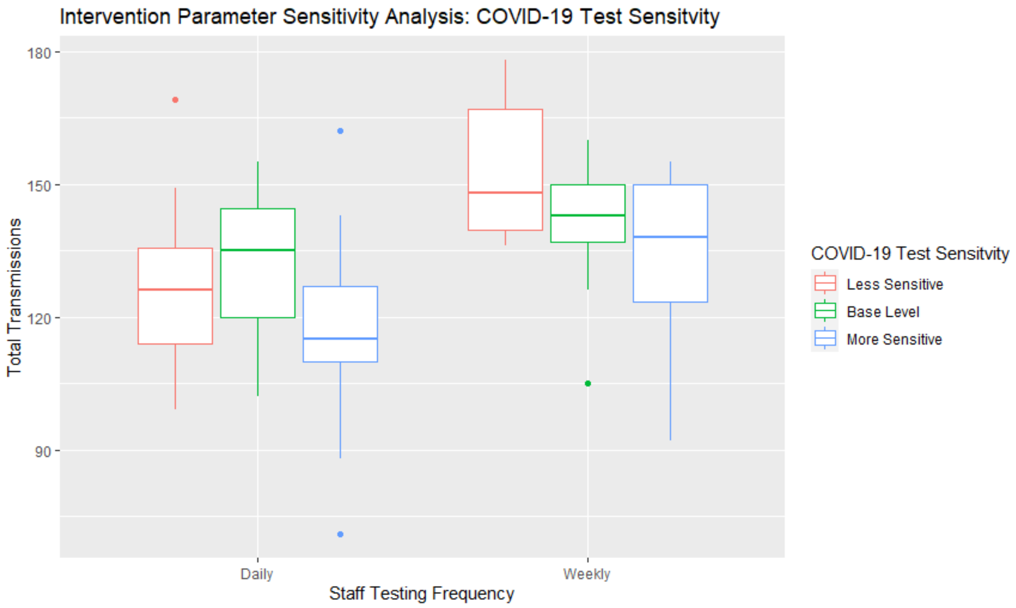

Figure 5.16: Box-plots showing the Total Transmission Counts Under the Implementation of Staff COVID-19 Testing Measures with Varied Levels of COVID-19 Diagnostic Test Sensitivity

Shifting focus to the sensitivity of Customer Dynamics related model outcomes to changes in the diagnostic COVID-19 test sensitivity. *Figure 5.17* below, shows the Average Shopping Time per Customer with Daily and Weekly staff Covid-19 Testing and differing levels in the related test sensitivity. Looking at the times observed, when testing is implemented at a **Weekly** level there appears to be little to no sensitivity of the average customer shopping time to changes in test sensitivity levels. However, at a **Daily** testing level there is a considerable increase in the average customer shopping times observed with increases in the diagnostic sensitivity of the COVID-19 tests used. The same relationship with observed sensitivity at a **Daily** testing level can be seen for other the Customer Dynamics related model outcomes of the average number of customers processed per day and the ratio of Customers Lost to Customers Processed in *Figures 7.29 and 7.30* in *Appendix A, Section 7* respectively. Indicating a decrease in the number of customers processed as well as an increase in the number of customers lost as the diagnostic sensitivity of the COVID-19 tests increases. This is likely due to the speed at which staff infections are identified, leading to shortages in staff as the number of self-isolating staff increases.

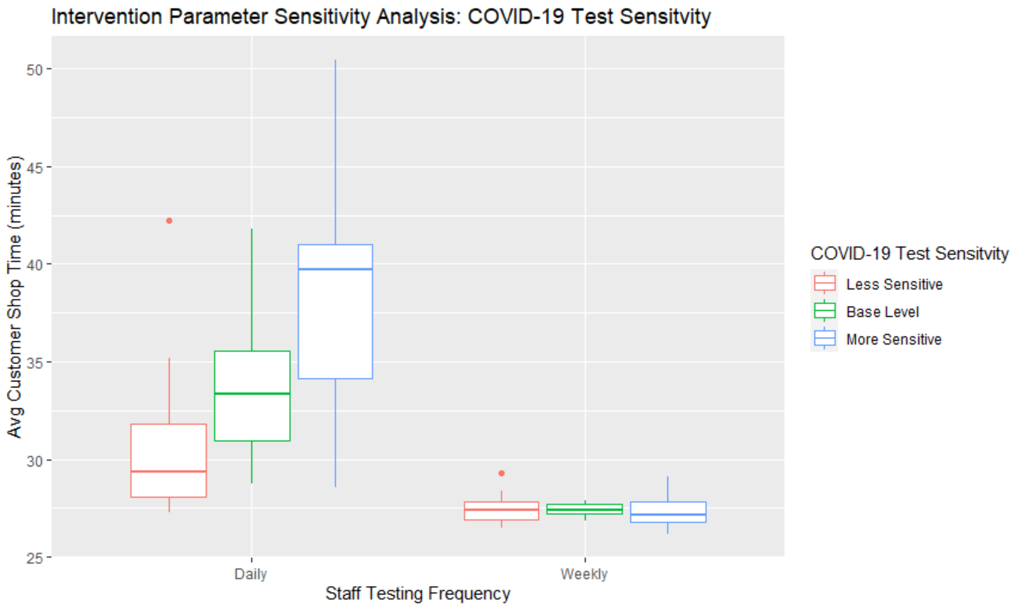

Figure 5.17: Box-plots showing the Average Shopping Time per Customer Under the Implementation of Staff COVID-19 Testing Measures with Varied Levels of COVID-19 Diagnostic Test Sensitivity

5.4.3 Super-Spreader Distribution

The final transmission control measure parameter assessed in the sensitivity analysis looking at the changes in the model outcome measures, is the **Super-Spreader Distribution** parameter. There are two transmission control measures that are directly affected by the Super-Spreader Distribution parameter, namely the Sanitization and Social Distancing transmission control measures. They are both primarily affected by the distribution of Super-Spreader levels amoung shop customers through the non-compliance behaviours associated with higher super-spreader levels which are defined to be proportional to an individuals contact counts. As above, the assessment begins by looking at the total transmissions for the Sanitization and Social Distancing scenarios with varied levels in the distribution of super-spreaders amongst customers in *Figure 5.18* below.

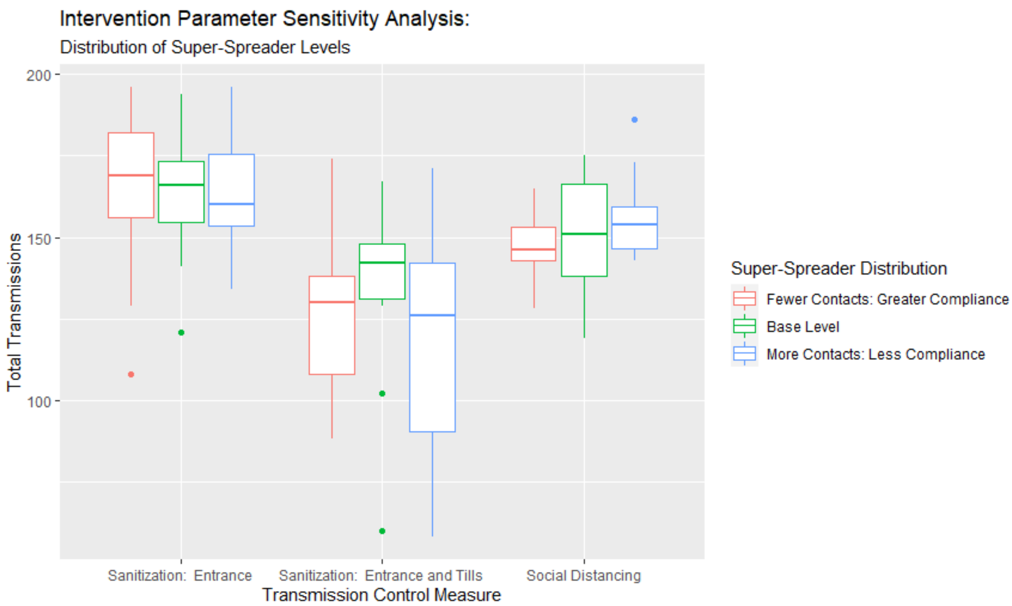

Figure 5.18: Box-plots showing the Total Transmission Counts Under the Implementation of Sanitization and Social Distancing Measures with Varied Distributions of Super-Spreader Levels Amongst Customers

Looking at the differences in the observed number of transmissions between the Sanitization and Social Distancing scenarios with varied levels in the distribution of super-spreaders amongst customers, there appears to be no evidence supporting sensitivity of the number of observed transmissions to changes in the distribution of super-spreaders amongst customers. The variation within control measures scenarios appears to be larger than any observed variation between scenarios with varied super-spreader distributions. Further exploration of the model outcome sensitivity to changes in super-spreader distribution shows the same trends in a lack of sensitivity for all of the outcome measures considered. This can be confirmed by looking at the relative plots for these outcomes in *Figures 7.31, 7.32, 7.33, and 7.34* in *Appendix A, Section 7* for the ratio of Total Transmissions to the Total Number of Infectious Customer Arrivals, Average Shopping Time per Customer, the Average number of Customers processed per day, and the ratio of Customers Lost to Customers Processed respectively.

Chapter 6

Discussion

With the context of existing literature regarding the transmission of COVID-19 further substantiated by the results produced by the Agent-Based simulation model developed; the discussion chapter primarily serves to evaluate the analysis outcomes produced, through an inspection of key findings in the results produced in comparison to existing literature and in the context of the research outcomes proposed.

The chapter begins by restating the proposed objectives with a reflection on the priority of objectives with respect to their impact and academic benefits, providing a brief assessment of the degree to which each of the outcomes has been achieved. This is followed by a discussion of the key findings taken from the results produced by the model, focusing on the related conclusions drawn from these findings and comparing these to findings proposed by existing research. The section that follows the discussion of the key findings in the analysis discusses the Limitations of the model and the impact they have on the reliability of the inferences drawn from the analysis outcomes. This includes propositions of components and features that would further enrich the model for further development. This is followed by a discussion of recommendations with respect to the ways in which the model findings could be implemented in real-world environments alongside the benefits of doing so. Other recommendations include a recommended direction for opportunities available for future related research. The chapter ends with some conclusionary remarks regarding the analysis conducted and some afterthoughts from the author discussing the research process and experience.

6.1 Research Purpose and Objectives Achieved

A key component of conducting academic research is the intention to utilise the progression of knowledge to the benefit of informed real-world practices. In the context of biomedical research regarding the improvement of treatments and controls in risk mitigation, the potential impact the production of meaningful and insightful information can have is highlighted by its ability to save and sustain lives through its implementation. This serves to highlight the benefits of achieving research objectives and to do so through sound, thoughtful approaches to the analysis provided.

6.1.1 Prioritisation of Objectives

Although the objectives set at the onset of the research process, in *Sections 1.3 and 1.4*, are multi-faceted in their aims to: implement complex transmission procedures and features into the model developed, provide engaging and informative platforms for the communication of research outcomes, and quantitatively incorporate the effects of Super-Spreaders and customer dynamics in the model produced. Beyond these aims, the primary objective of the proposed research project is to evaluate the effectiveness of the COVID-19 transmission control measures used in supermarket settings world-wide.

The evaluation of the effectiveness of the COVID-19 transmission control measures used in the setting of established essential services, has the ability to provide insightful approaches to optimising their implementation in practice. This serves to have a direct impact not only on reducing the transmission of a potentially life-threatening virus, but also to ensure that the resources that facilitate the implementation of these measures are optimised to have the greatest impact they can. The direct impact that achieving this objective can have on public health and safety makes its achievement the highest priority in conducting the research proposed.

The remaining research objectives proposed can be seen to achieve aims with respect to either: the ability the project has to engage audiences and provide the ability to clearly communicate outcomes to a wide audience with varied levels of contextual literacy, or to include advanced features in model development with the intention of improving the accuracy to which the model is able to replicate the real-world environment it describes.

The need to produce an analytical model that best represents the setting in which the outcomes will be applied is essential to providing meaningful and insightful recommendations for the implementation of the model's key findings. Looking at the objectives relating to the inclusion of replicating customer dynamics in a supermarket, incorporating COVID-19 transmission dynamics in the supermarket setting, the impact of Super-Spreaders on disease transmission, and the heterogeneous chances of transmission and infectiousness between individuals, seen in real-world interactions. Achieving each of these objectives serves to produce a model that more accurately replicates real-world interactions, allowing more accurate and informed outcomes to be produced. This highlights the need to prioritise achieving these set objectives.

However, important consideration must be made for the evidence that the inclusion of attractive, informative and interesting visual aids in the communication of research, results in substantial increases in the level of understanding seen in those that engage with the paper. This has been specifically noted to have substantial impacts on the understanding of risk-related research. The course of the COVID-19 pandemic has emphasised the need to inform and educate the greater public regarding the implementation of self-governed transmission controls and risks associated with the avoidance of taking precautionary actions. Additionally, the individuals likely to implement and enforce changes in the control measures enforced in supermarket environments are not likely to be individuals in the field of academic COVID-19 research. These considerations highlight the importance of achieving objectives relating to the production of an aesthetically attractive and effective tool to communicate the project's research outcomes simply, and in a way that is easily communicated to both academic peers and layman individuals outside of the field. Additionally, an exciting, interpretative tool provides marketable components facilitating an expansion of its reach and engagement.

6.1.2 Outcome Assessment

Beginning with a brief look at the objectives seeking to include advanced features in model development with the intention of improving the accuracy to which the model is able to replicate the real-world environment it describes. The approach to achieving each of the corresponding objectives is referenced as follows:

- **Research Objective 1**: The core features of this objective are described by the procedures regarding customer movement and dynamics in *Blue* in *Figure 4.3*, combined with input parameters seen in *Table 4.3*, and validated in *Tables 4.4 and 4.5.*
- **Research Objective 2**: The core features of this objective are described by the procedures regarding transmission dynamics in *Purple* in *Figure 4.3* for customers and in *Blue* in *Figure 4.4* for staff members, combined with input parameters seen in *Table 4.9.2*, and validated in *Tables 4.4 and 4.5.*
- **Research Objective 4 and 5**: The effects of Super-Spreaders and factored into the model in several components. Firstly, the model highlights the role of supermarket staff as super-spreaders due to the high number of person-to-person contacts associated with their profession. The role of customers as super-spreader individuals is two-fold, firstly a distribution of customers grouped according to their contact profiles enables the implementation of heterogeneous chances of infectiousness for individuals with higher contacts (**Objective 5**). Secondly, the grouping of customers by super-spreader level facilitates the inclusion of control measure non-compliance described in *Section 4.8.* Lastly, the large number

of individuals and interactions that take place in the supermarket environment speaks to its role as a super-spreader place.

Looking at **Research Objective 3**, involving the objective of creating an aesthetically pleasing and engaging environment through which to communicate research outcomes. This is achieved through the choice of an Agent-Based modelling environment that facilitates a visual representation of the simulation model developed, featuring both 2-Dimensional and 3-Dimensional interactive visual monitoring. The use of this feature is optimised through the detailed design of familiar and catching design objects to be placed in the environment, highlighted in *Section 4.2*. The features allowing model flexibility to changes in parameter values are provided by the various adjustable parameter input sliders and choosers seen in *Figures 8.1 and 8.2* in *Appendix B, Section 8*.

The primary objective of the paper described by **Research Objective 6** and the Research Question for the paper, regarding the evaluation of the most effective use of available control measures to reduce COVID-19 transmission in a supermarket environment in a South African setting, is discussed in more detail in the section below. The necessary features are described regarding the implementation of control measures in *Section 4.8*, with evaluation metric for each measure scenario described in *Section 4.6.2*.

6.2 Key Findings

The discussion of the key findings highlighted by the results produced by the agent-based model designed for the analysis in this paper follows a similar thematic process to that seen in the results chapter above. The discussion of key findings begins with the evaluation of findings related to the Isolated implementation of control measures, which serves once again to evaluate the relative effectiveness of each transmission control measure without the inclusion of interactions between control measures preventing the ability to attribute changes in model outcomes entirely to a single measure. The focus then evaluates the key findings relating to the combined implementation of the transmission control measures described.

6.2.1 Isolated Individual Control Measure Evaluation

In looking at the limited quantitative literature evaluating transmission control measures for COVID-19 that are available, the common theme among them is the evaluation of the considered measures implemented in isolation. This approach is a necessary step in the evaluation process as it facilitates the ability to attributed changes in model outcomes entirely to the implementation of the control measure in question. A major drawback from this approach is that the related literature and effects are distinctly theoretical in nature, as the real-world implementation of measures to control transmission is rarely, if ever, used in isolation without the consideration and implementation of other additional controls. This inhibits the availability of observational data recording the effects of isolated control implementation. The key findings from the evaluation of the relative effectiveness of the different transmission control measures are described as follows:

Vaccines as the Most Effective Tool Controlling Infectious Disease

The data produced by the analysis from the developed model suggests that the use of vaccination as a COVID-19 transmission control measure is the most effective of the control measures implemented, not only in terms of their ability to substantially decrease the number of transmissions that occur but also in their ability to do so without impacting customer dynamics in the shop environment. The considerable decrease in the number of occurring transmissions throughout the shop environment shown by each successive implementation-level of the **Vaccine Scenario** control measure shown in *Figures 5.2, 5.3, 7.3, and 7.4* in *Section 5.2.1* and *Appendix A, Section 7*, provide quantitative evidence substantiating the statements made by the World Health Organisation (WHO) and Centre for Disease Control (CDC) regarding the use of vaccinations as the most effective tool for combating vaccine-preventable disease[21] discussed in the relative review of literature in *Section 2.1.4*. The discussion of this effectiveness explored by Omer et al. (2009)[57] and Siddiqui et al. (2013)[75] highlights the importance of vaccine coverage and uptake in the population as the major limiting factor in the effectiveness that these control strategies can have in preventing transmission. This too is supported by the analysis data reported, with notable differences in the reduction in transmission seen between the scenarios of *No Vaccine* use (which additionally serves as an analogous interpretation of very low vaccine coverage), *Standard Vaccine Schedule* use at coverage levels seen at the point of analysis in South Africa, and *Full Vaccine Mandate* use (which may serve as an analogous representation of very high vaccine coverage).

The use of the *Staff Vaccine Mandate* speaks to the proposal of essential service worker vaccination as a priority discussed Mulberry et al. (2021)[52]. The data produced by the model for this control use provides quantitative evidence of the effectiveness that this approach can have on reducing transmissions with a lower demand on vaccine resources.

An important aspect of control measure implementation that fails to be addressed in literature is the need for control measures to be streamlined enough to minimize the impact they have on the regular operation of tasks in the workplace and general lifestyle. With a focus on this secondary measure of evaluating effectiveness, the use of Vaccine-related control measures is seen to be the only control strategy with no negative impacts on Customer Dynamics with reference to processing and waiting times, as well as service load and customer counts shown in *Figures 7.5, 5.5, 5.6, 7.8, and 5.7* in *Section 5.2.1* and *Appendix A, Section 7.* This serves to further support the effectiveness of vaccination controls and their high regard in literature.

Unexpected Results and the Indirect Impact of Implementation on Transmission

Notable results that require further discussion were the negative effects of the implementation of Capacity Limiting and Sanitization at the shop Entrance, with respect to an increase in the number of transmissions that took place as seen in *Figures 5.2 and 5.3.* The data shown in the analysis evaluating the isolated implementation of these measures supports evidence in contradiction to the expected reductions proposed by Olivier et al. (2020) [56] and Charpentier et al. (2020) [12]. The reduced transmissions described in these papers discusses the manner in which capacity limiting reduces contacts and thereby transmission is entirely qualitative in its approach. Although this has the ability to guide the implementation of these measures in models and real-world practice, they fail to account for any indirect effect that the implementation of capacity limiting has on transmission through adjusted behaviours. More specifically, the focus placed on the reduction of contacts inside the location with limited capacity overshadows any consideration for the increase in contacts that might occur by waiting for entry. The quantitative approach taken by Tupper et al. (2020)[81] has the same shortcomings in the approach used to model intervention effectiveness. Looking at the increase in average shop-queuing times and the associated increased transmissions for these three control measure scenarios in *Figures 5.5 and 5.3* respectively, highlights the need to account for the indirect effects of control measure implementation on transmissions. The changes in human dynamics and associated contacts that result from implementing a new control measure have the potential to negatively impact transmission potential, even to the extent of out-competing the benefits of implementing the measure it aims to achieve. This is the concept that is supported by the data relating to these scenarios.

Another key finding from the results produced in relation to the isolated implementation of the control measures that warrants discussion is the impact of Staff COVID-19 Testing strategies on customer dynamics. The demonstration of increased average customer shopping and queuing times with the implementation of Staff COVID-19 Testing seen in *Figures 7.5, 5.5, 5.6 and 5.7*, as well the increase in lost customers seen in *Figures 5.8*, supports evidence of indirect effects of staff testing on the operating capabilities of the shop environment. The data suggests that considerable changes in dynamics resulting from an excess of staff in self-isolation contributes to a decrease in the till station processing capabilities. These effects would be highly dependent on the number of staff members available, suggesting that it may not be a reliable representation of real-world effects. As the setting of this impact is very specific with respect to the environment the control measure is implemented in, there are research gaps present regarding interactions between transmission control measures and customer dynamics in a supermarket setting. This makes confirmation and evaluation of these observed outcomes difficult to validate. It is important to note the complex nature of staff structures and their variation from place to place. This makes modelling these structures difficult and highlights the potential for inaccuracy in relating the staff structure presented to those seen in the majority of similar settings. This is discussed further in the section regarding model limitations below. With a shift in focus placed on the effects the implementation of Staff COVID-19 Testing has on Transmission dynamics, the use of Staff COVID-19 Testing is shown to be the most effective transmission control measure in reducing the number of transmissions that take place according to the data produced by the model. This serves to support the importance and effectiveness of regular COVID-19 testing on essential-service workers as described by Stock et al. (2020)[78]. This highlights the role that essential service workers place as super-spreaders, due to the number of contacts and interactions involved with their work. As the model developed included the self-isolation of symptomatic COVID-19 cases with the development of symptoms as described in the *Progress Disease* procedure seen in *Section 4.4.3*, the results produced speak to the transmission potential that asymptomatic cases of COVID-19 have for essential-service workers. This directly aligns with the findings discussed by Stock et al. (2020)[78].

6.2.2 Combined Control Measure Evaluation

The findings regarding the combined implementation of the transmission control measures considered, build on the findings taken from the initial isolated control measure evaluation above by allowing the existence of interactions to take place between the control measures implemented. The benefit to this approach, as mentioned in the section above, is that the real-world implementation of transmission controls are rarely seen in isolation, making the evaluation of their combined implementation better suited to capturing the effects seen in the real-world setting the model aims to replicate.

The key findings mentioned above, specifically those relating to vaccination use as the most effective control measure, are seen to maintain their associated underlying impacts when used in combination with other control measures in this section. Therefore it is not necessary to restate the observed effects seen above in the subsections to follow, but rather to emphasise any effects that expand on them as they interact with other transmission controls.

The Importance of Implementing Social Distancing

The initial Isolated evaluation of implementing Social Distancing measures in the shop environment appeared to show no considerable difference between scenarios relating to the use of social distancing compared to those without when looking at *Figures 5.2 and 5.3*. This would appear to fail to provide evidence from the data supporting the findings seen in the papers by Vardoulakis et al. (2020)[83], Kennedy et al. (2020)[32] and Tupper et al. (2020)[81] which all describe reduced transmission with the implementation of Social Distancing. The reason for this is likely to be the short queuing times presented in the base model, reducing the impact of social distancing in queue interactions. The papers by Vardoulakis et al. and Kennedy et al. are qualitative in nature, describing the effects of distanced interactions and the resulting reduction in transmission. These studies fail to account for implementational variation and the effects situational implementation has on changes in the opportunities for interactions in the first place. The quantitative approach used by Tupper et al. (2020) also fails to account for these changes, by taking the approach of modelling social distancing effects through a homogeneous reduction in contacts and negating the heterogeneous nature of interactions in the implementation of social distancing.

Interestingly, when looking at the implementation of social distancing measures in combination with other measures, such as capacity limiting or sanitization with respect to the number of resulting transmissions seen in *Figures 5.2 and 5.3*; the beneficial effects of social distancing described in the papers above begin to arise. A specific mention is made of the scenarios relating to the implementation of social distancing measures in combination with capacity limiting and/or sanitization measures. The evidence for interaction effects between these measures suggested by the data highlights two key points. Firstly, the extended queue times shown by *Figures 5.5 and 7.21* for the implementation of capacity limiting and sanitization control measures enables more opportunity for transmission and interactions in the queues. This increase in queue interacts facilitates the environment for the benefits of social distancing measures to take place by spreading out the individuals in the queues. Secondly, the benefits of social distancing thereby act to reduce the negative effects of increased shop-queue interactions with the isolated implementation of capacity limiting and sanitization control measures seen above. This reduction is able to successfully reduce the increase in shop-queue interactions to a large enough extent that the use of capacity limiting and entrance sanitization control measures in combination with social distancing is now able to reduce total transmissions as seen in *Figure 5.11* and more specifically in the shop-queue transmissions in *Figure 5.12.* The data relating to transmission control measures utilising the combination of these measures provides support for the existence of interaction effects between control measures that extend beyond an additive change/reduction in relating transmission counts.

As the data produced utilising the combined implementation of control measures provides a better representation of the manner in which control measures are implemented in real-world practice, it may be the case that the beneficial findings described in the papers by Vardoulakis et al. (2020)[83], Kennedy et al. (2020)[32] and Tupper et al. (2020)[81] with respect to social distancing are defined from this perspective. However, it is important to state that this assumption is not explicitly stated in the papers mentioned.

Strategic Control Choices and Minimizing Required Resources

An important factor to consider in the approach to selecting the optimal combination of control measures to implement is the implementation cost of each control. This involves not only the financial costs of measures like Staff COVID-19 Testing, as emphasized by Stock et al. (2020)[78] but also the labour and time costs as well. It follows that optimal strategies would enable the use of as few measures as possible. Looking at the transmission counts in *Figure 5.11*, the use of vaccinations at a *Full Vaccine Mandate* level would reduce transmissions to the extent that it would be unnecessary to implement any other measures. This further supports the effectiveness of vaccine use described by Omer et al. (2009)[57] and Siddiqui et al. (2013)[75]. Due to the difficulty in implementing this measure to the extent of a full mandate, combined with any related ethical considerations in doing so described by Gostin et al. (2021)[26]; we consider implementations of combinations made with a use-level of Staff mandates and at the current coverage schedule as well. With the use of a staff vaccine mandate, optimal results can be seen with the combined use of entrance and till sanitization combined with social distancing, negating the need to use capacity limits or testing. At a Standard Vaccine Coverage Schedule the optimal combination of controls further expands on the previous combination with the inclusion of daily staff testing. It is worth noting that the costs of regular testing at that level would greatly outweigh the financial cost of staff vaccinations, with the additional consideration of the customer dynamic impacts seen to be associated with daily staff testing seen in *Figures 5.8 and 7.22.* Additionally, the impact of staff vaccination has considerably greater effects in terms of transmission reduction.

The inclusion of regular testing of staff in the optimal combination for a standard vaccine schedule further highlights the benefits of testing essential service workers described by Stock et al. (2020)[78], while the increased benefit of its replacement with a staff vaccine mandate serves to demonstrate further support of the claims to vaccines as the most effective measure available as described by Omer et al. (2009)[57] and Siddiqui et al. (2013)[75].

6.3 Model Limitations and Further Development

In drawing inference from results produced by the analysis discussed above, it is important to understand the limitations the model has in its replication of real-world settings and the associated implications this has on the interpretation of model findings. Establishing an understanding of the limitations placed on the model developed helps to contextualise and frame the model's implementation, preventing the potential for the inaccurate extrapolation of the model's results and findings beyond the scope of its definition.

One of the nuances of simulation-based model development is the understanding that the models developed have the ever-present opportunity to be developed, improved, and better defined. This comes with an associated need to be able to simplify and limit the scope of the features one aims to include. This is necessary in order to place a limit on the computational requirements that grow with increasingly complex models, shift the focus from including more features to defining and describing existing features well, and to define a point of completion for the model in order to progress the research process to using the developed model for analysis. The simplification of the simulated environment comes with limitations on its ability to account for many of the intricate elements present in the system it replicates. However, this is combined with an ever-present opportunity for further development and growth in the research model. This section highlights several of the limitations associated with the agent-based model developed, combined with the opportunities for future development to better account for the limitations presented.

6.3.1 Rigidity of Environment Structure and Implications on Scalability

The first model limitation to be discussed is the rigidity in the definition of the shop environment used. The rigidity mentioned refers to the model's inability to change the structural layout of the environment, with specific reference to the number and placement of points of interest (POIs) in the shop, the number and placement of till stations available, the positioning and placement of queues, entry, and exit, and any other related elements of the layout. In real-world supermarket settings, the layout of the shop is seen to vary from shop to shop, these changes in layout may present with considerable differences in the movement of customers through the space and the resulting interactions that take place between them. Additionally, the variation of elements like the number of tills or queues for the tills is likely to present considerable differences in the customer dynamics for the shop due to the direct impact these elements have on queue processing. The lack of variability that the model has with respect to these elements is the key factor inhibiting the model's scalability, as described in *Section 4.7*. If one was to attempt to scale the number of customers that approach the shop up in order to assess model outcomes for a shop environment with considerably more traffic than the shop described by the model, the fixed number of processing stations at the tills would result in a considerable difference in customer processing times.

The inclusion of the ability to increase the number of tills or vary the queuing structure to structures like those with a 1:1 queue to till station structure as seen in many supermarket settings, would be a good place to start for the consideration of further model development. The role that the inclusion of these features would play in providing model scalability, would create a considerable impact on the usability of the model in specific relation to larger supermarket spaces. The next element to be considered for further development would be a prioritisation of the POIs in the shop. The real-world experience of consumer practices in a supermarket involves a considerably higher proportion of customers in areas for perishable and refrigerated products than would be seen in areas such as cleaning products or toiletries. Additionally, customers that visit a shop with the intention of doing a small quick shop have a considerably higher demand for these perishable products than the non-perishable/non-food related products involved in a more extensive shop. The addition of POI prioritisation would allow a more accurate representation of real-world consumer practices and the interactions that would occur between customers as a result of them.

6.3.2 Time-step Definition and Limits to Smaller-Scale Processes

One of the major limitations to the model developed is the definition of minute increments in simulation time with each time step executed. This limitation places the restriction on the time related model effects to exist in discrete minute spaces, meaning that any changes or effects that would happen in shorter or more specific time-frames would be rounded to minute intervals. Although this may seem negligible, the cumulative effects of these approximations may present considerable effects over extended simulation periods. The effects of this can be seen in the effects of including hand sanitization at the shop entrance as a control measure on the associated average shop queuing times. This necessitated the definition of the measure to form an analogous representation of time-consuming barriers to entering the shop such as filling out a contact tracing form. Further model development that allowed for the definition of time steps to correspond with shorter intervals would allow notable improvements in the model's capability to more accurately represents time-related changes on a small scale. An important consideration should be made for the increase in processing requirements and simulation durations that would result from these changes.

6.3.3 Simplified Definition of Customer Behaviours

The simplification of the complex consumer behaviours that are presented in real-world shopping interactions used in the model presents challenges in accurately representing real-world practices. An example of this that presented in the analysis of the model was the excessively increased shopping times for customers in the scenarios of *Daily* Staff COVID-19 testing that resulted from considerable reductions in processing capabilities with reduced operating staff numbers. In these scenarios, maximum waiting times were seen to far exceed the duration customers would allow in real-world practices. Further development of the model's consumer behaviours to include the use of Reneging or to allow the choice of balking to rely on the number of available staff in addition to the queue lengths on arrival. The inclusion of these additions would provide the model with the necessary tools to adapt to changes in the shop's processing capabilities and to allow the presentation of more realistic customer dynamics outcomes. In future, this could be further developed to demonstrate the effects that customer understanding of control measure implementation would have on accepted wait times. For example, customers could be seen to accept longer wait times in queues resulting from capacity limiting than what would be expected in standard shop operation. Other model developments could include the variation in the number of customers that visit the shop depending on the day of the week. The increased traffic on weekends may present unique changes and challenges to the control measures considered.

6.3.4 Exclusion of Additional Controls and External Reactions to Implementation

Another limitation of the model developed is its failure to account for the use of other control measures such as temperature checking, curfews or lockdown implementation. These controls may present changes in both customer and transmission dynamics, either through a change in transmission chances, such as the exclusion of customers with high temperatures, or through the change in customer arrivals that may present with the imposition of lockdown limitations/curfews. Additionally, the model fails to account for the external reactions to the control measures that might arise outside of the shop environment, such as a change in the number of customers that might be able to visit the shop with the implementation of a full vaccine mandate. The gradual inclusion of features accounting for these effects to the model would allow for improved accuracy in the model's representation of real-world practices.

A limitation presented in the model that is control related, albeit relating to an included control, is the failure to account for the effects that the specificity of staff COVID-19 tests may have by indicating false positives for staff and thereby further reducing the available staff members.

6.3.5 Simplification of Staff Transmission Dynamics

A noteworthy limitation in the model presented is the simplification of some elements in disease transmission. The most identifiable limitation is the model's assumption of no external staff transmissions. Although the number of direct contacts staff members experience in the workplace makes any source of exposure considerably more likely to come from the shop environment, the possibility of external exposure is not negligible. The further development of the model to be able to include the chances of these transmissions would present a more realistic representation of staff transmission. The role that staff members play as super-spreaders may indicate that the inclusion of these effects could present a noticeable change in transmission dynamics in the shop.

A limitation of the model relating to the simplification of staff transmission dynamics is the lack of uncertainty presented in the transition times between disease states. In real-world manifestations of COVID-19 progression, there is considerable variation in the time-frames between states. The inclusion of this uncertainty in the model would provide more realistic indications of transmission risks and dynamics. It may be worth noting that as the staff members are the only individuals in the system that experience these transitions, the small sample size may produce larger variation in the resulting outcomes that would be impacted by variation in these time-frames.

6.3.6 Super-Spreader Definition

The working dynamics of super-spreaders and the role they play in disease transmission is known to be highly complex, the presentation of super-spreader behaviours that are risk-seeking, the effects of clinical super-spreader individuals, or the ways that super-spreader behaviours influence the behaviour of others are all elements of the phenomenon that is presented with a lack of available research. This makes accounting for the existing effects accurately in mathematical models a challenging task. Although the model presented provides accounts for the effects of super-spreaders in a more defined approach than the majority of epidemiology models in present literature. The opportunity to further account for additional super-spreader effects and their ability to influence the behaviour of others leaves considerable space for development.

6.3.7 Limited Availability and Reliability of Data

As mentioned in the introduction and literature review chapters, the novel nature of COVID-19 means that the availability and reliability of data is still considerably less defined than other infectious diseases. As research around COVID-19 transmission dynamics and effective transmission control measures develops, the uncertainty of parameters is gradually reduced. This allows the ability to specify model parameters with higher degrees of accuracy. Additionally, the arrival of new COVID-19 variants and mutations may present with considerable differences in transmissiblity or vaccine efficacy. It is important to consider the high levels of parameter sensitivity for parameters such as those relating to the chance of direct transmission, till service times, population prevalence, contaminant dissipation, and diagnostic test sensitivity. The addition of more accurate estimates for these sensitive parameters will go a long way in improving the accuracy of the effects estimated by the model.

The structure of the model developed as a tool allowing for variation through user specified values in the model parameters, provides the flexibility to account for these changes while remaining usable for determining model outcomes. However considerable changes in transmission mechanisms or population immunity may require adjustments to the model to account for these changes. This may be considered further development as a byproduct of COVID-19 research development.

6.4 Recommendations

As the research focus involves the use of actionable and accessible practices in its real-world implementation, the presentation of model recommendations is two-fold. The first presentation of recommendations focuses on the implementation of research outcomes to provide informed choices in the use of transmission control measures in real-world practice. The next set of recommendations describes the opportunities for further related research. This serves to facilitate the driving mechanism underpinning academic research, which describes the understanding that all available knowledge is formed by the progression of research and the exploration of unknown phenomena by building on the insight gained through previous research efforts.

6.4.1 Control Measures in Practice

As one of the key findings presented in the analysis identifies the effectiveness of vaccines as the best tool for combating the spread of COVID-19, it follows that the primary recommendations based on these findings are focused on the approaches to best utilise these benefits. As described by the model findings, the primary factor limiting the effectiveness of available vaccines is uptake and coverage. The presence of vaccine-hesitancy has been identified as one of the world's greatest threats to public health. The existence of attitudes against the adoption of vaccination is largely founded in the existence of extensive misinformation relating to vaccine safety. As such the most effective tool in fighting this phenomenon is education. The need to communicate research to the public in ways that are relatable and easy to understand is becoming increasingly important in the presence of sensationalised misinformation. The utilisation of tools available for identifying this misinformation is becoming increasingly adopted by public platforms and the presentation of public-facing visual dashboards communicating related statistics is rapidly growing in popularity. A key recommendation presented is a need to contribute to and facilitate the communication platforms for accessible, reliable information relating to vaccines and control measure compliance for public access. In the South African context of limited literacy, the use of simplified communication tools and visual data representations that expand beyond the need for written communication should be a priority in order to effectively reach the larger South African audiences. Special consideration should be made to directly communicate the need to vaccinate essential-service workers, highlighting their role as Super-Spreaders (due to the nature of their professions), and emphasizing the ability vaccination of essential-service workers has to create substantial reductions in the perpetuation of COVID-19.

Beyond the use of vaccines, emphasis should be given to implementing social distancing practises in areas susceptible to restricted flow and movement of people. The role that education and information plays in enforcing these measures is highlighted by the need for individuals to self-regulate and comply with these measures. Ultimately, the majority of available control measures provide effective capabilities in reducing transmission. However, their greatest barrier to entry is a lack of adoption. A comprehensive understanding of risk and effectiveness in guiding control measures provides the necessary tools to facilitate a willingness to adhere to measures mitigating that risk. Specific emphasis should be placed on understanding the risks and roles of asymptomatic cases with respect to COVID-19. The overwhelming association with a lack of symptoms as an indication of health is a driving force allowing asymptomatic cases to perpetuate the pandemic.

6.4.2 Opportunities for Further Research

The major gaps in research highlighted by this study involve a lack of accounting for the indirect effects of control measure implementation on transmission dynamics. The indirect effects resulting from control measure implementation are highly dependant on the settings in which they are implemented due to the role the environment or setting plays in guiding human movement and dynamics. This presents the opportunity for extensive further research with respect to the implementation of transmission control measures in a wide range of specifically defined environments. Additionally, this could be expanded to investigations of the relating effects for other infectious diseases.

6.5 Conclusionary Remarks

By systematically building on the concepts and ideas presented in widely available COVID-19 epidemiological models from an agent-based perspective, the agent-based model developed provided the flexibility to capture and evaluate the inherently heterogeneous natures of direct contacts and infection, compliance, and consumer behaviours. Features that are typically difficult to include in more traditional epidemiological modelling approaches. By defining a more specific model setting, the opportunity to implement better-defined movement dynamics in the model developed; which, in turn, facilitated an ability to capture the indirect effects the implementation of control measures in this setting would have on transmission, providing a more defined comprehensive understanding of the impact the control measures implemented are likely to show in real-world practice. The choice of environmental setting as a supermarket environment provided the practical benefits of better incorporating the effects of super-spreaders in the model, with the identification of :

- Supermarkets as a super-spreader place
- Staff as super-spreader individuals due to their role as essential service workers and the high-contact nature of the work
- Customers as super-spreader individuals with varied contact rates and associated heterogeneity in their chances of prior exposure to COVID-19
- The effects of non-compliance super-spreader behaviour exhibited by customers in the shop.

These deliberately implemented features to the Agent-Based model provided a comprehensive, well-defined framework to assess the relative effectiveness of the available COVID-19 transmission control measures. Leveraging this information to be able to provide informed guidance of the most effective use of available control measures to reduce COVID-19 transmission in a supermarket environment in South Africa, without considerably impacting the customer shopping experience.

Additionally, the model developed, features the increasingly important ability to communicate the research outcomes investigated in a way that's relatable, engaging, innovative, and easy to understand. Featuring an interactive visual interface with the flexibility to adapt to ever-changing disease transmission dynamics.

The model was able to effectively capture the benefits of the various control measures described by their definition in literature, providing data in the analysis that supported many of the findings for these measures while expanding on their effects and benefits by incorporating additional influences on implementation outcomes. The analysis successfully provided data supporting well-established claims to the effectiveness of vaccination in controlling vaccine-preventable disease, while contextualising the extent of this effectiveness through the direct comparison to the other available control measures.'

Ultimately the model developed, in combination with its analytical findings, was able to successfully meet all presented research objectives in the process of providing a substantiated answer to the research question proposed, thus providing the information and resources to implement an informed approach to utilising the available measures to prevent COVID-19 transmissions, with the potential to make a considerable impact in the fight against COVID-19.

Bibliography

[1] Andreas Ahrens, Ojaras Purvinis, Detlef Hartleb, Jelena Zaščerinska, and Diana Micevičienė. Analysis of a business environment using burstiness parameter: the case of a grocery shop. In *Proceedings of the 9th international conference on pervasive and embedded computing and communication systems, 19-20 September, 2019, Vienna, Austria. Vol. 1: PECCS*, pages 49–56. SciTePress, 2019.

[2] Christian L Althaus. Ebola superspreading. *The Lancet Infectious Diseases*, 15(5):507–508, 2015.

[3] Elizabeth L Anderson, Paul Turnham, John R Griffin, and Chester C Clarke. Consideration of the aerosol transmission for covid-19 and public health. *Risk Analysis*, 40(5):902–907, 2020.

[4] Johan Arndt and Sigmund Gronmo. The time dimension of shopping behavior: Some empirical findings. *ACR North American Advances*, 1977.

[5] Olivier Bargain and Ulugbek Aminjonov. Trust and compliance to public health policies in times of covid-19. *Journal of public economics*, 192:104316, 2020.

[6] Eric Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the national academy of sciences*, 99(suppl 3):7280–7287, 2002.

[7] Tobias S Brett and Pejman Rohani. Transmission dynamics reveal the impracticality of covid-19 herd immunity strategies. *Proceedings of the National Academy of Sciences*, 117(41):25897–25903, 2020.

[8] Kenneth P Burnham and David R Anderson. Multimodel inference: understanding aic and bic in model selection. *Sociological methods & research*, 33(2):261–304, 2004.

[9] Emma Cave. Covid-19 super-spreaders: Definitional quandaries and implications. *Asian bioethics review*, 12:235–242, 2020.

[10] CDC. Covid-19: Daily life and going out. `https://www.cdc.gov/coronavirus/2019-ncov/daily-life-coping/index.html`. Accessed: December 01, 2021.

[11] CDC. Covid-19: If you are sick or caring for someone. `https://www.cdc.gov/coronavirus/2019-ncov/if-you-are-sick/index.html`. Accessed: December 01, 2021.

[12] Arthur Charpentier, Romuald Elie, Mathieu Laurière, and Viet Chi Tran. Covid-19 pandemic control: balancing detection policy and lockdown intervention under icu sustainability. *Mathematical Modelling of Natural Phenomena*, 15:57, 2020.

[13] Cory Clark, Andrés Davila, Maxime Regis, and Sascha Kraus. Predictors of covid-19 voluntary compliance behaviors: An international investigation. *Global transitions*, 2:76–82, 2020.

[14] Cochrane. *Analysing data and undertaking meta-analyses: Sensitivity Analyses*, volume 5.1, chapter 9. Cochrane Training Handbook.

[15] Andrew T Crooks and Alison J Heppenstall. Introduction to agent-based modelling. In *Agent-based models of geographical systems*, pages 85–105. Springer, 2012.

[16] Gaston De Serres, France Markowski, Eveline Toth, Monique Landry, Danielle Auger, Marlène Mercier, Philippe Bélanger, Bruno Turmel, Horacio Arruda, Nicole Boulianne, et al. Largest measles epidemic in north america in a decade—quebec, canada, 2011: contribution of susceptibility, serendipity, and superspreading events. *The Journal of infectious diseases*, 207(6):990–998, 2013.

[17] Donald L DeAngelis and Stephanie G Diaz. Decision-making in agent-based modeling: A current review and future prospectus. *Frontiers in Ecology and Evolution*, page 237, 2019.

[18] Isabel Delany, Rino Rappuoli, and Ennio De Gregorio. Vaccines for the 21st century. *EMBO molecular medicine*, 6(6):708–720, 2014.

[19] Marie Laure Delignette-Muller and Christophe Dutang. fitdistrplus: An R package for fitting distributions. *Journal of Statistical Software*, 64(4):1–34, 2015.

[20] Colin Eden. Cognitive mapping and problem structuring for system dynamics model building. *System dynamics review*, 10(2-3):257–276, 1994.

[21] Centers for Disease Control, Prevention (CDC, et al. Ten great public health achievements–united states, 1900-1999. *MMWR. Morbidity and mortality weekly report*, 48(12):241–243, 1999.

[22] Centers for Disease Control and Prevention. Reduced risk of reinfection with sars-cov-2 after covid-19 vaccination - kentucky, may–june 2021. `https://www.cdc.gov/mmwr/volumes/70/wr/mm7032e1.htm`, Aug 2021. Accessed: December 01, 2021.

[23] Rocio Garcia-Retamero and Edward T Cokely. Communicating health risks with visual aids. *Current Directions in Psychological Science*, 22(5):392–399, 2013.

[24] Rocio Garcia-Retamero and Edward T Cokely. Designing visual aids that promote risk literacy: a systematic review of health research and evidence-based design heuristics. *Human factors*, 59(4):582–627, 2017.

[25] Rocio Garcia-Retamero, Edward T Cokely, and Ulrich Hoffrage. Visual aids improve diagnostic inferences and metacognitive judgment calibration. *Frontiers in Psychology*, 6:932, 2015.

[26] Lawrence O Gostin. Covid-19 vaccine mandates—a wider freedom. In *JAMA Health Forum*, volume 2, pages e213852–e213852. American Medical Association, 2021.

[27] Zachary C Hartman, Daniel M Appledorn, and Andrea Amalfitano. Adenovirus vector induced innate immune responses: impact upon efficacy and toxicity in gene therapy and vaccine applications. *Virus research*, 132(1-2):1–14, 2008.

[28] Ava John-Baptiste, Marc S Moulin, and Shehzad Ali. Are covid-19 models blind to the social determinants of health? a systematic review protocol. *BMJ open*, 11(7):e048995, 2021.

[29] Albert R Jonsen, Mark Siegler, and William J Winslade. Clinical ethics: a practical approach to ethical decisions in clinical medicine. 1982.

[30] Hajime Kanamori. Rethinking environmental contamination and fomite transmission of sars-cov-2 in the healthcare. *Journal of Infection*, 82(1):e17–e18, 2021.

[31] MJ Keeling and L Danon. Mathematical modelling of infectious diseases. *British Medical Bulletin*, 92(1), 2009.

[32] Deanna M Kennedy, Gustavo José Zambrano, Yiyu Wang, and Osmar Pinto Neto. Modeling the effects of intervention strategies on covid-19 transmission dynamics. *Journal of Clinical Virology*, 128:104440, 2020.

[33] Young Chan Kim, Barbara Dema, and Arturo Reyes-Sandoval. Covid-19 vaccines: breaking record times to first-in-human trials. *npj Vaccines*, 5(1):1–3, 2020.

[34] Yunhwan Kim, Hohyung Ryu, and Sunmi Lee. Agent-based modeling for super-spreading events: A case study of mers-cov transmission dynamics in the republic of korea. *International journal of environmental research and public health*, 15(11):2369, 2018.

[35] Jackie Kleynhans, Stefano Tempia, Nicole Wolter, Anne von Gottberg, Jinal N Bhiman, Amelia Buys, Jocelyn Moyes, Meredith L McMorrow, Kathleen Kahn, F Xavier Gómez-Olivé, et al. Sars-cov-2 seroprevalence in a rural and urban household cohort during first and second waves of infections, south africa, july 2020–march 2021. *Emerging infectious diseases*, 27(12):3020, 2021.

[36] Susan E Kline, Linda L Hedemark, and Scott F Davies. Outbreak of tuberculosis among regular patrons of a neighborhood bar. *New England Journal of Medicine*, 333(4):222–227, 1995.

[37] Marek Kochańczyk, Frederic Grabowski, and Tomasz Lipniacki. Super-spreading events initiated the exponential growth phase of covid-19 with r0 higher than initially estimated. *Royal Society open science*, 7(9):200786, 2020.

[38] Sanjiv Kumar, Shreya Jha, Sanjay Kumar Rai, et al. Significance of super spreader events in covid-19. *Indian journal of public health*, 64(6):139, 2020.

[39] Nikolaos C Kyriakidis, Andrés López-Cortés, Eduardo Vásconez González, Alejandra Barreto Grimaldos, and Esteban Ortiz Prado. Sars-cov-2 vaccines strategies: a comprehensive review of phase 3 candidates. *npj Vaccines*, 6(1):1–17, 2021.

[40] Kathy Leung, Mark Jit, Eric HY Lau, and Joseph T Wu. Social contact patterns relevant to the spread of respiratory infectious diseases in hong kong. *Scientific reports*, 7(1):1–12, 2017.

[41] Yuguo Li, Ignatius TS Yu, Pengcheng Xu, Joseph Hun Wei Lee, Tze Wai Wong, Peng Lim Ooi, and Adrian C Sleigh. Predicting super spreading events during the 2003 severe acute respiratory syndrome epidemics in hong kong and singapore. *American journal of epidemiology*, 160(8):719–728, 2004.

[42] Brandon Lieberthal and Allison M Gardner. Connectivity, reproduction number, and mobility interact to determine communities' epidemiological superspreader potential in a metapopulation network. *PLOS Computational Biology*, 17(3):e1008674, 2021.

[43] Elisabeth Mahase. Covid-19: Pfizer vaccine efficacy was 52% after first dose and 95% after second dose, paper shows, 2020.

[44] Dasha Majra, Jayme Benson, Jennifer Pitts, and Justin Stebbing. Sars-cov-2 (covid-19) superspreader events. *Journal of Infection*, 82(1):36–40, 2021.

[45] MASHA, HE2RO, and SACEMA. Estimating cases for covid-19 in south africa: Assessment of alternative scenarios. `https://www.nicd.ac.za/wp-content/uploads/2020/11/SACovidModellingReport_LongTermProjections_050920_final.pdf`, Sep 2020. Accessed: December 01, 2021.

[46] A Meiksin. Dynamics of covid-19 transmission including indirect transmission mechanisms: a mathematical analysis. *Epidemiology & Infection*, 148, 2020.

[47] Paloma Merino, Jesús Guinea, Irene Muñoz-Gallego, Patricia González-Donapetry, Juan Carlos Galán, Nerea Antona, Gustavo Cilla, Silvia Hernáez-Crespo, José Luis Díaz-de Tuesta, Ana Gual-de Torrella, et al. Multicenter evaluation of the panbio™ covid-19 rapid antigen-detection test for the diagnosis of sars-cov-2 infection. *Clinical Microbiology and Infection*, 27(5):758–761, 2021.

[48] Sharmistha Mishra, David N Fisman, and Marie-Claude Boily. The abc of terms used in mathematical models of infectious diseases. *Journal of Epidemiology & Community Health*, 65(1):87–94, 2011.

[49] AA Momoh, MO Ibrahim, IJ Uwanta, and SB Manga. Mathematical model for control of measles epidemiology. *International Journal of Pure and Applied Mathematics*, 87(5):707–717, 2013.

[50] Timothy Mountford. Design of clinical trials project 1: Vaccines for covid-19. July 2020.

[51] Timothy Mountford. Investigating the effect of alcohol related injury on resources available for treating covid-19. July 2020.

[52] Nicola Mulberry, Paul Tupper, Erin Kirwin, Christopher McCabe, and Caroline Colijn. Vaccine rollout strategies: The case for vaccinating essential workers early. *PLOS Global Public Health*, 1(10):e0000020, 2021.

[53] Mark J Mulligan, Kirsten E Lyke, Nicholas Kitchin, Judith Absalon, Alejandra Gurtman, Stephen Lockhart, Kathleen Neuzil, Vanessa Raabe, Ruth Bailey, Kena A Swanson, et al. Phase i/ii study of covid-19 rna vaccine bnt162b1 in adults. *Nature*, 586(7830):589–593, 2020.

[54] Department of Health RSA. Latest covid-19 case statistics. `https://sacoronavirus.co.za/`, Dec 2021. Accessed: December 01, 2021.

[55] Department of Health RSA. Latest vaccine statistics. `https://sacoronavirus.co.za/latest-vaccine-statistics/`, Dec 2021. Accessed: December 01, 2021.

[56] Laurentz E Olivier, Stefan Botha, and Ian K Craig. Optimized lockdown strategies for curbing the spread of covid-19: A south african case study. *Ieee Access*, 8:205755–205765, 2020.

[57] Saad B Omer, Daniel A Salmon, Walter A Orenstein, M Patricia Dehart, and Neal Halsey. Vaccine refusal, mandatory immunization, and the risks of vaccine-preventable diseases. *New England Journal of Medicine*, 360(19):1981–1988, 2009.

[58] Giulia Pazzaglia, Marco Mameli, Luca Rossi, Marina Paolanti, Adriano Mancini, Primo Zingaretti, and Emanuele Frontoni. People counting on low cost embedded hardware during the sars-cov-2 pandemic. In *International Conference on Pattern Recognition*, pages 521–533. Springer, 2021.

[59] Lucia Campos Pellanda, Eliana Márcia da Ros Wendland, Alan John Alexander McBride, Luciana Tovo-Rodrigues, Marcos Roberto Alves Ferreira, Odir Antônio Dellagostin, Mariangela Freitas da Silveira, Aluisio Jardim Dornellas de Barros, Pedro Curi Hallal, and Cesar Gomes Victora. Sensitivity and specificity of a rapid test for assessment of exposure to sars-cov-2 in a community-based setting in brazil. *MedRxiv*, 2020.

[60] Pfizer. A phase 1/2/3, placebo-controlled, randomized, observer-blind, dose-finding study to evaluate the safety, tolerability, immunogenicity, and efficacy of sars-cov-2 rna vaccine candidates against covid-19 in healthy individuals, 2020.

[61] Stanley A Plotkin. Vaccines: past, present and future. *Nature medicine*, 11(4):S5–S11, 2005.

[62] Management PnP Kenilworth and Management Woolworths Kenilworth. Research survey investigating local supermarket customer dynamics, Nov 2021.

[63] Deepak Pradhan, Prativa Biswasroy, Pradeep Kumar Naik, Goutam Ghosh, and Goutam Rath. A review of current interventions for covid-19 prevention. *Archives of medical research*, 51(5):363–374, 2020.

[64] Kiesha Prem, Alex R Cook, and Mark Jit. Projecting social contact matrices in 152 countries using contact surveys and demographic data. *PLoS computational biology*, 13(9):e1005697, 2017.

[65] R Core Team. *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria, 2021.

[66] P Sen Rathindra. Operations research: Algorithms and applications. *PHI Learning Pvt. Ltd*, 2010.

[67] R. A. Rigby and D. M. Stasinopoulos. Generalized additive models for location, scale and shape,(with discussion). *Applied Statistics*, 54:507–554, 2005.

[68] Alessia Rochira, Flora Gatti, Gabriele Prati, Terri Mannarini, Angela Fedi, Fortuna Procentese, Cinzia Albanesi, Irene Barbieri, Christian Compare, Silvia Gattino, et al. An integrated model of compliance with covid-19 prescriptions: Instrumental, normative, and affective factors associated with health-protective behaviors. *International Journal of Behavioral Medicine*, pages 1–13, 2022.

[69] Hussin A Rothan and Siddappa N Byrareddy. The epidemiology and pathogenesis of coronavirus disease (covid-19) outbreak. *Journal of autoimmunity*, page 102433, 2020.

[70] South African Government News Agency (SAnews). Rapid antigen testing price lowered following competition commission investigation. `https://www.sanews.gov.za/south-africa/rapid-antigen-testing-price-lowered-following-competition-commission-investigation`, Dec 2021. Accessed: February 14, 2022.

[71] Joshua L Santarpia, Danielle N Rivera, Vicki Herrera, M Jane Morwitzer, Hannah Creager, George W Santarpia, Kevin K Crown, David M Brett-Major, Elizabeth Schnaubelt, M Jana Broadhurst, et al. Transmission potential of sars-cov-2 in viral shedding observed at the university of nebraska medical center. *MedRxiv*, 2020.

[72] Thomas Schlake, Andreas Thess, Mariola Fotin-Mleczek, and Karl-Josef Kallen. Developing mrna-vaccine technologies. *RNA biology*, 9(11):1319–1330, 2012.

[73] Leonardo Setti, Fabrizio Passarini, Gianluigi De Gennaro, Pierluigi Barbieri, Maria Grazia Perrone, Massimo Borelli, Jolanda Palmisani, Alessia Di Gilio, Prisco Piscitelli, and Alessandro Miani. Airborne transmission route of covid-19: Why 2 meters/6 feet of inter-personal distance could not be enough. *International journal of environmental research and public health*, 17(8):2932, 2020.

[74] Matt Shipman. Vaccine q&a: Vaccines 101, mrna and adenoviruses. pages 1–4, 2020.

[75] Mariam Siddiqui, Daniel A Salmon, and Saad B Omer. Epidemiology of vaccine hesitancy in the united states. *Human vaccines & immunotherapeutics*, 9(12):2643–2648, 2013.

[76] Michael Small, Chi Kong Tse, and David M Walker. Super-spreaders and the rate of transmission of the sars virus. *Physica D: Nonlinear Phenomena*, 215(2):146–158, 2006.

[77] G Aernout Somsen, Cees van Rijn, Stefan Kooij, Reinout A Bem, and Daniel Bonn. Small droplet aerosols in poorly ventilated spaces and sars-cov-2 transmission. *The Lancet Respiratory Medicine*, 8(7):658–659, 2020.

[78] Ariel D Stock, Edward R Bader, Phillip Cezayirli, Julio Inocencio, Samantha A Chalmers, Reza Yassari, Vijay Yanamadala, and Emad Eskandar. Covid-19 infection among healthcare workers: serological findings supporting routine testing. *Frontiers in medicine*, page 471, 2020.

[79] HA Taha. Operations research: an introduction (preliminary ed.). *Applied Queueing Theory*, 1968.

[80] Lehana Thabane, Lawrence Mbuagbaw, Shiyuan Zhang, Zainab Samaan, Maura Marcucci, Chenglin Ye, Marroon Thabane, Lora Giangregorio, Brittany Dennis, Daisy Kosa, et al. A tutorial on sensitivity analyses in clinical trials: the what, why, when and how. *BMC medical research methodology*, 13(1):1–12, 2013.

[81] Paul Tupper, Himani Boury, Madi Yerlanov, and Caroline Colijn. Event-specific interventions to minimize covid-19 transmission. *Proceedings of the National Academy of Sciences*, 117(50):32038–32045, 2020.

[82] Neeltje Van Doremalen, Trenton Bushmaker, Dylan H Morris, Myndi G Holbrook, Amandine Gamble, Brandi N Williamson, Azaibi Tamin, Jennifer L Harcourt, Natalie J Thornburg, Susan I Gerber, et al. Aerosol and surface stability of sars-cov-2 as compared with sars-cov-1. *New England journal of medicine*, 382(16):1564–1567, 2020.

[83] Sotiris Vardoulakis, Meru Sheel, Aparna Lal, and Darren Gray. Covid-19 environmental transmission and preventive public health measures. *Australian and New Zealand Journal of Public Health*, 2020.

[84] M Vidovic. Reverse transcription polymerase chain reaction. In *Neuroscience Methods*, pages 203–208. CRC Press, 2019.

[85] Eric-Jan Wagenmakers and Simon Farrell. Aic model selection using akaike weights. *Psychonomic bulletin & review*, 11(1):192–196, 2004.

[86] Jonathan A Ward, Andrew J Evans, and Nicolas S Malleson. Dynamic calibration of agent-based models using data assimilation. *Royal Society open science*, 3(4):150703, 2016.

[87] CHAD WELLS, Abhishek Pandey, Seyed Moghadas, Burton H Singer, Gary Krieger, Richard JL Herron, David E Turner, Justin P Abshire, Kimberly M Phillips, A Michael Donoghue, et al. Comparative analyses of all fda eua-approved rapid antigen tests and rt-pcr for covid-19 quarantine and surveillance-based isolation. *medRxiv*, 2021.

[88] South Africa Western Cape Department of Health in collaboration with the National Institute for Communicable Diseases. Risk factors for coronavirus disease 2019 (covid-19) death in a population cohort study from the western cape province, south africa. *Clinical Infectious Diseases*, 73(7):e2005–e2015, 2021.

[89] Uri Wilensky. *NetLogo Software*. Center for Connected Learning and Computer-Based Modeling, Northwestern University. Evanston, IL, 1999.

[90] Uri Wilensky and William Rand. *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. Mit Press, 2015.

[91] Zhe Xu, Lei Shi, Yijin Wang, Jiyuan Zhang, Lei Huang, Chao Zhang, Shuhong Liu, Peng Zhao, Hongxia Liu, Li Zhu, et al. Pathological findings of covid-19 associated with acute respiratory distress syndrome. *The Lancet respiratory medicine*, 8(4):420–422, 2020.

[92] Dhanusha Yesudhas, Ambuj Srivastava, and M Michael Gromiha. Covid-19 outbreak: history, mechanism, transmission, structural studies and therapeutics. *Infection*, 49(2):199–213, 2021.

[93] James A Yorke, NEAL Nathanson, GIULIO Pianigiani, and JOHN Martin. Seasonality and the requirements for perpetuation and eradication of viruses in populations. *American Journal of Epidemiology*, 109(2):103–123, 1979.

[94] Maartje E Zonderland. Basic queuing theory. In *Appointment Planning in Outpatient Clinics and Diagnostic Facilities*, pages 13–26. Springer, 2014.

Chapter 7

Appendix A: Additional Key Figures

7.1 External Literature: Additional Figures

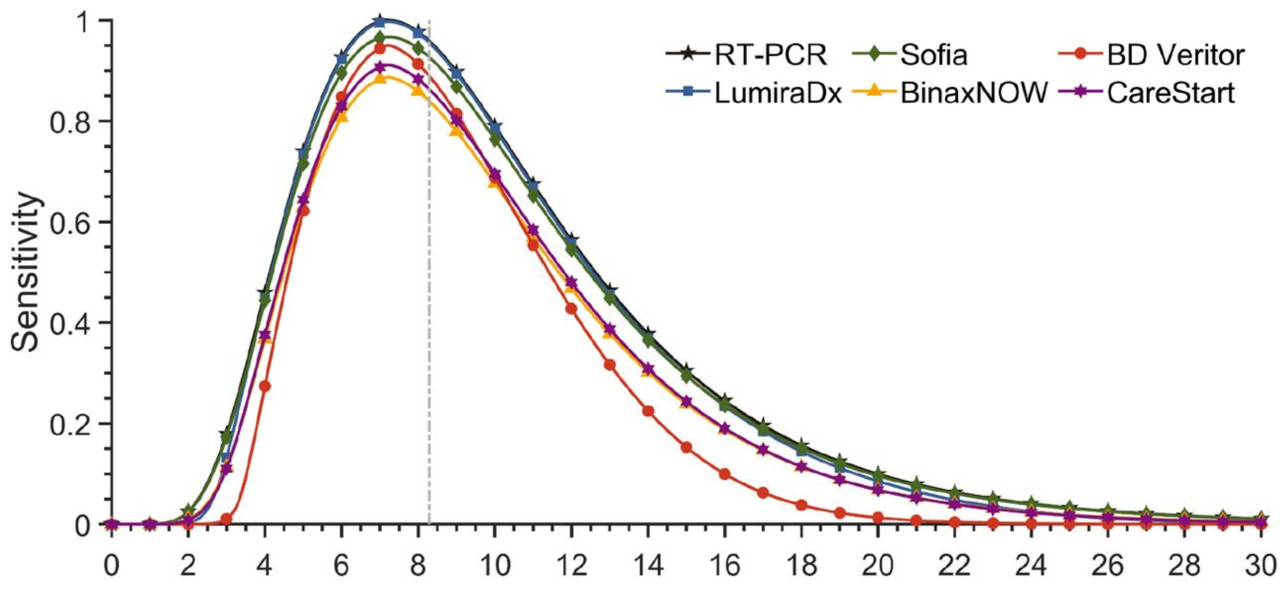

Figure 7.1: Line Graph showing the Diagnostic COVID-19 Test Sensitivity for the RT-PCR Test and all FDA EUA-approved Rapid Antigen Tests in a Comparative Study by Wells et al. (2021) [87]

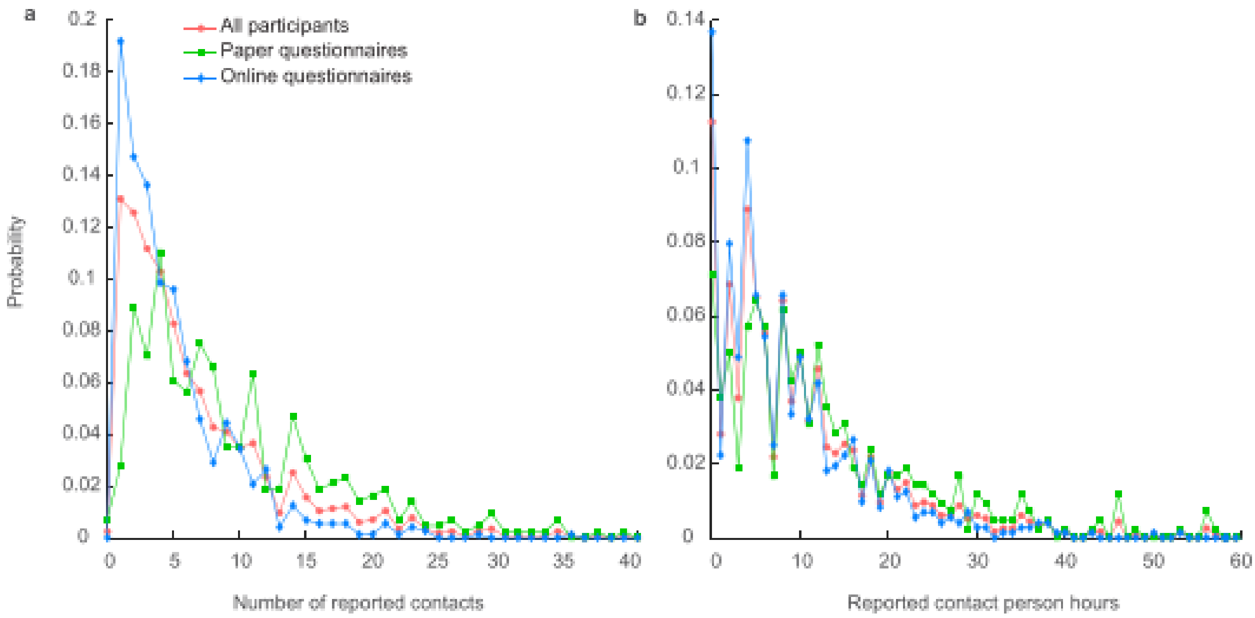

Figure 7.2: Line Graphs showing the Distribution of Populations relative to their Contact Counts in a Study by Leung et al. (2017) [40]

7.2 Transmission Control Measures: Additional Figures

7.2.1 Isolated Transmission Control Measures

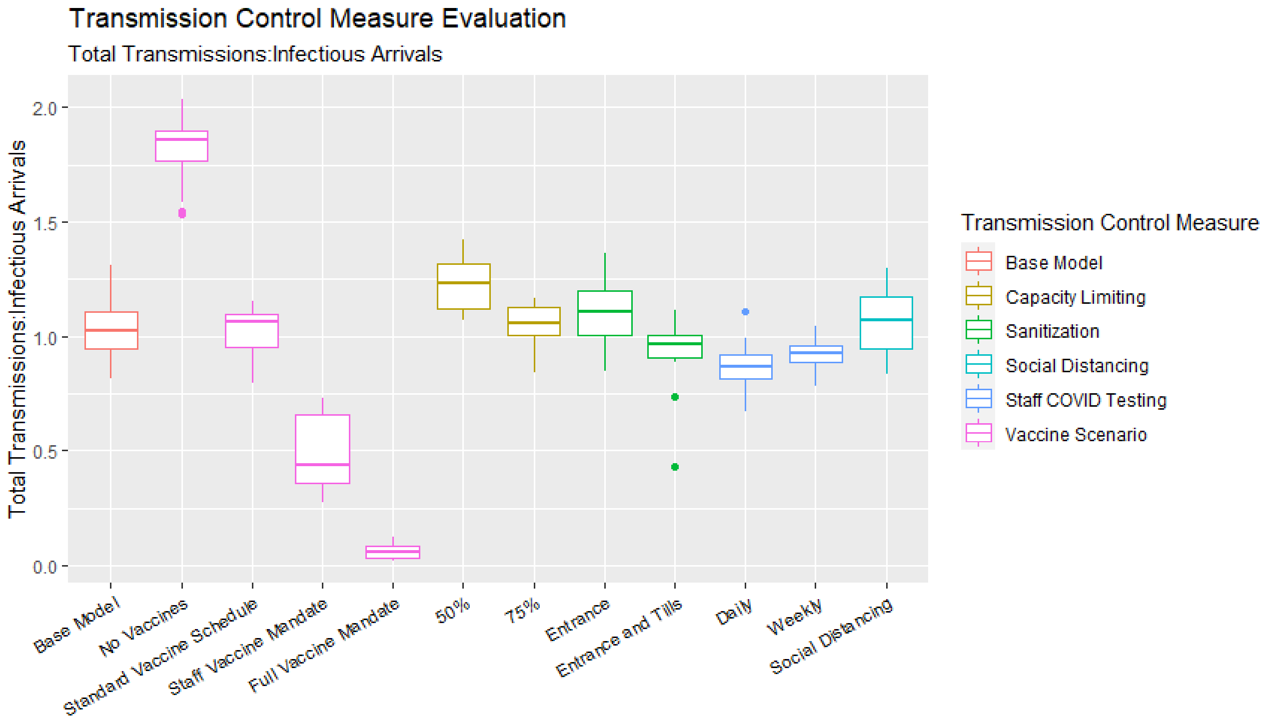

Figure 7.3: Box-plots showing the Ratio of Total Transmissions to the No. of Infectious Arrivals under each Isolated Control Measure Scenario

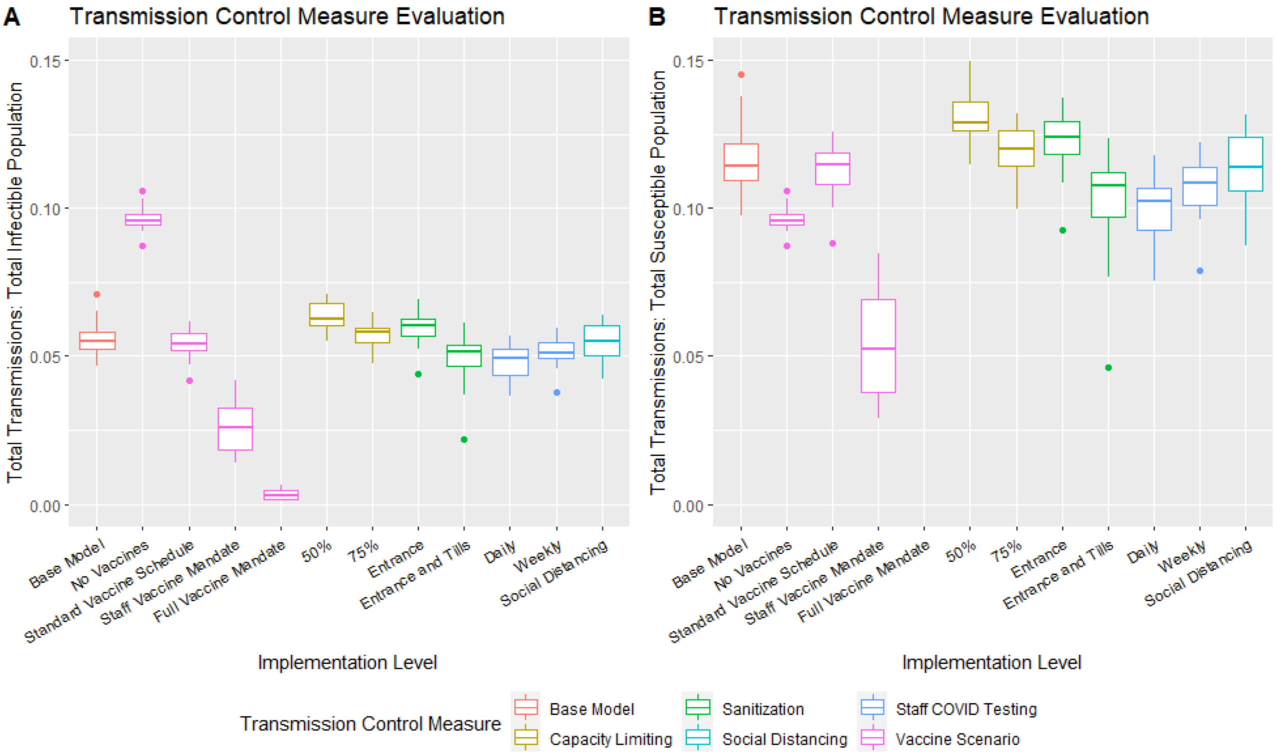

Figure 7.4: Box-plots showing the Ratio of Total Transmissions: Receptive Arrivals (A) and Total Transmissions: Susceptible Arrivals (B) under each Isolated Control Measure Scenario

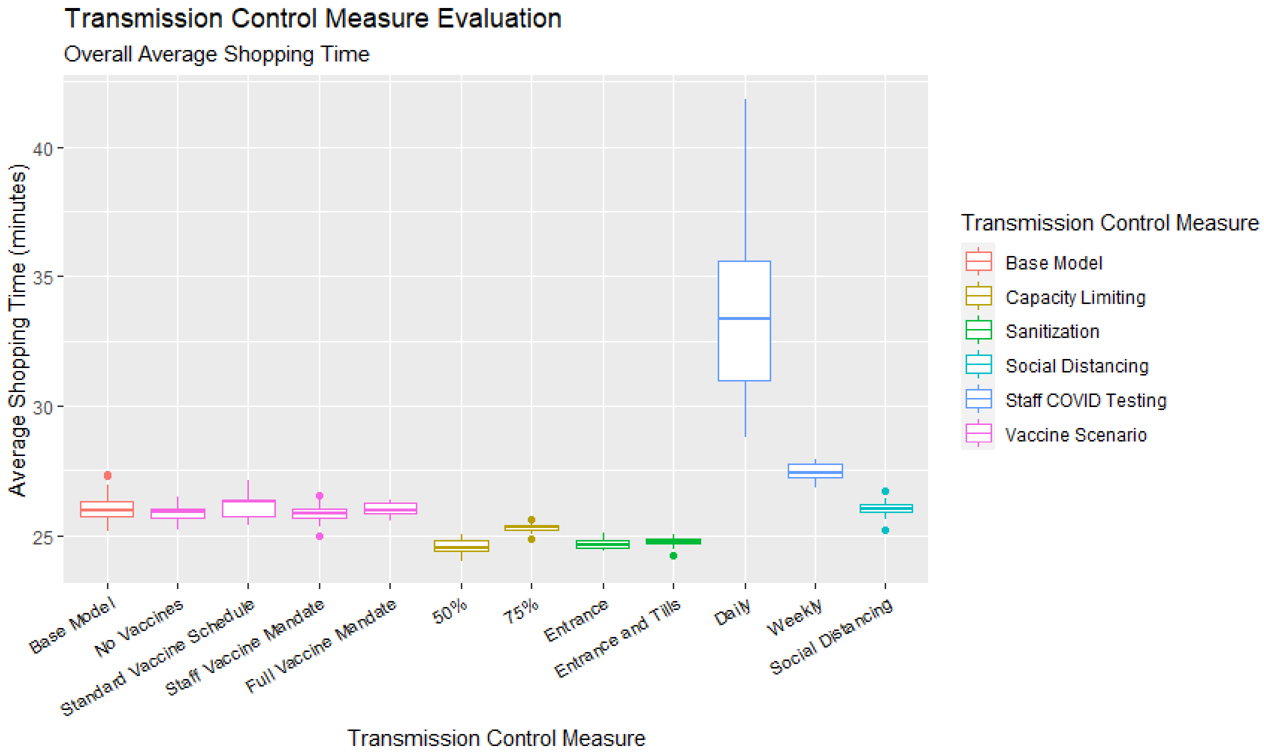

Figure 7.5: Box-plots showing the Average Customer Shopping Time under each Isolated Control Measure Scenario

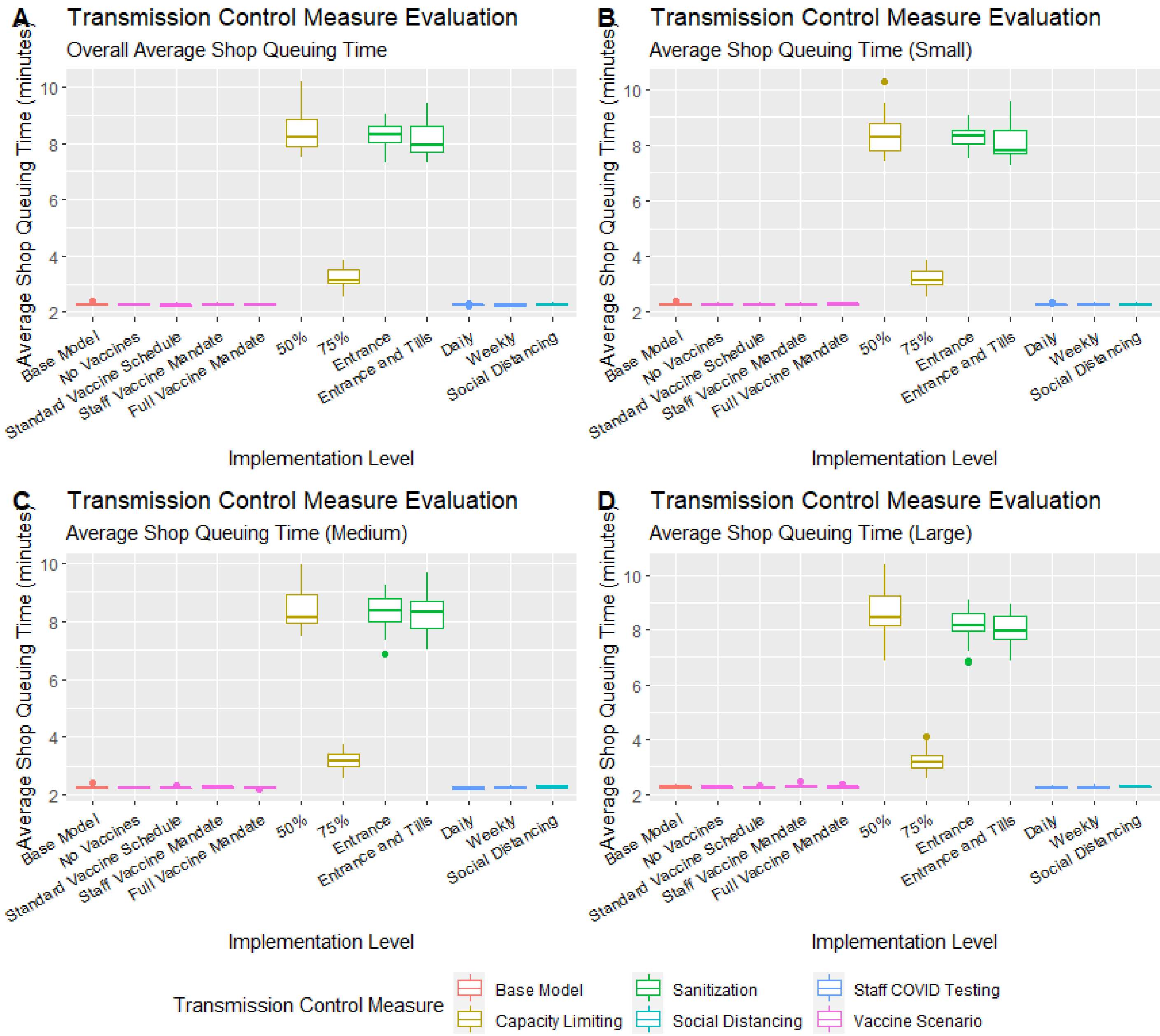

Figure 7.6: Box-plots showing the Average Shop Queuing Time per Shop-Size under each Isolated Control Measure Scenario

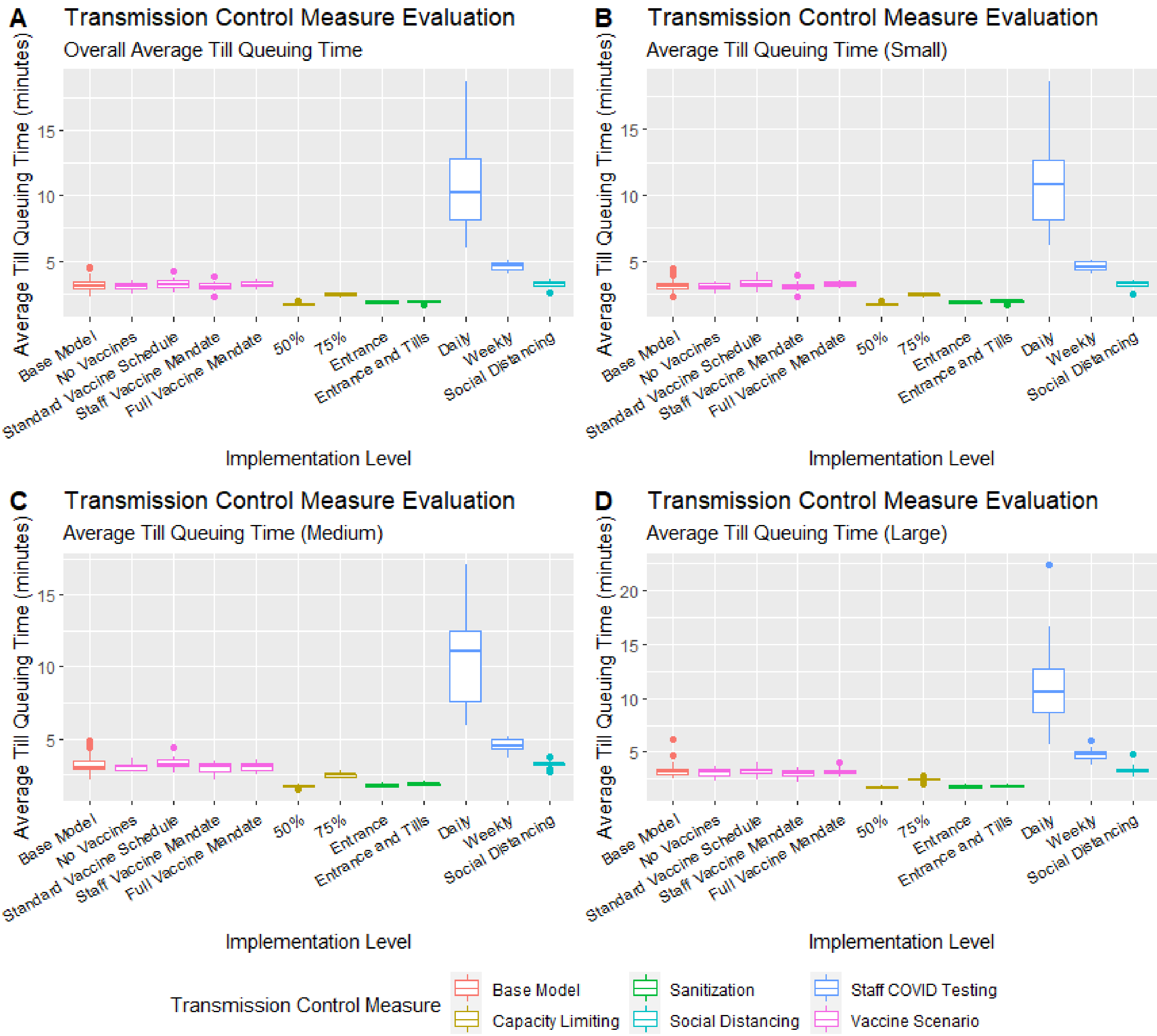

Figure 7.7: Box-plots showing the Average Till Queuing Time per Shop-Size under each Isolated Control Measure Scenario

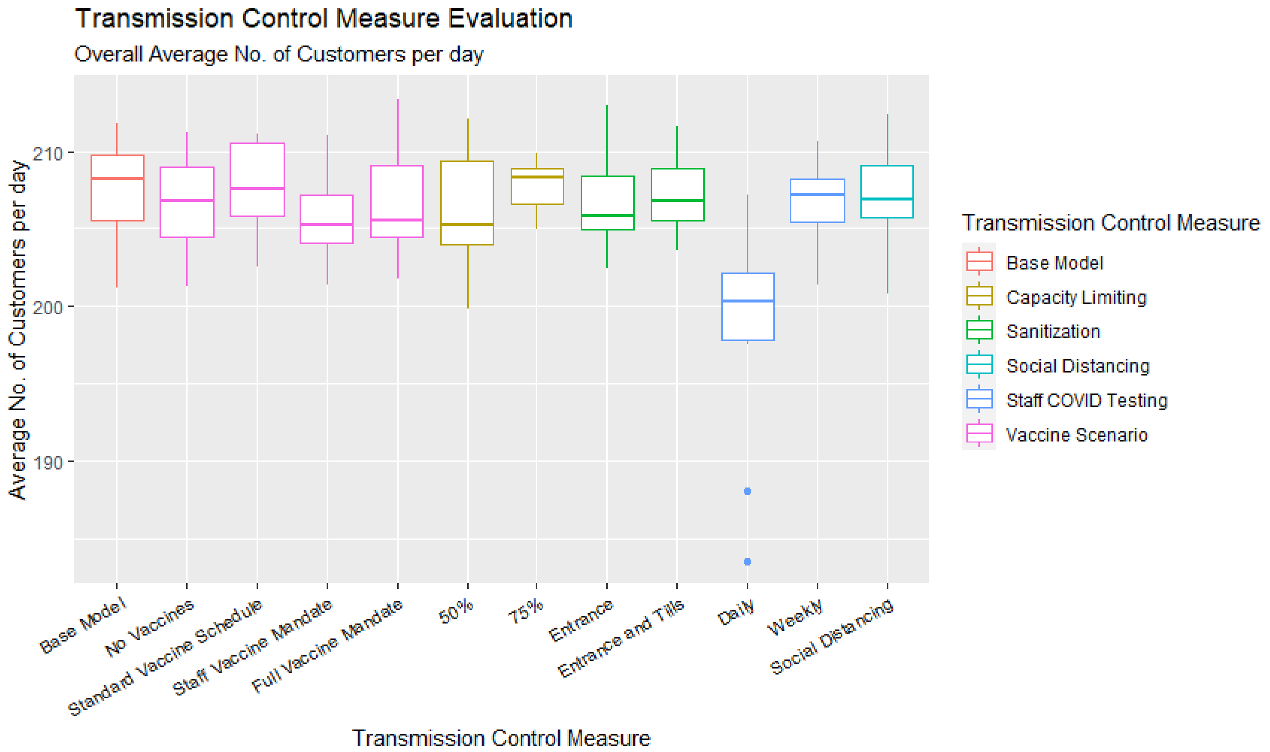

Figure 7.8: Box-plots showing the Average No. of Customers per day under each Isolated Control Measure Scenario

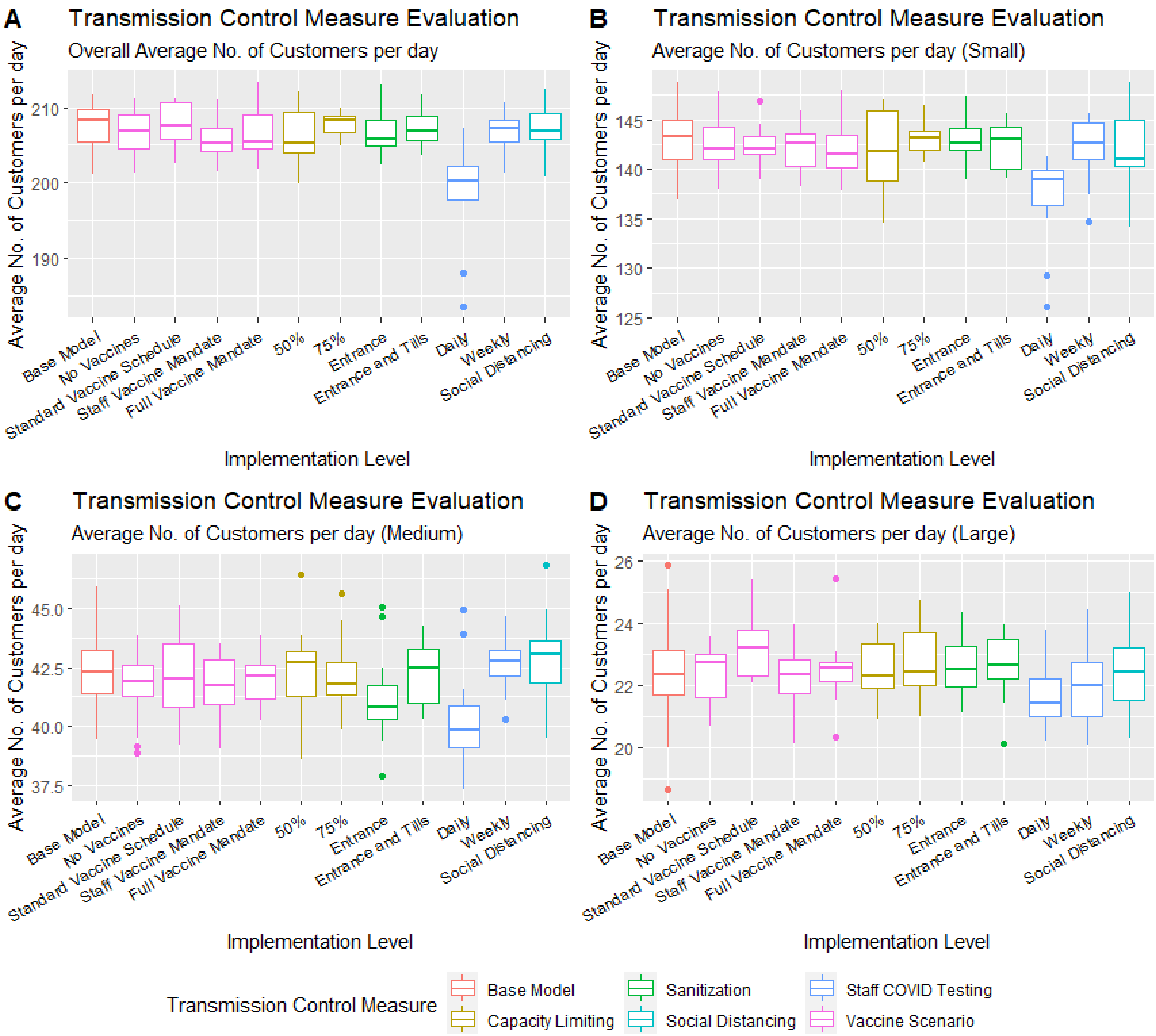

Figure 7.9: Box-plots showing the Average No. of Customers per day per Shop-Size under each Isolated Control Measure Scenario

7.2.2 Isolated Transmission Control Measures at Varied Prevalence

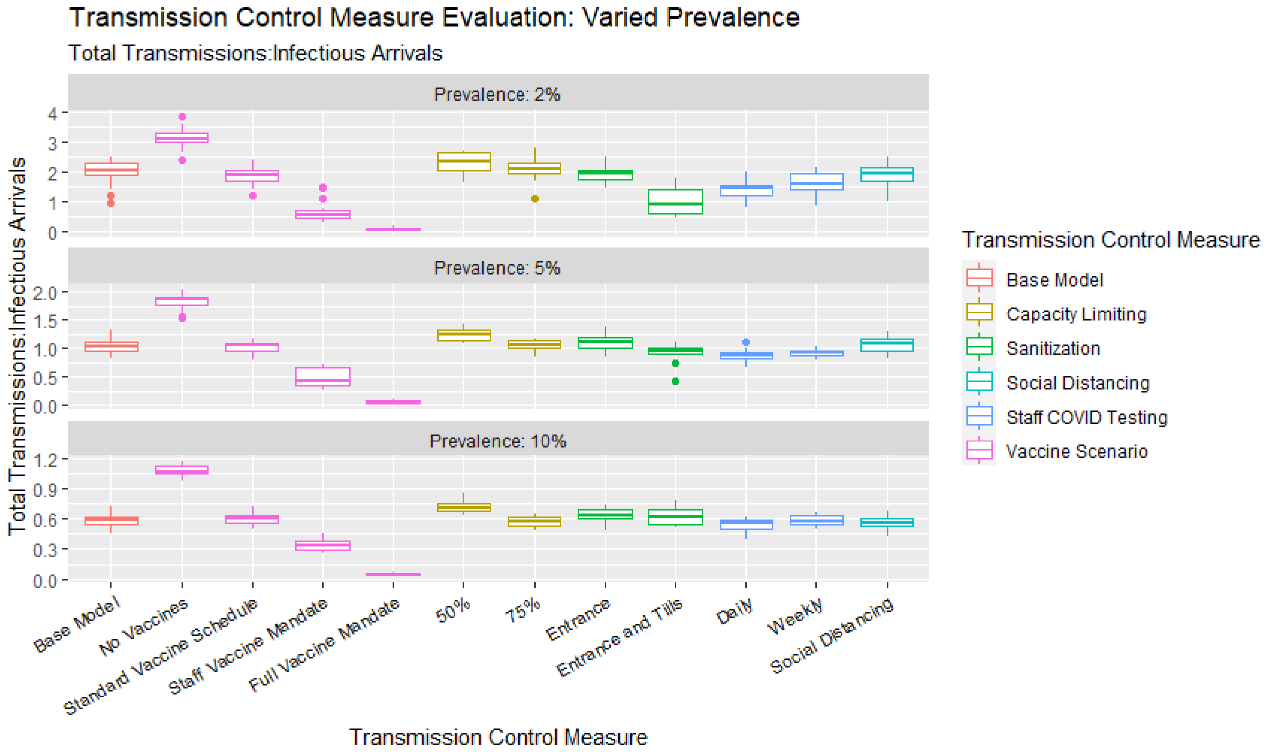

Figure 7.10: Box-plots showing the Ratio of Total Transmissions to Infectious Customer Arrivals under each Isolated Control Measure Scenario with Varied Prevalence

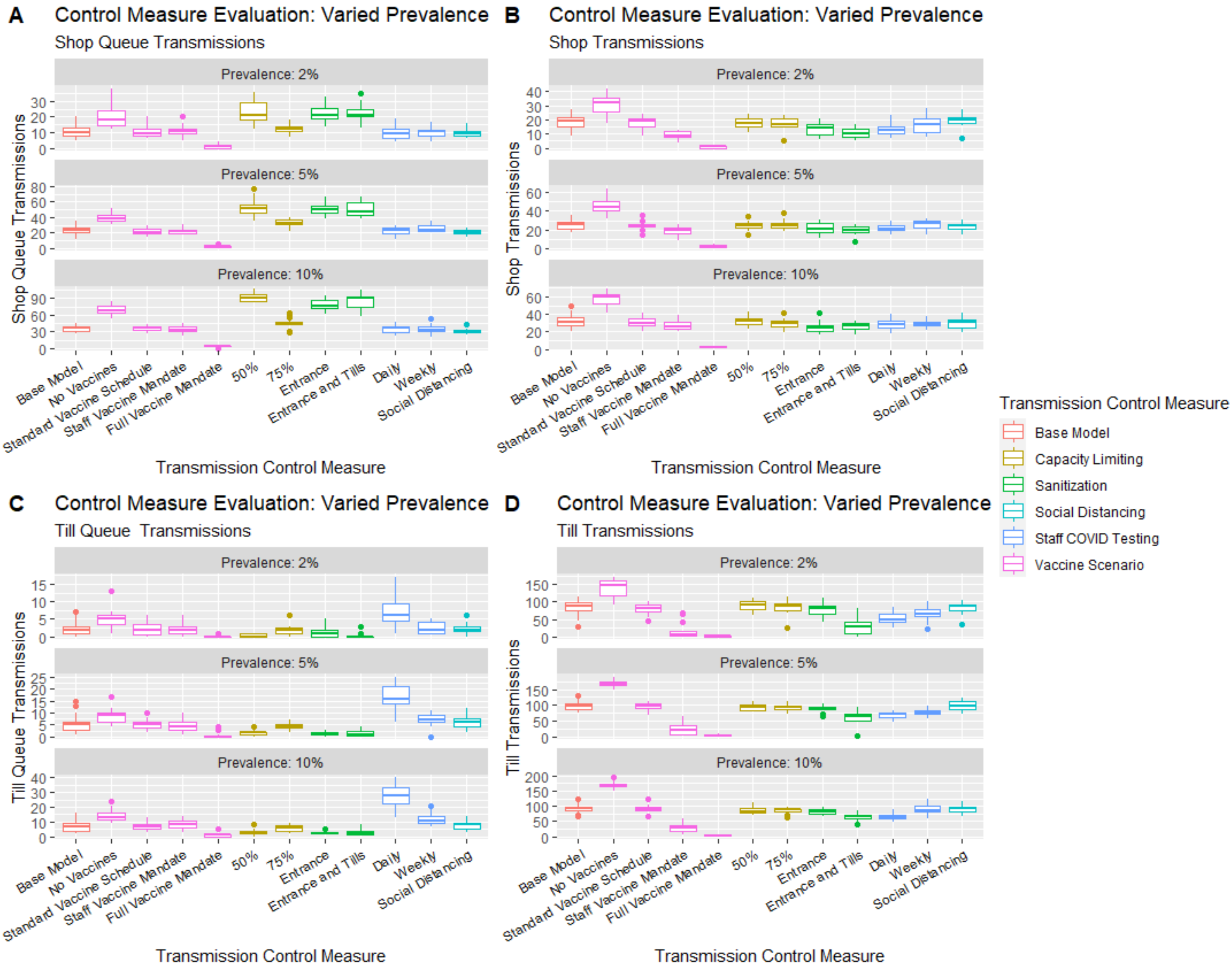

Figure 7.11: Box-plots showing the Total Transmission Count at each Location in the Shop under each Isolated Control Measure Scenario with Varied Prevalence

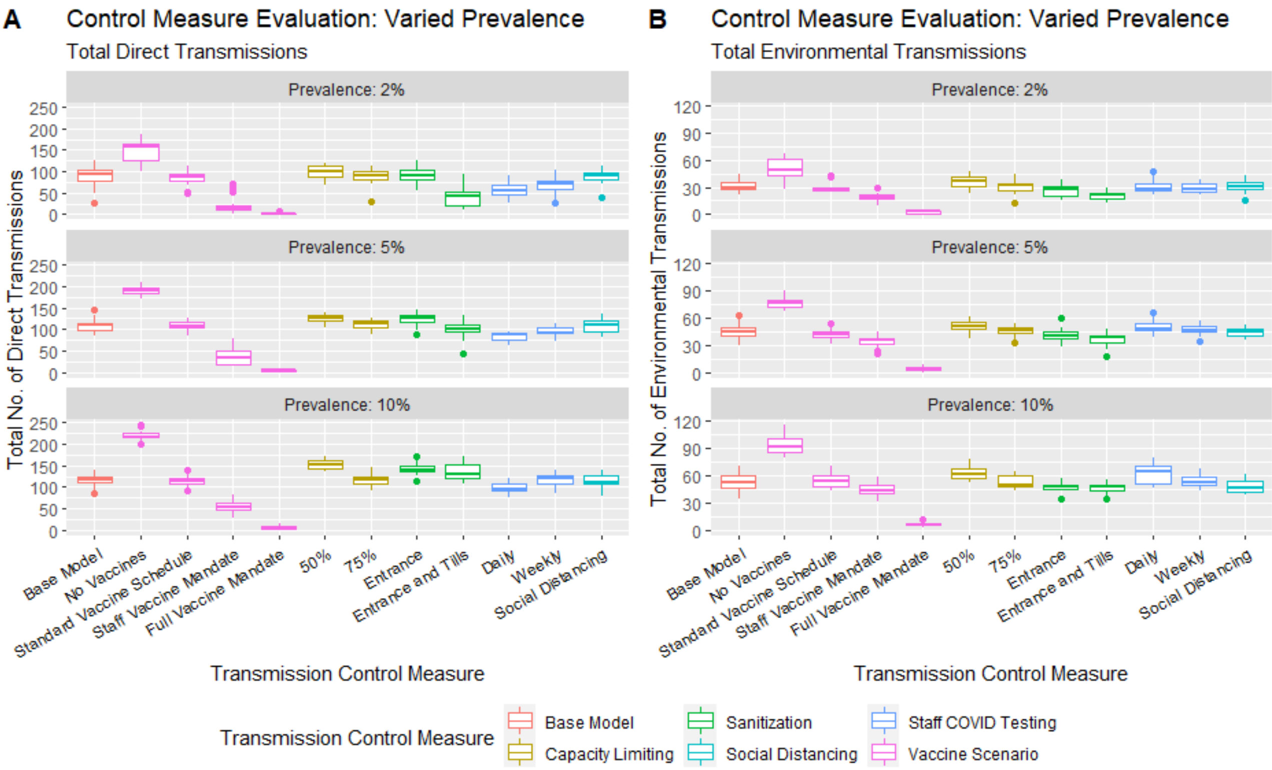

Figure 7.12: Box-plots showing the Total Direct (A) and Environmental (B) Transmission Counts under each Isolated Control Measure Scenario with Varied Prevalence

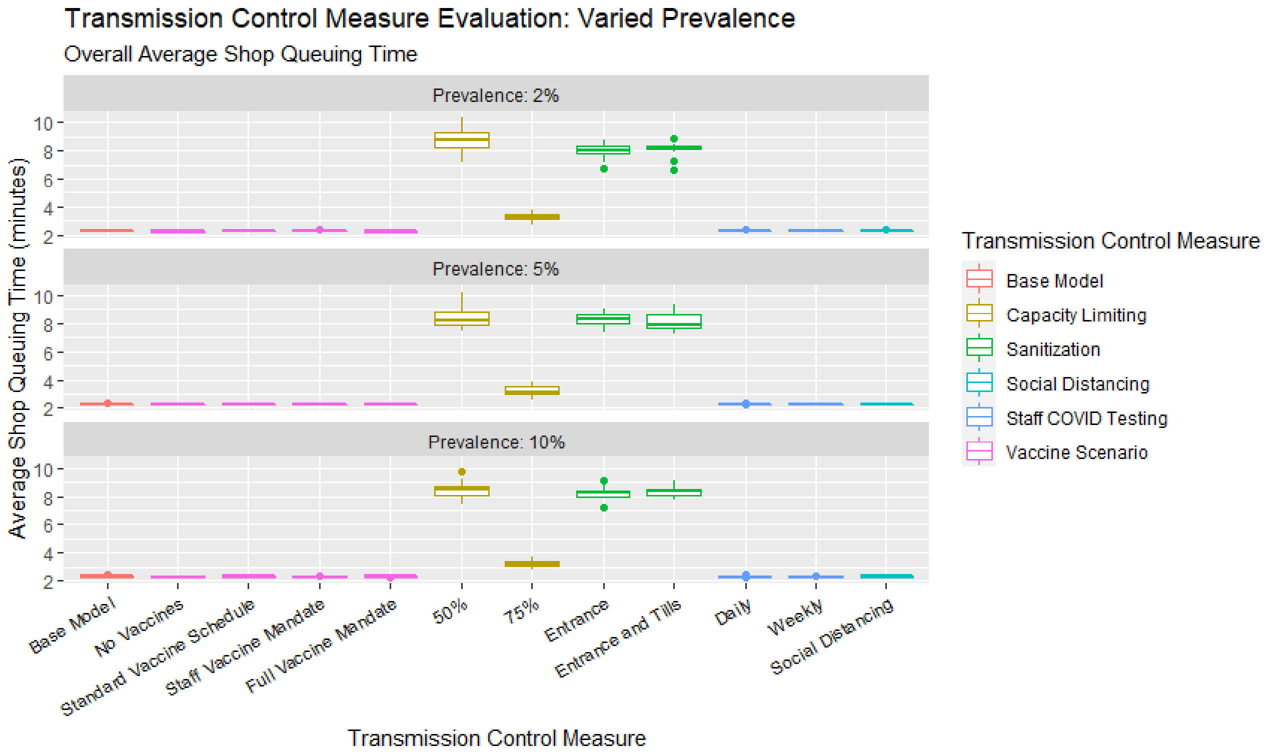

Figure 7.13: Box-plots showing the Average Customer Shop Queuing Time under each Isolated Control Measure Scenario with Varied Prevalence

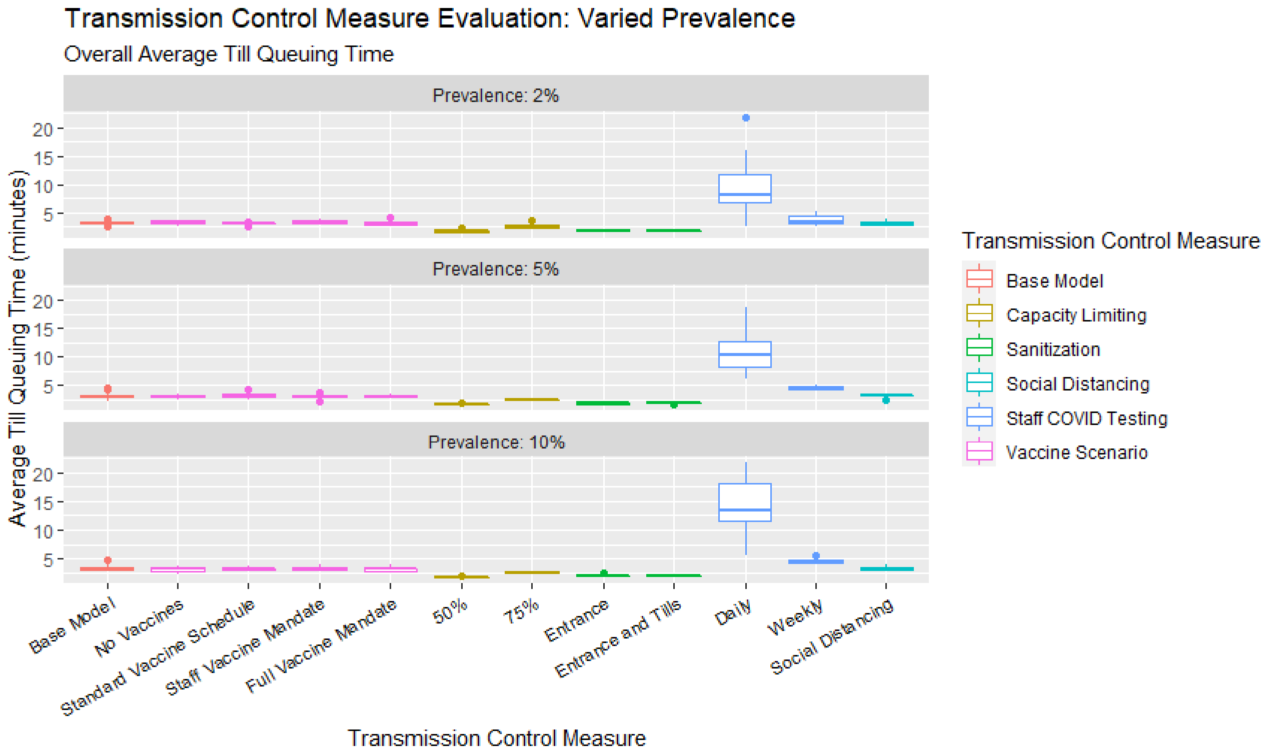

Figure 7.14: Box-plots showing the Average Customer Till Queuing Time under each Isolated Control Measure Scenario with Varied Prevalence

7.2.3 Combined Transmission Control Measure Evaluation

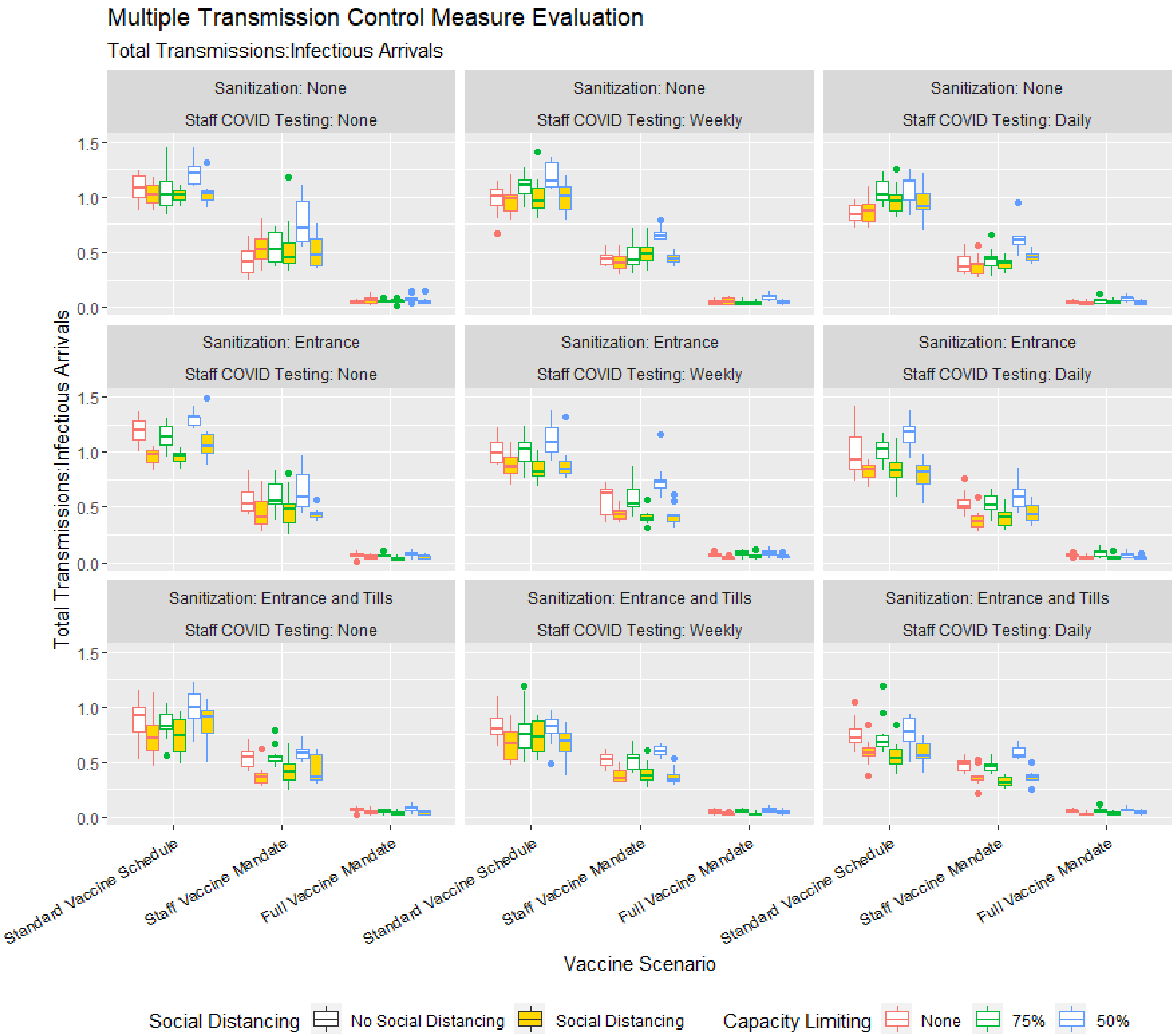

Figure 7.15: Box-plots showing the Ratio of Total Transmissions to Infectious Customer Arrivals under each Combined Control Measure Scenario

Figure 7.16: Box-plots showing the Total Transmission Count in the Shop Products Areas under each Combined Control Measure Scenario

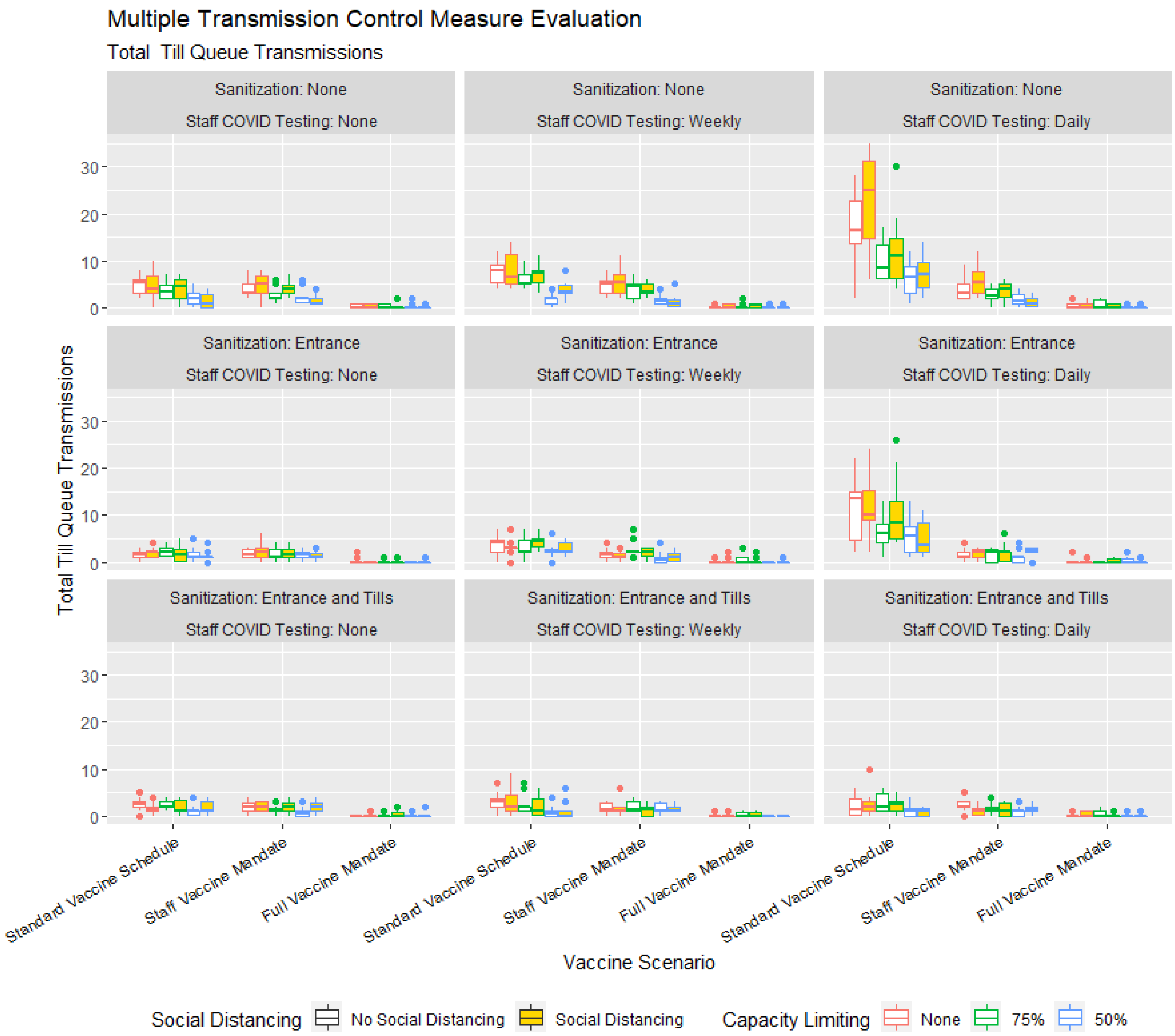

Figure 7.17: Box-plots showing the Total Transmission Count in the Till Queue under each Combined Control Measure Scenario

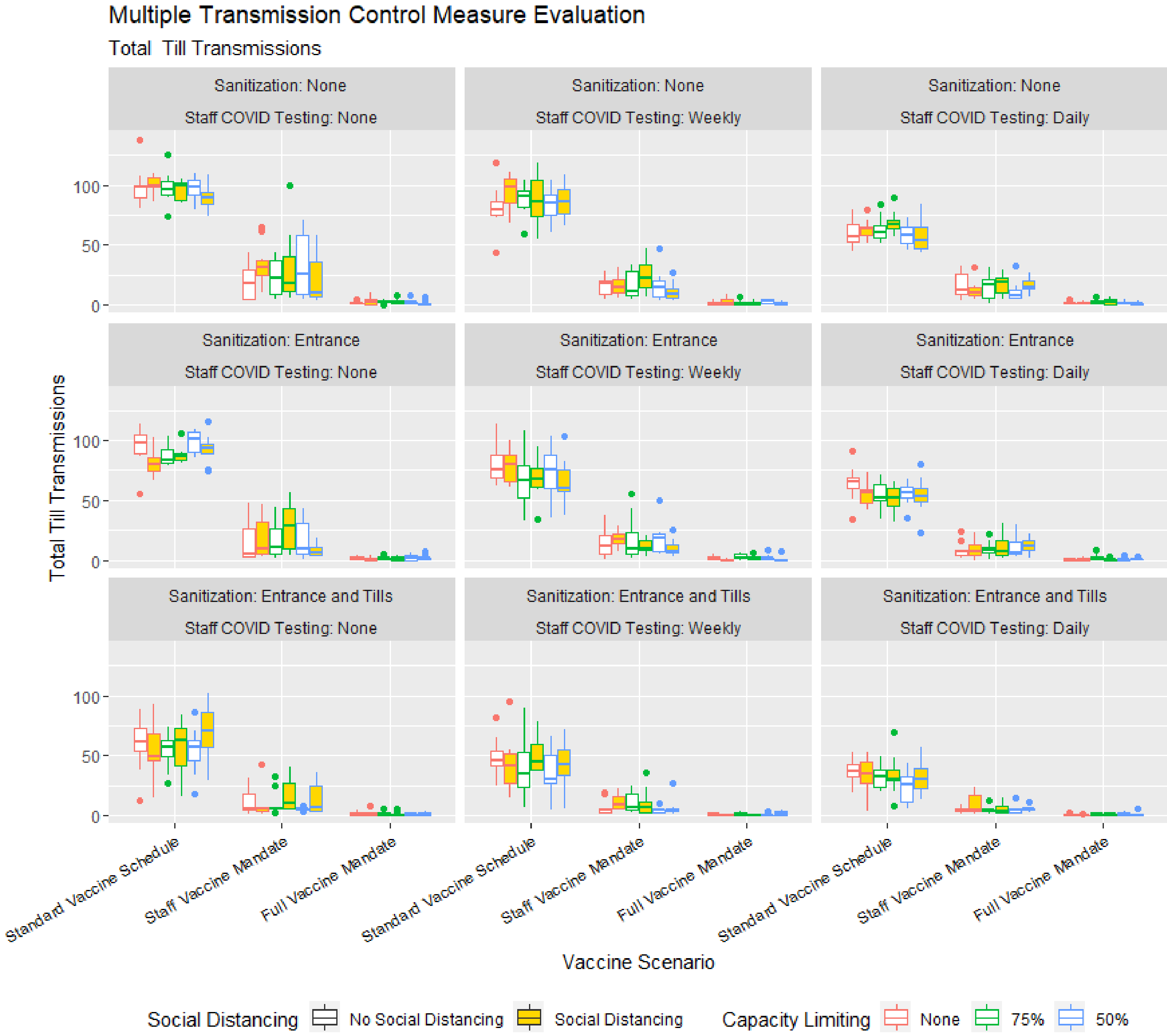

Figure 7.18: Box-plots showing the Total Transmission Count at the Tills under each Combined Control Measure Scenario

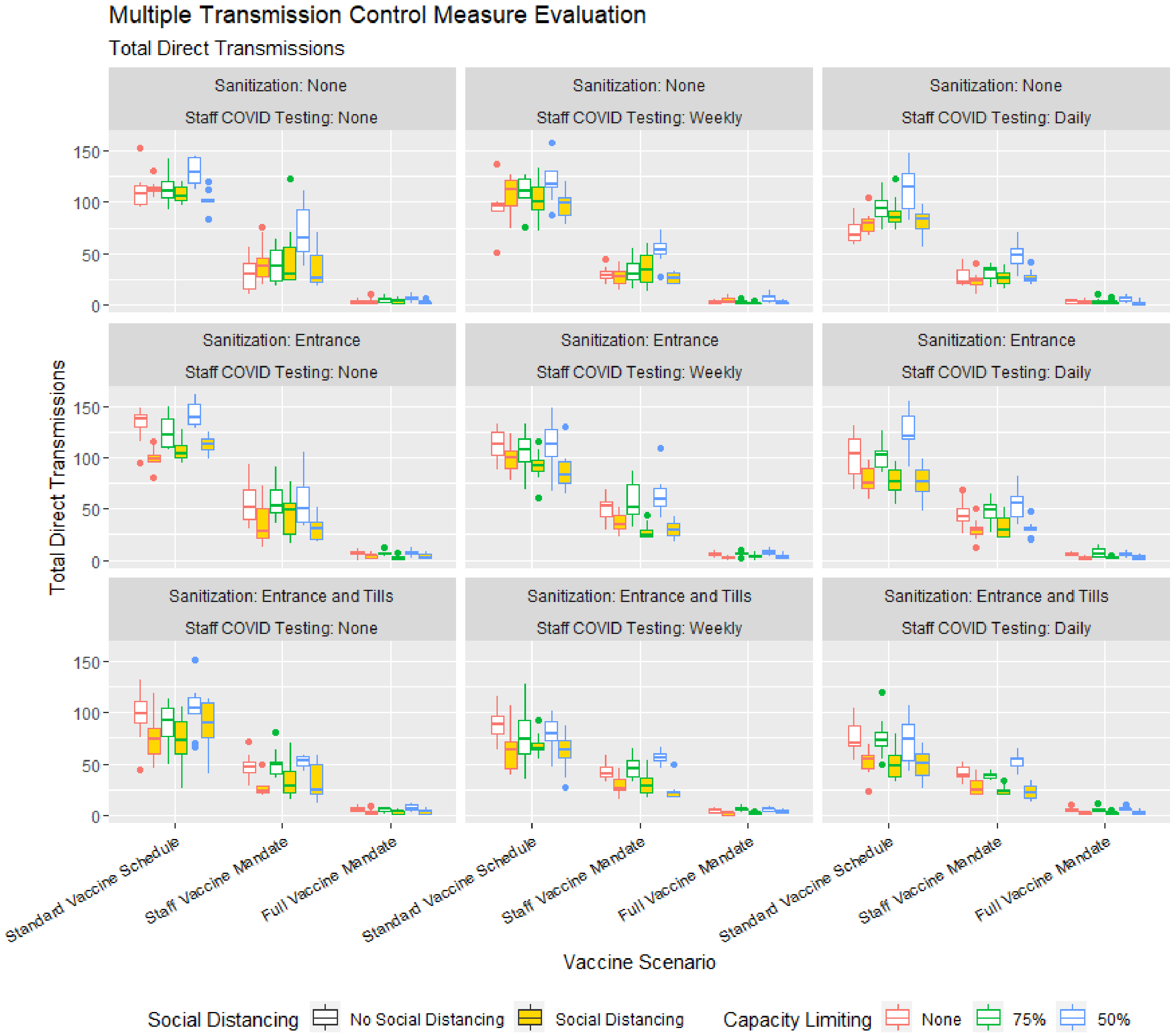

Figure 7.19: Box-plots showing the Total Direct Transmission Count under each Combined Control Measure Scenario

Figure 7.20: Box-plots showing the Total Environmental Transmission Count under each Combined Control Measure Scenario

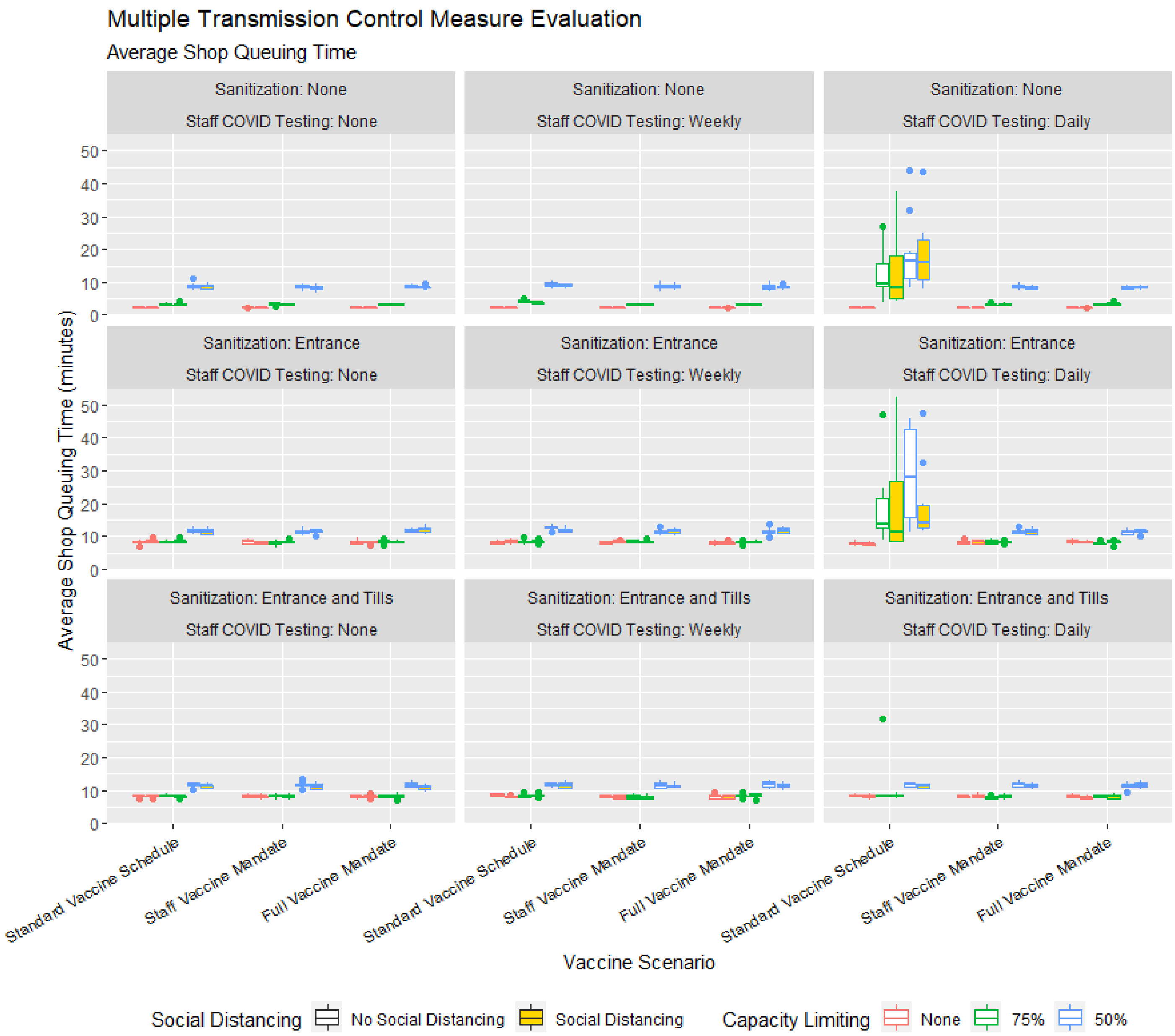

Figure 7.21: Box-plots showing the Average Customer Shop Queuing Time under each Combined Control Measure Scenario

Figure 7.22: Box-plots showing the Average Customer Till Queuing Time under each Combined Control Measure Scenario

Figure 7.23: Box-plots showing the Maximum Customer Shop Queuing Time under each Combined Control Measure Scenario

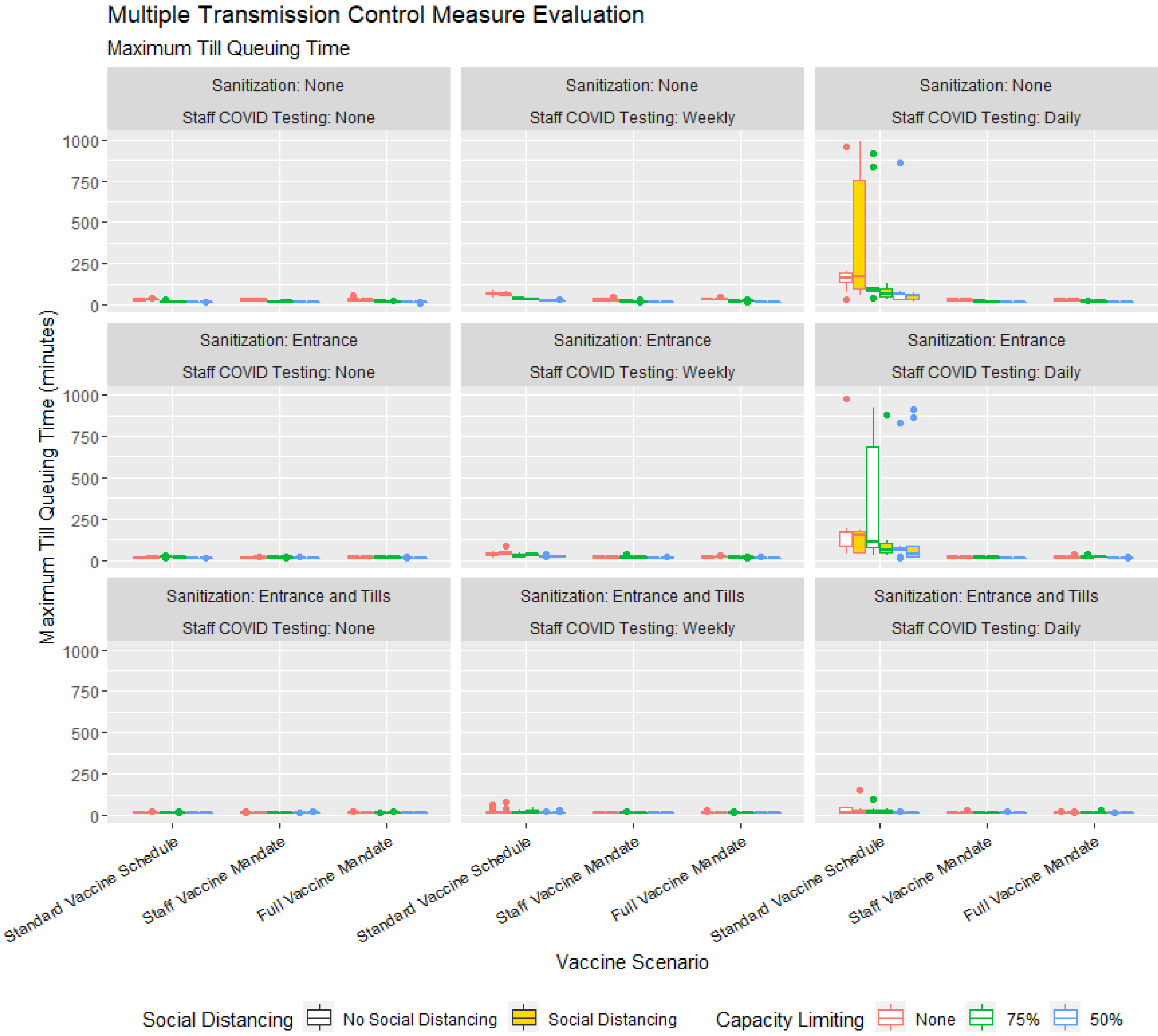

Figure 7.24: Box-plots showing the Maximum Customer Till Queuing Time under each Combined Control Measure Scenario

7.2.4 Sensitivity Analysis of Transmission Control Measure Parameters

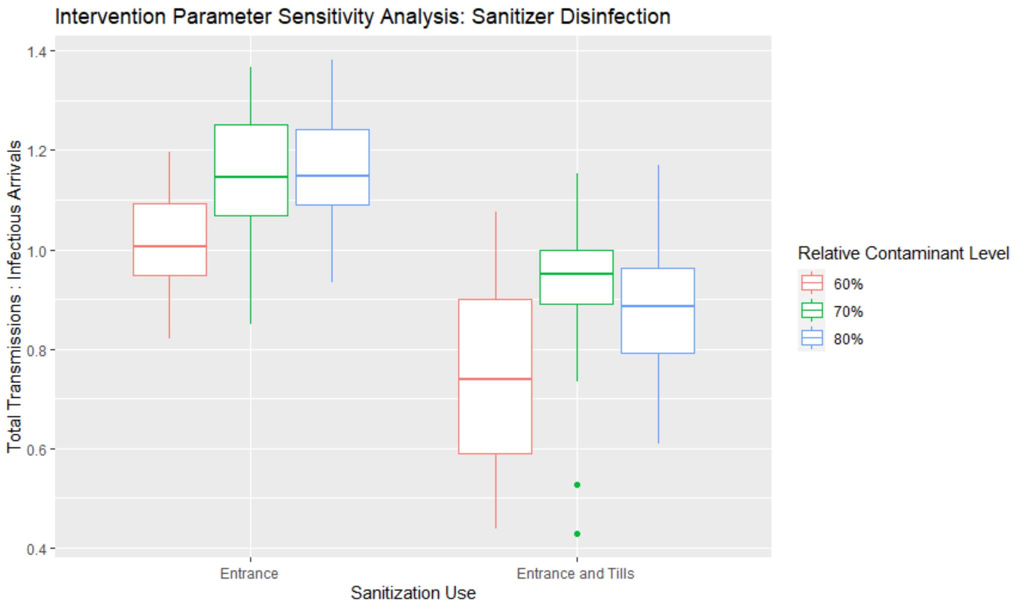

Figure 7.25: Box-plots showing the Ratio of Total Transmissions : Infectious Customer Arrivals Under the Implementation of Sanitization Measures with Varied Levels of Viral Contaminant Reduction

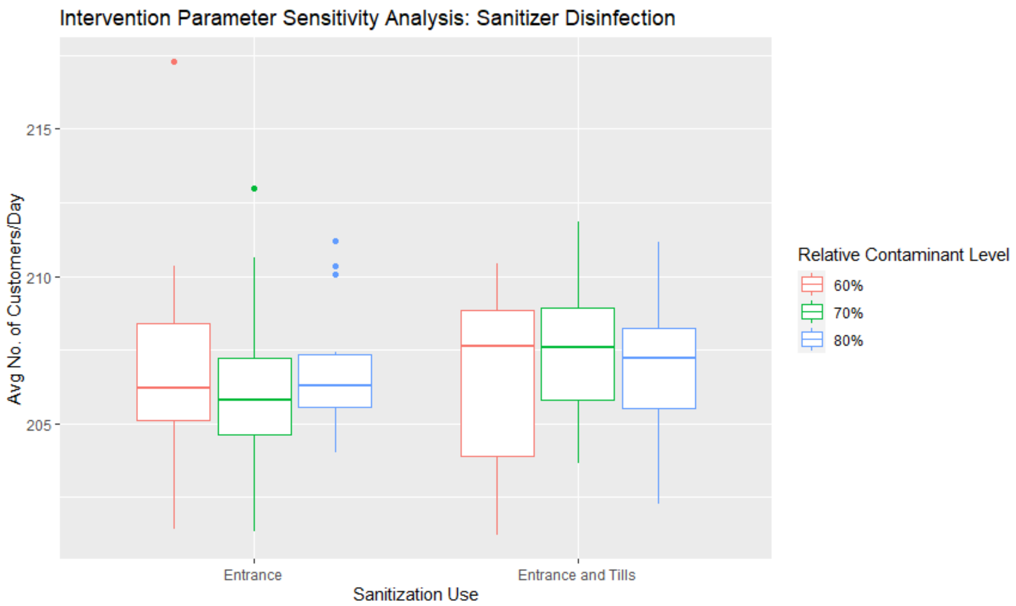

Figure 7.26: Box-plots showing the Average No. of Customers per Day Under the Implementation of Sanitization Measures with Varied Levels of Viral Contaminant Reduction

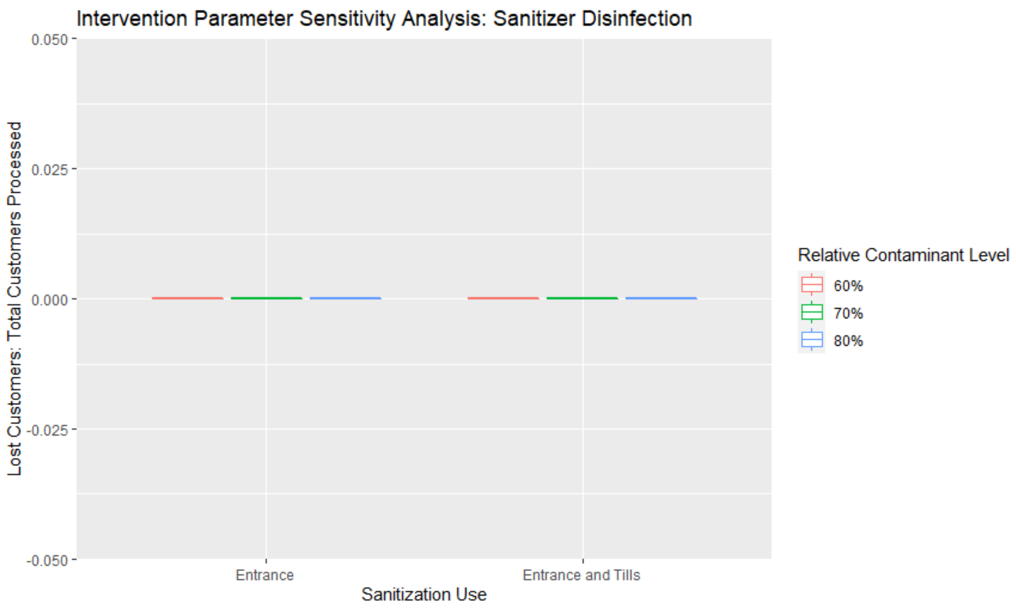

Figure 7.27: Box-plots showing the Ratio of Customers Lost to Customers Processed Under the Implementation of Sanitization Measures with Varied Levels of Viral Contaminant Reduction

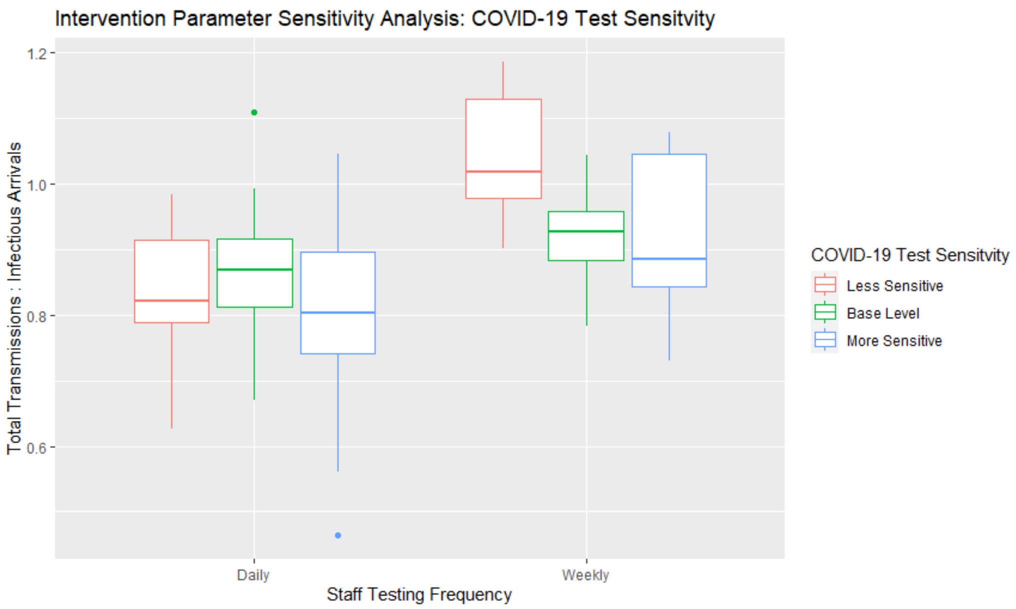

Figure 7.28: Box-plots showing the Ratio of Total Transmissions : Infectious Customer Arrivals Under the Implementation of Staff COVID-19 Testing Measures with Varied Levels of COVID-19 Diagnostic Test Sensitivity

7.3 Supermarket Survey Data

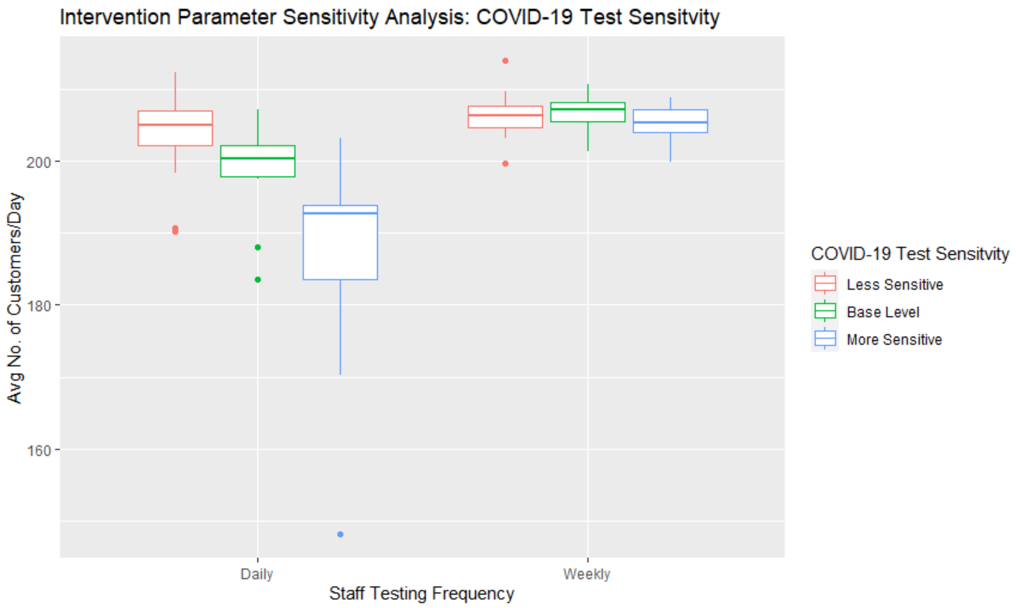

Figure 7.29: Box-plots showing the Average No. of Customers per Day Under the Implementation of Staff COVID-19 Testing Measures with Varied Levels of COVID-19 Diagnostic Test Sensitivity

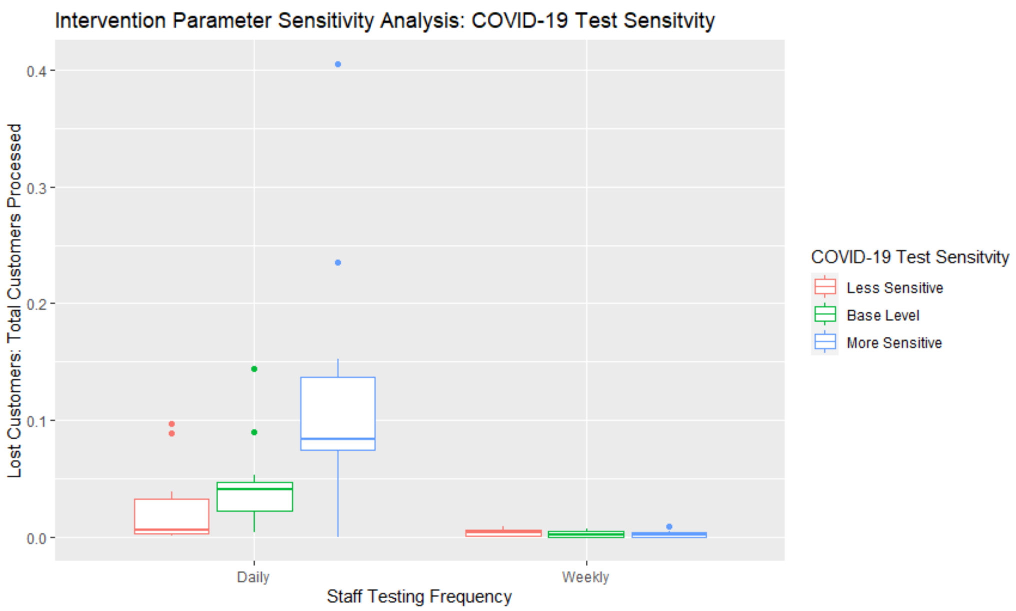

Figure 7.30: Box-plots showing the Ratio of Customers Lost to Customers Processed the Implementation of Staff COVID-19 Testing Measures with Varied Levels of COVID-19 Diagnostic Test Sensitivity

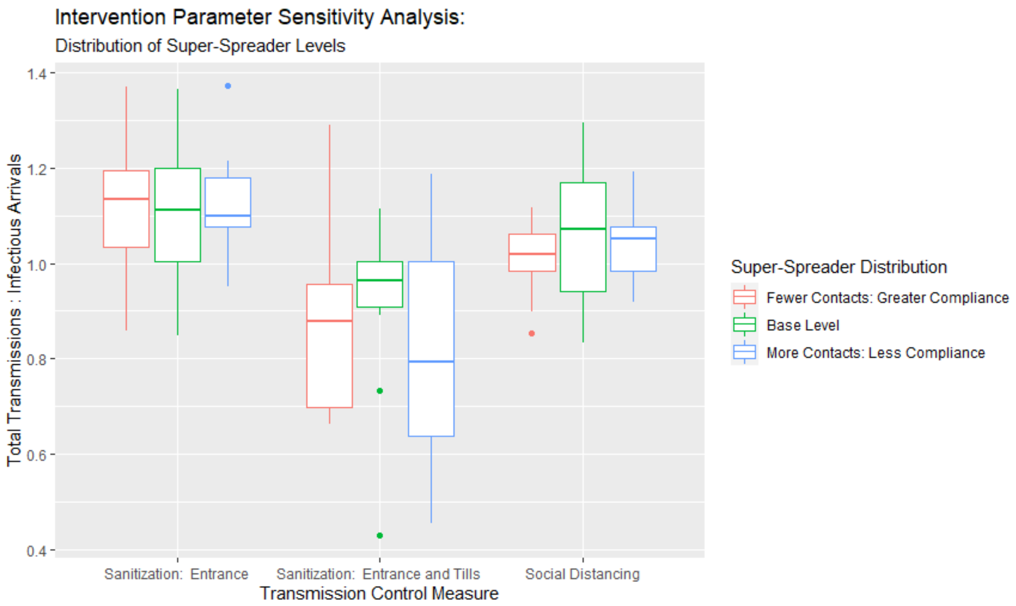

Figure 7.31: Box-plots showing the Ratio of Total Transmissions : Infectious Customer Arrivals Under the Implementation of Sanitization and Social Distancing Measures with Varied Distributions of Super-Spreader Levels Amongst Customers

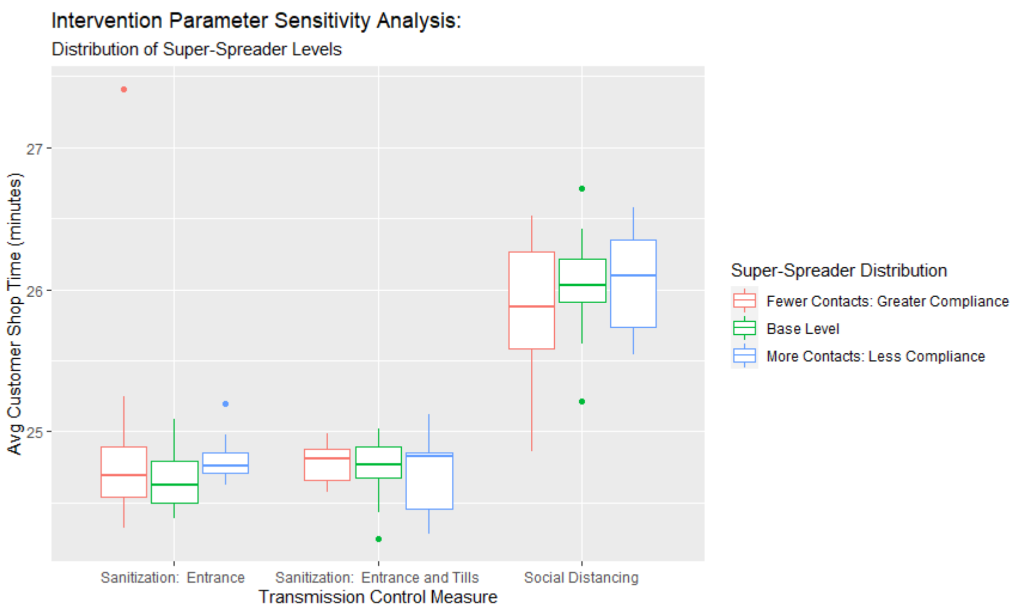

Figure 7.32: Box-plots showing the Average Customer Shopping Time Under the Implementation of Sanitization and Social Distancing Measures with Varied Distributions of Super-Spreader Levels Amongst Customers

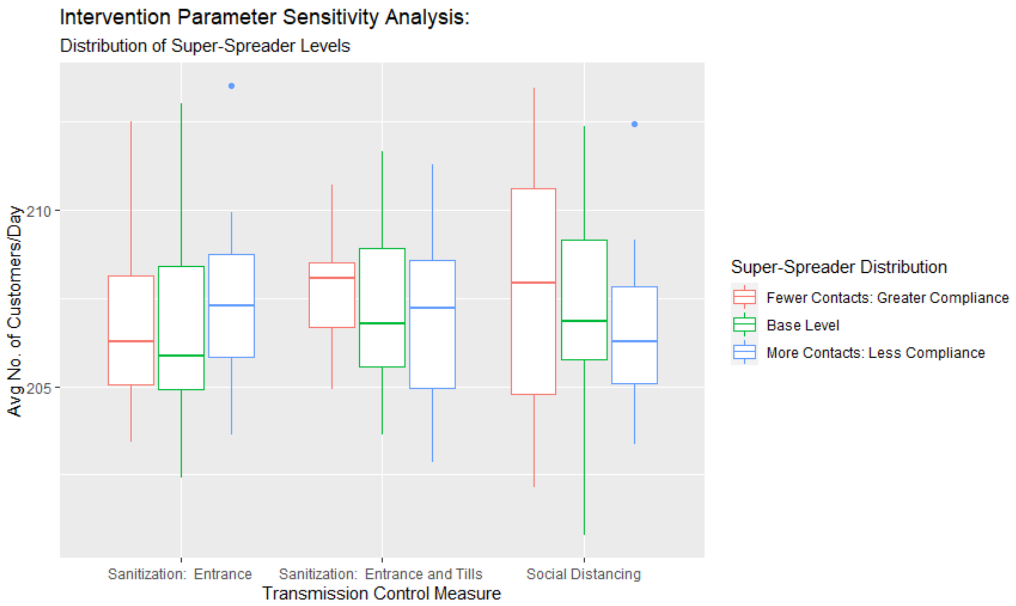

Figure 7.33: Box-plots showing the Average No. of Customers per Day Under the Implementation of Sanitization and Social Distancing Measures with Varied Distributions of Super-Spreader Levels Amongst Customers

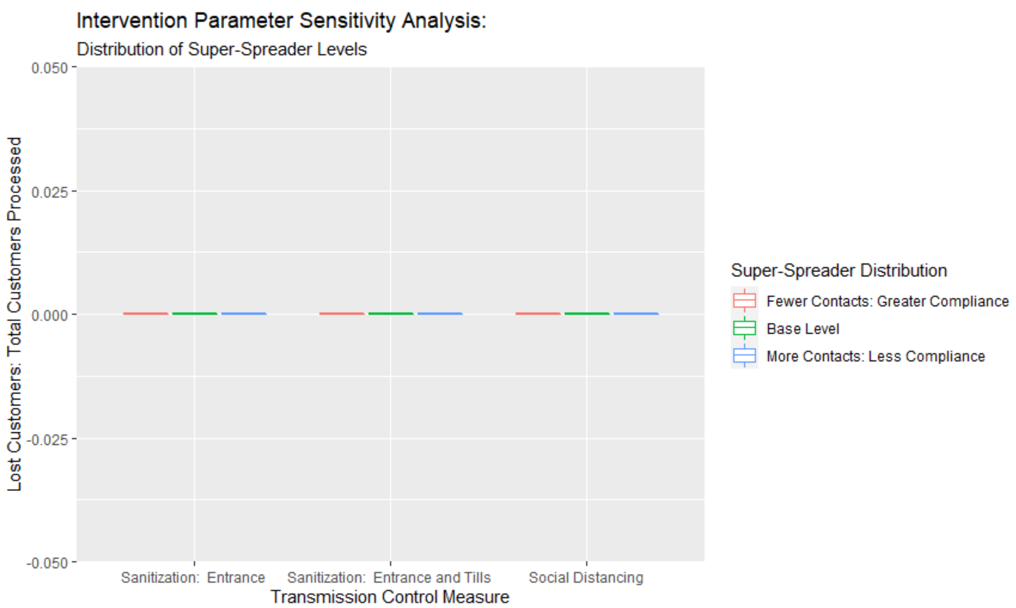

Figure 7.34: Box-plots showing the Ratio of Customers Lost to Customers Processed Under the Implementation of Sanitization and Social Distancing Measures with Varied Distributions of Super-Spreader Levels Amongst Customers

Timothy Mountford | Shop Customer Dynamics Survey | Masters Dissertation Research

Research Survey Investigating Local Supermarket Customer Dynamics

Store: Woolworths, Kenilworth

Survey Respondent: Store Management

---

1. On average, how many customers do you think visit the store per day?
   50 to 100 Customers
2. What percentage of the customers visiting the store have a small, quick shop?
   60 %
3. What per percentage of the customers visiting the store have a medium sized shop?
   30 % to 20 %
4. What per percentage of the customers visiting the store have a large sized shop?
   10 %
5. How long does a customer spend in the shop on average?
   30 Minutes to 45 Minutes
6. If the number of customers allowed in the shop was limited at any point during COVID-19 lockdown, what was the approximate capacity limit?
   25 Customers

Date: 06/12/2021

Signed: ___

Figure 7.35: Customer Dynamics Survey Completed by the Woolworths, Kenilworth Store Manager

Timothy Mountford Shop Customer Dynamics Survey Masters Dissertation Research

Research Survey Investigating Local Supermarket Customer Dynamics

Store: Pick n Pay Local, Kenilworth

Survey Respondent: Store Management

1. On average, how many customers do you think visit the store per day?
   1000 - 1200
2. What percentage of the customers visiting the store have a small, quick shop?
   50%
3. What per percentage of the customers visiting the store have a medium sized shop?
   20%
4. What per percentage of the customers visiting the store have a large sized shop?
   30%
5. How long does a customer spend in the shop on average?
   20min to 40 min
6. If the number of customers allowed in the shop was limited at any point during COVID-19 lockdown, what was the approximate capacity limit?
   15 Customers

Date: 06-12-2021 **Signed:**

Figure 7.36: Customer Dynamics Survey Completed by the Pick n Pay Local, Kenilworth Store Manager

Chapter 8

Appendix B: NetLogo Simulation Additional Figures

8.1 Additional Interface Elements

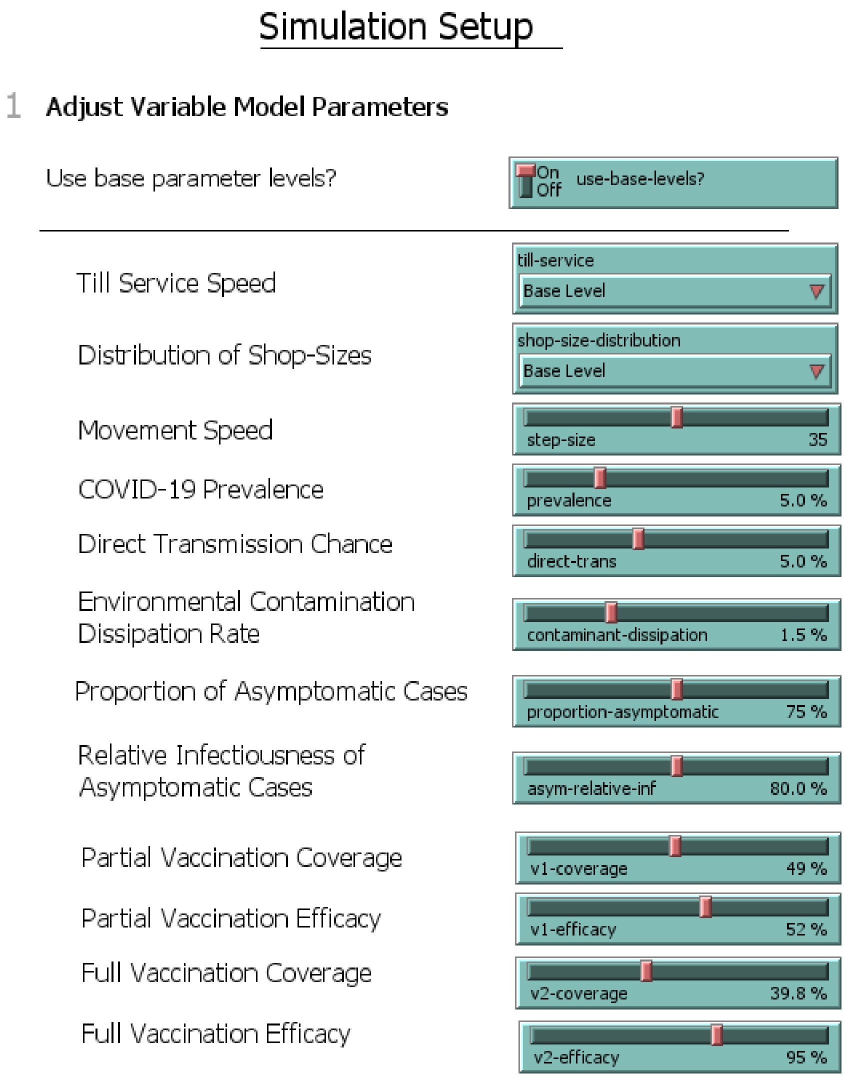

Figure 8.1: NetLogo Simulation Interface Sliders and Choosers for Variable Base Model Input Parameters

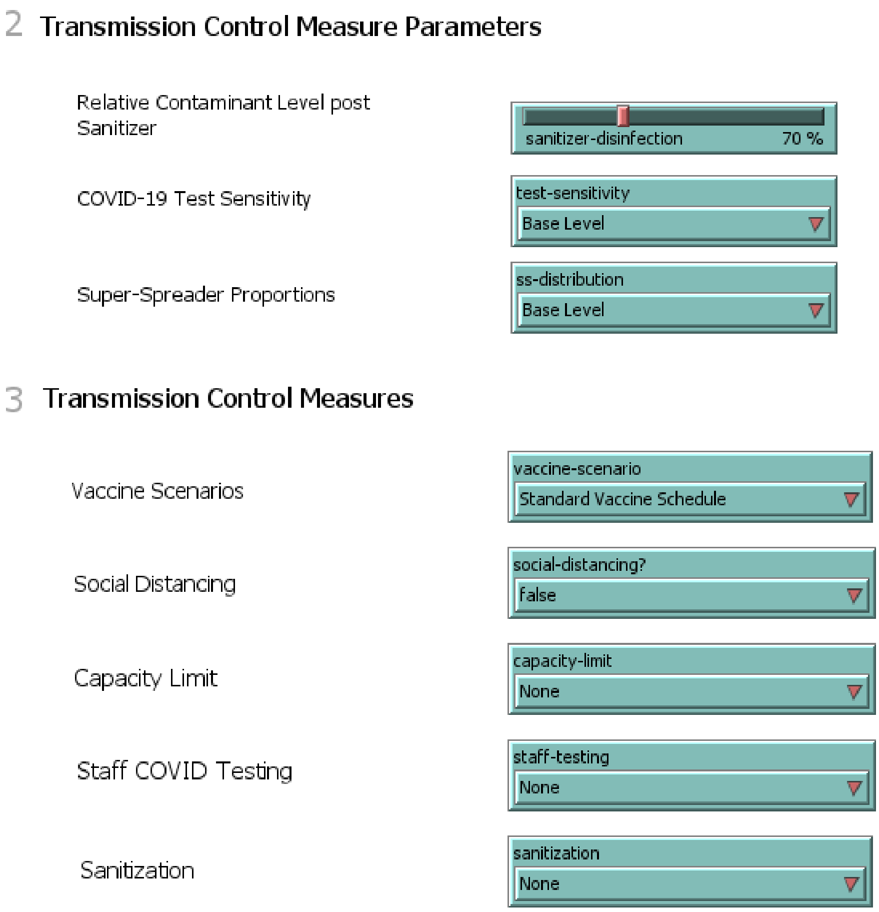

Figure 8.2: NetLogo Simulation Interface Sliders and Choosers for Variable Control Measure Input Parameters

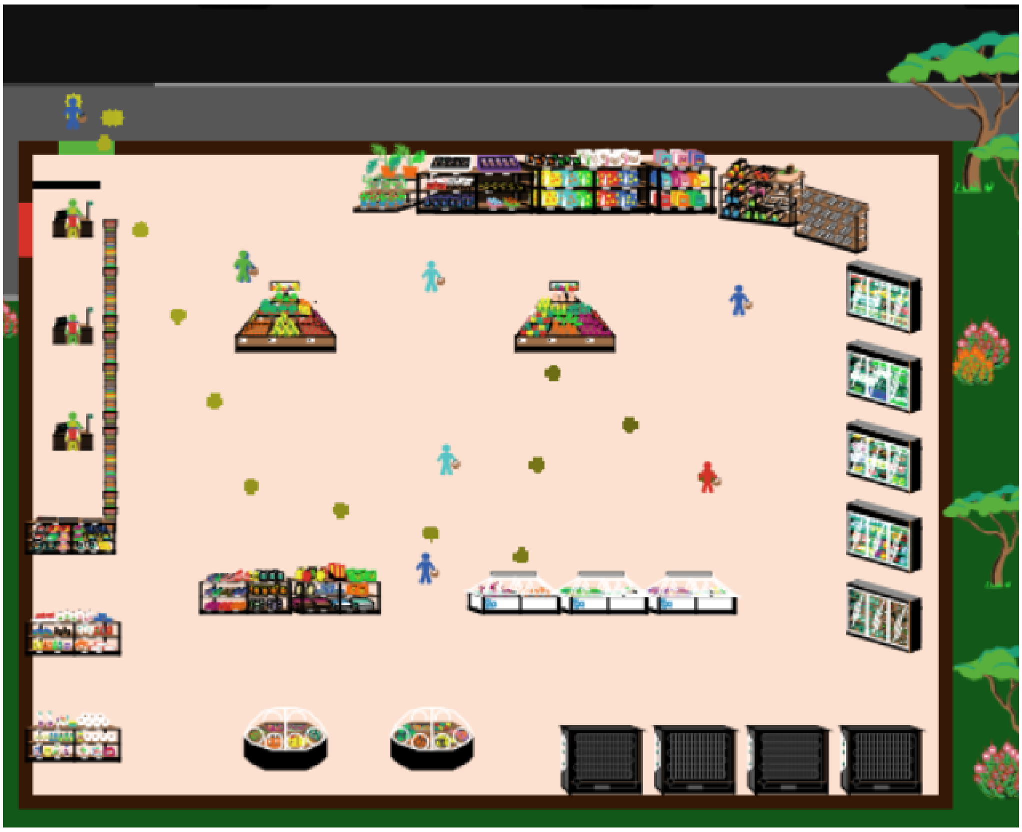

Figure 8.3: NetLogo Simulation Environment with Enabled View of Environmental Contamination

8.2 Environment Components

Figure 8.4: NetLogo Simulation Shop Shelf Designs

Figure 8.5: NetLogo Simulation Shop Fridge Designs

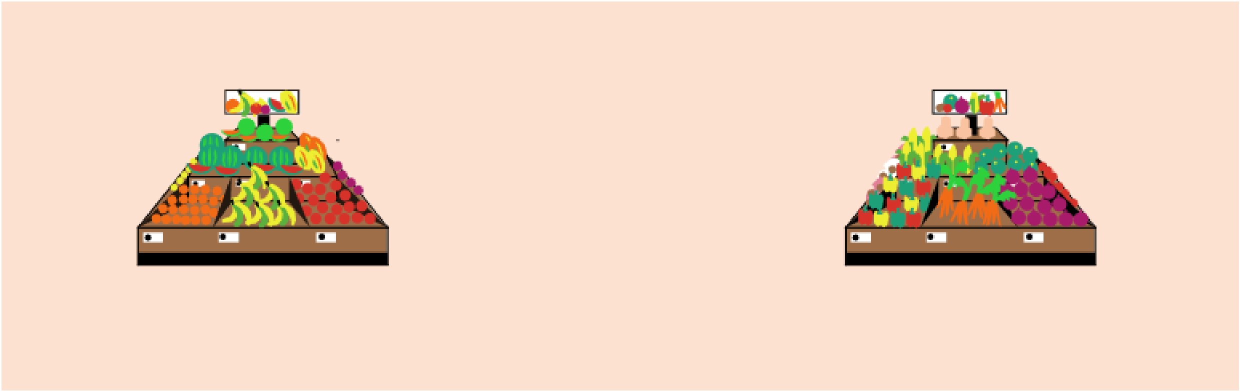

Figure 8.6: NetLogo Simulation Fresh Produce Island Designs

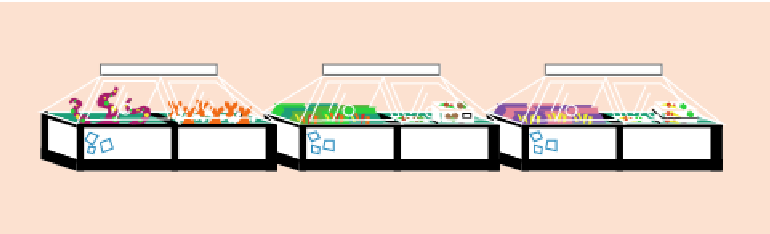

Figure 8.7: NetLogo Simulation Shop Freezer Designs

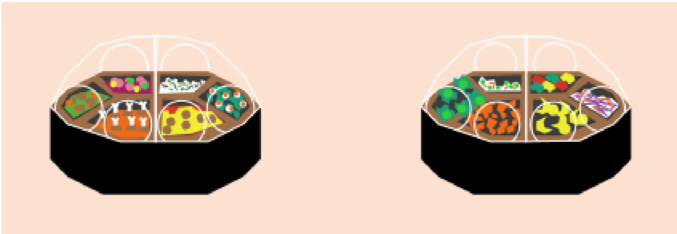

Figure 8.8: NetLogo Simulation Prepared Food Island Designs

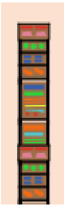

Figure 8.9: NetLogo Simulation Shop In-Queue Merchandise Designs

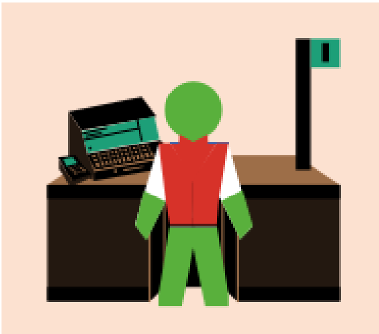

Figure 8.10: NetLogo Simulation Shop Till Station Design

Figure 8.11: NetLogo Simulation Staff House Design

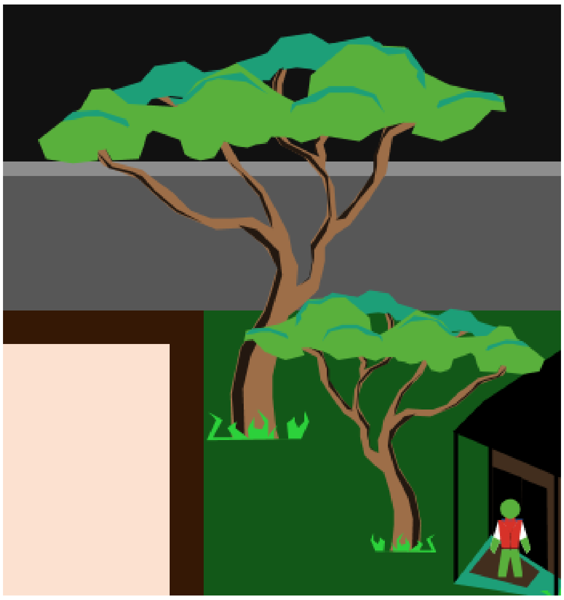

Figure 8.12: NetLogo Simulation Acacia Designs

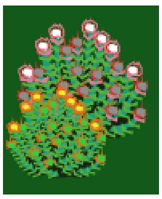

Figure 8.13: NetLogo Simulation Pincushion Designs

Figure 8.14: NetLogo Simulation Parking Lot Design

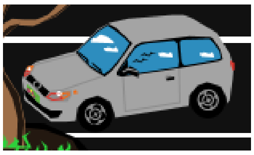

Figure 8.15: NetLogo Simulation Car Design

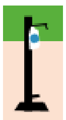

Figure 8.16: NetLogo Simulation Sanitizer Design

Chapter 9

Appendix C: Distributions of Simulation Outcome Metrics

9.1 Univariate Sensitivity Analysis

Total Transmissions

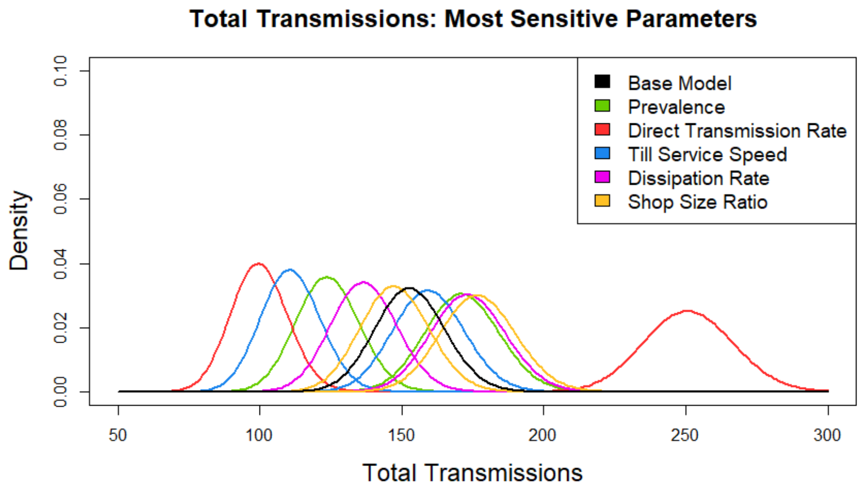

Figure 9.1: Distribution Plots showing the Change in the Total Number of Transmissions resulting from Changes in More Sensitive Model Parameters

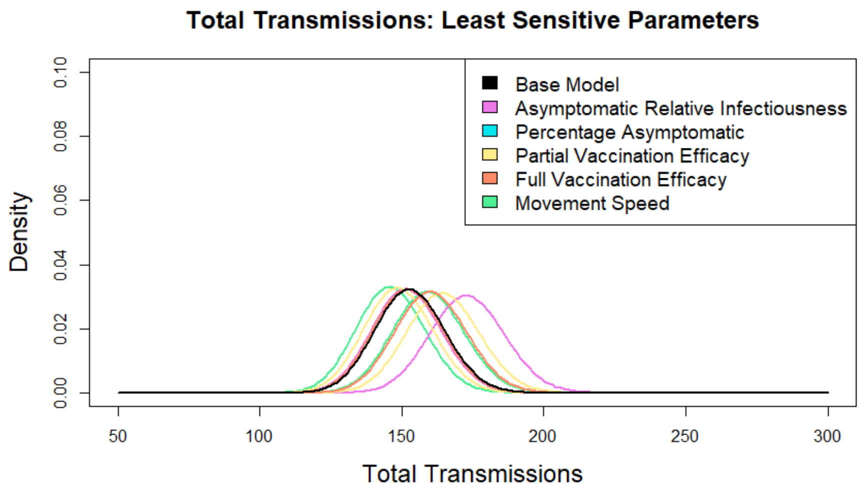

Figure 9.2: Distribution Plots showing the Change in the Total Number of Transmissions resulting from Changes in Less Sensitive Model Parameters

Total Transmissions:Infectious Arrivals

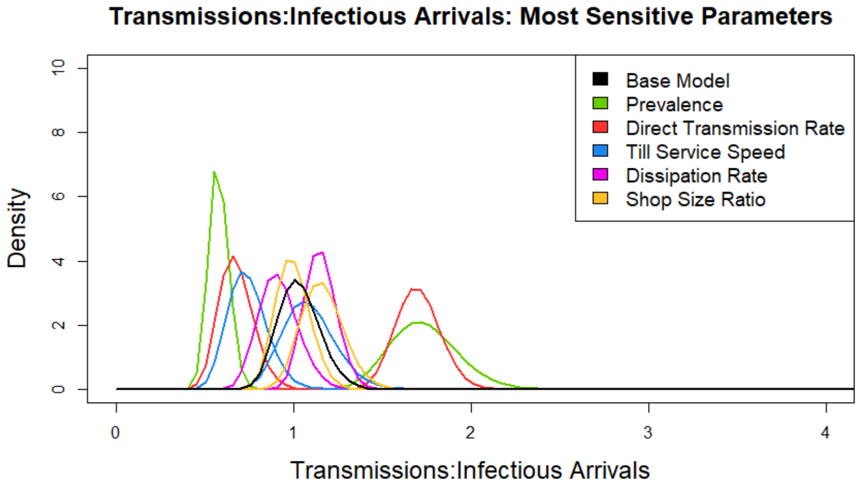

Figure 9.3: Distribution Plots showing the Change in the Ratio of Total Transmissions to Infectious Arrivals resulting from Changes in More Sensitive Model Parameters

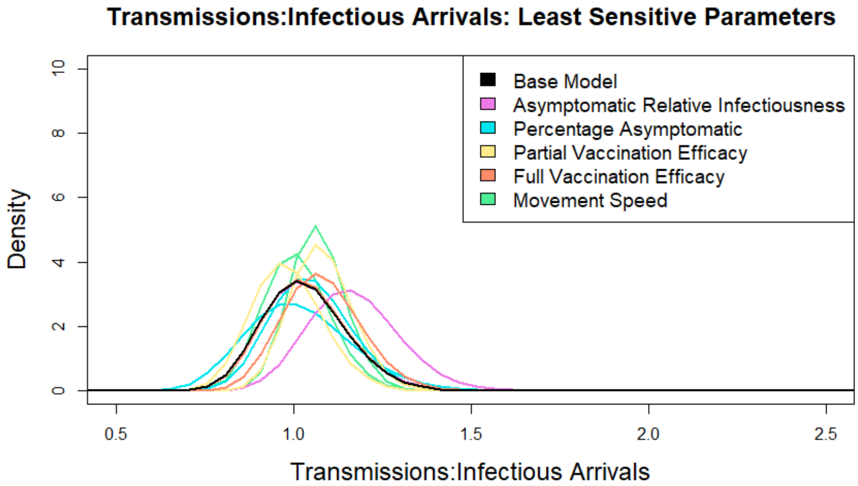

Figure 9.4: Distribution Plots showing the Change in the Ratio of Total Transmissions to Infectious Arrivals resulting from Changes in Less Sensitive Model Parameters

Average Shop Time

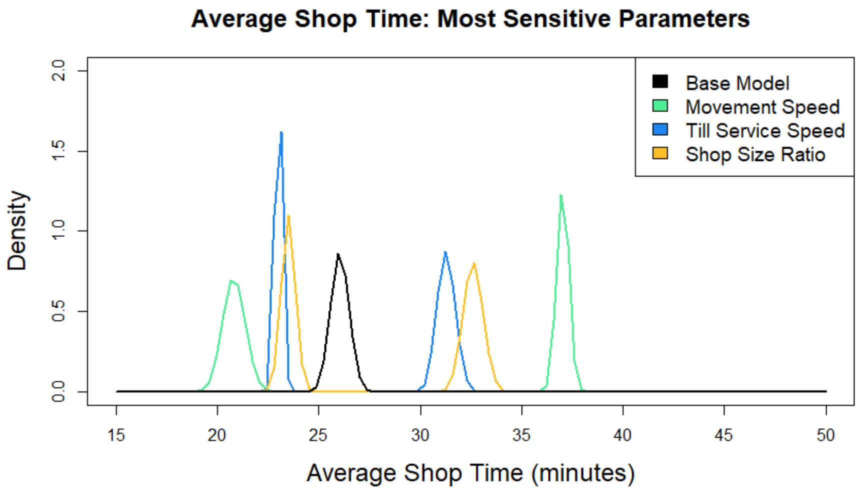

Figure 9.5: Distribution Plots showing the Change in the Average Shopping Time resulting from Changes in More Sensitive Model Parameters

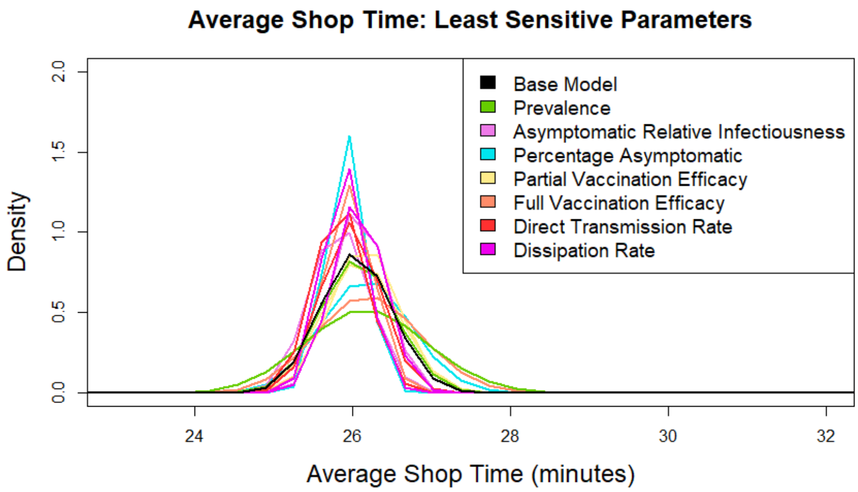

Figure 9.6: Distribution Plots showing the Change in the Average Shopping Time resulting from Changes in Less Sensitive Model Parameters

Average No. of Customers per day

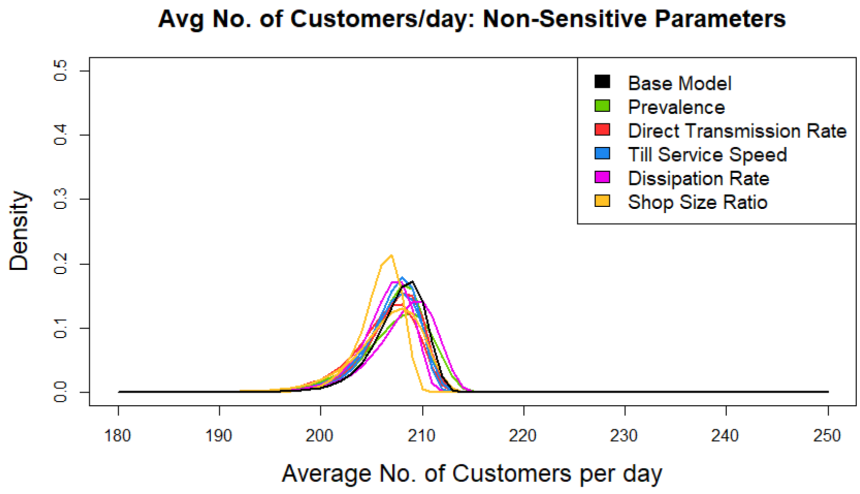

Figure 9.7: Distribution Plots showing the Change in the Average No. of Customers per Day resulting from Changes in More Sensitive Model Parameters

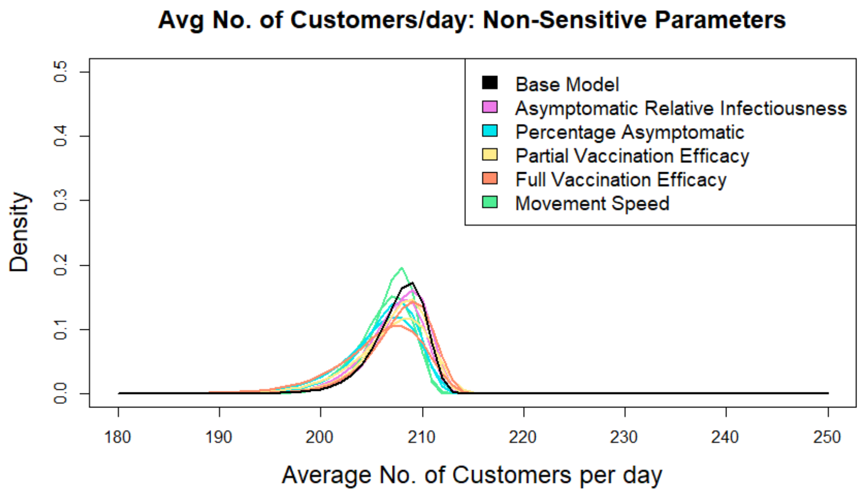

Figure 9.8: Distribution Plots showing the Change in the Average No. of Customers per Day resulting from Changes in Less Sensitive Model Parameters

Customers Lost:Customers Processed

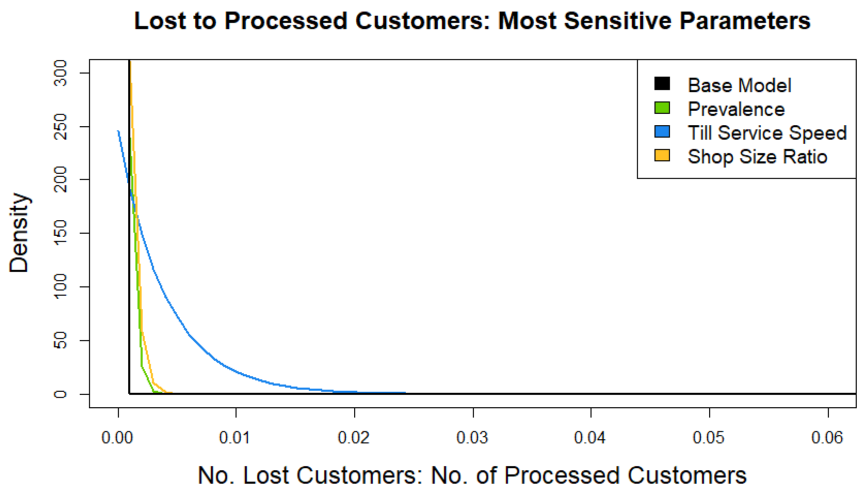

Figure 9.9: Distribution Plots showing the Change in the Ratio of the No. of Customers Lost to the No. of Customers Processed resulting from Changes in More Sensitive Model Parameters

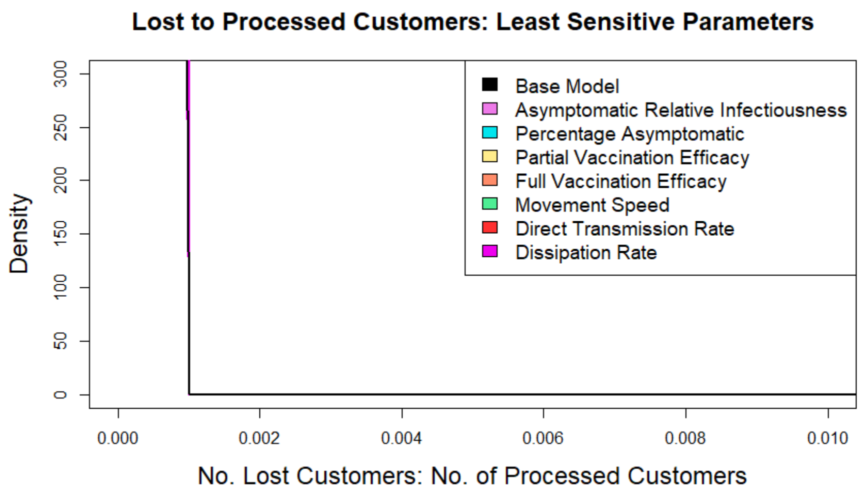

Figure 9.10: Distribution Plots showing the Change in the Ratio of the No. of Customers Lost to the No. of Customers Processed resulting from Changes in Less Sensitive Model Parameters

9.2 Transmission Control Measure Outcomes

Vaccines and Vaccine Mandates

Total Transmissions : Infectious Arrivals

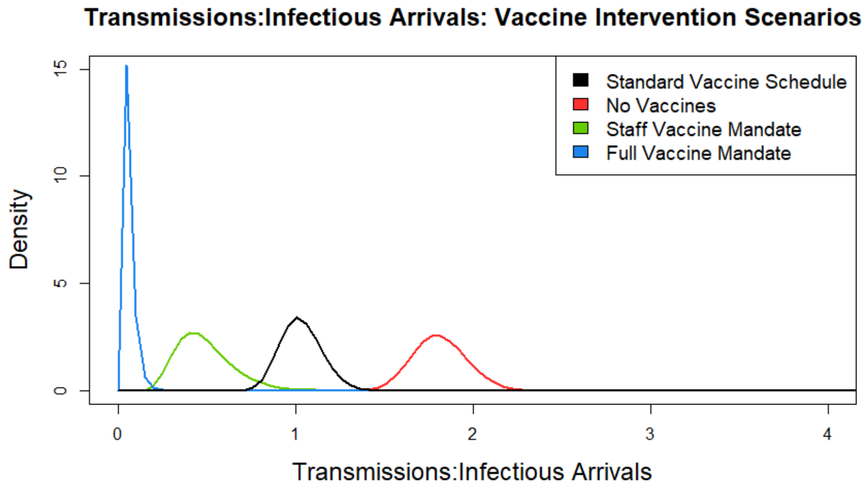

Figure 9.11: Distribution Plots showing the Change in the Ratio of Total Transmissions to Infectious Arrivals resulting from the Implementation of Vaccine-related Control Measures

Total Transmissions

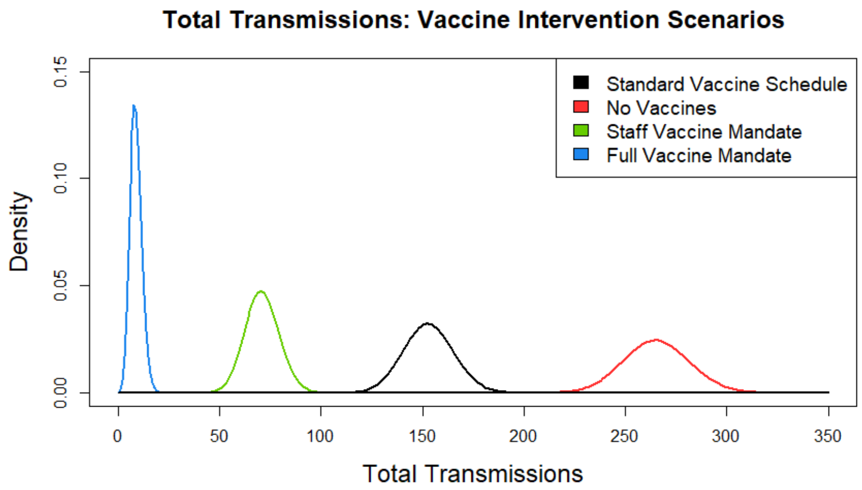

Figure 9.12: Distribution Plots showing the Change in the Total Transmissions resulting from the Implementation of Vaccine-related Control Measures

Average Shop Time

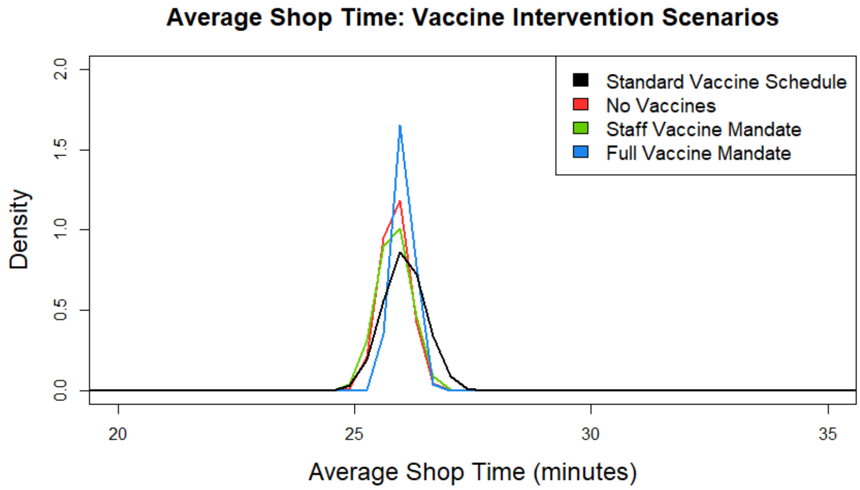

Figure 9.13: Distribution Plots showing the Change in the Average Shop Time resulting from the Implementation of Vaccine-related Control Measures

Average No. of Customers per day

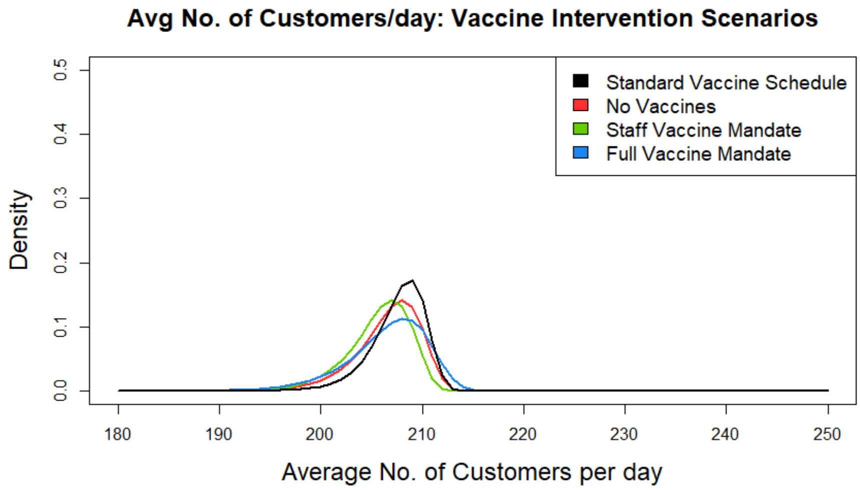

Figure 9.14: Distribution Plots showing the Change in the Average No. of Customers per day resulting from the Implementation of Vaccine-related Control Measures

Customers Lost:Customers Processed

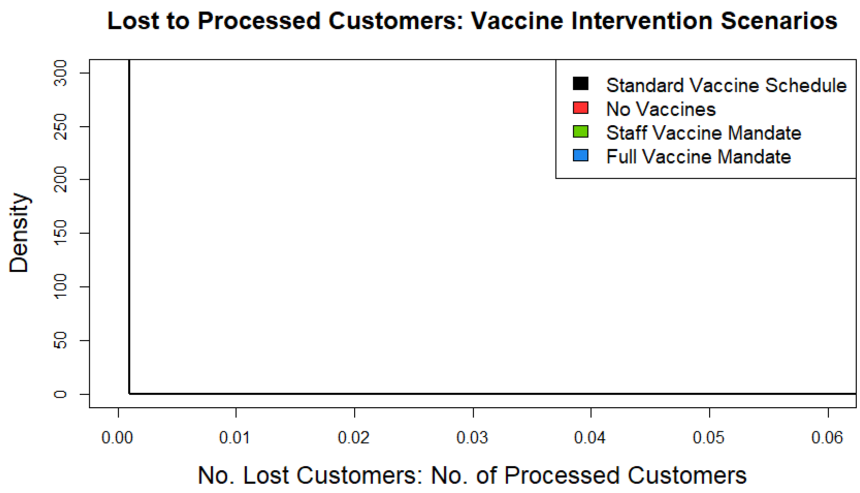

Figure 9.15: Distribution Plots showing the Change in Customers Lost:Customers Processed resulting from the Implementation of Vaccine-related Control Measures

Maximum Shop Queue Time

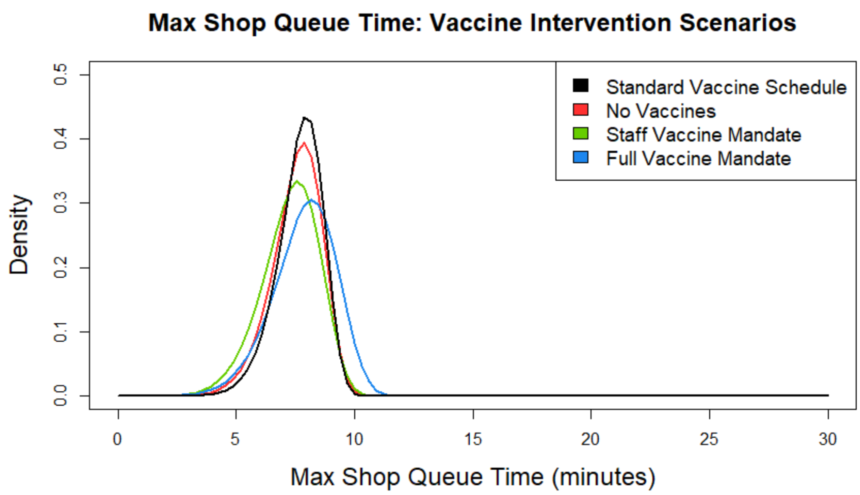

Figure 9.16: Distribution Plots showing the Change in the Maximum Till Queue Time resulting from the Implementation of Vaccine-related Control Measures

Maximum Till Queue Time

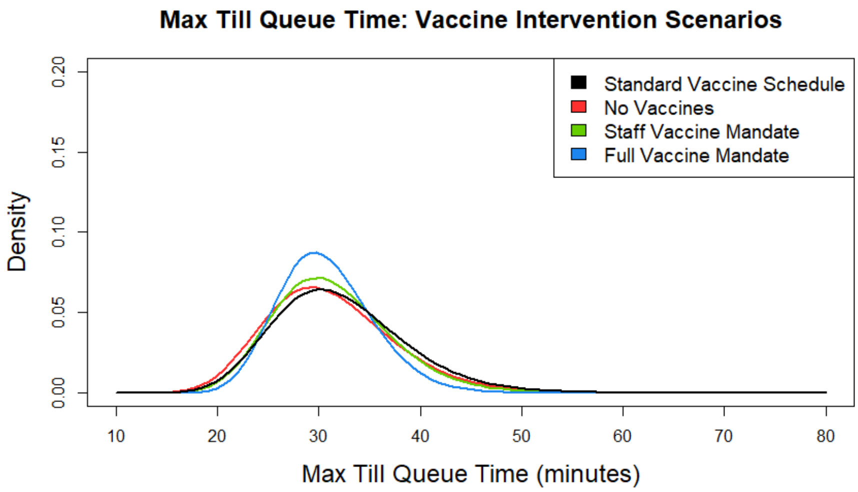

Figure 9.17: Distribution Plots showing the Change in the Maximum Till Queue Time resulting from the Implementation of Vaccine-related Control Measures

Social Distancing

Total Transmissions : Infectious Arrivals

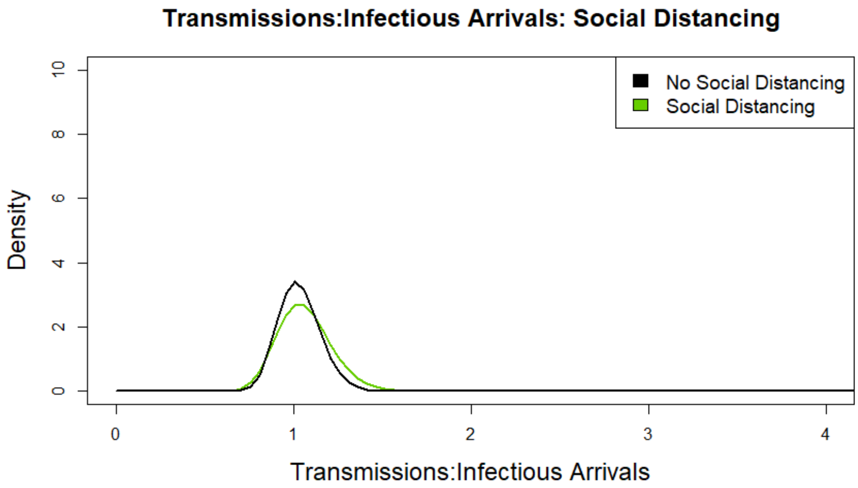

Figure 9.18: Distribution Plots showing the Change in Total Transmissions : Infectious Arrivals resulting from the Implementation of Social Distancing Control Measures

Total Transmissions

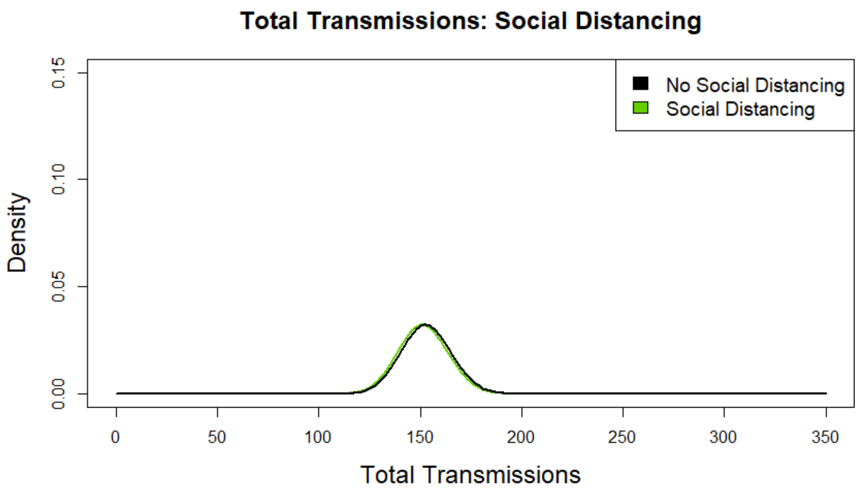

Figure 9.19: Distribution Plots showing the Change in Total Transmissions resulting from the Implementation of Social Distancing Control Measures

Average Shop Time

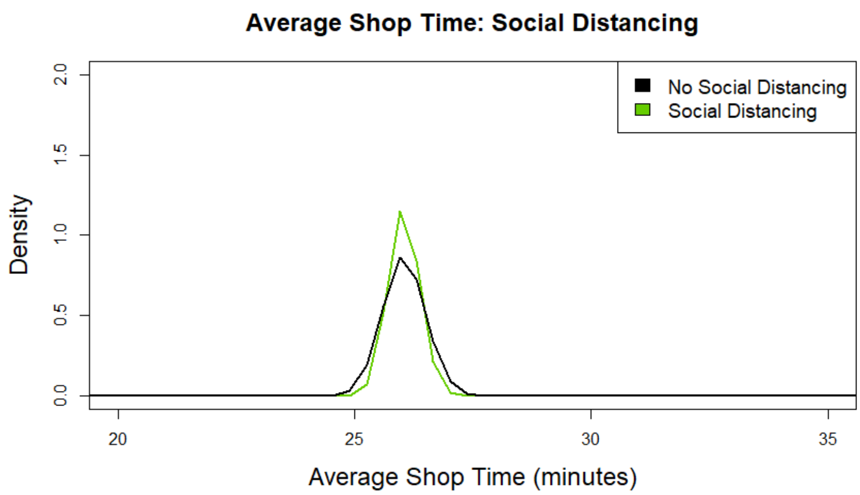

Figure 9.20: Distribution Plots showing the Change in Average Shop Time resulting from the Implementation of Social Distancing Control Measures

Average No. of Customers per day

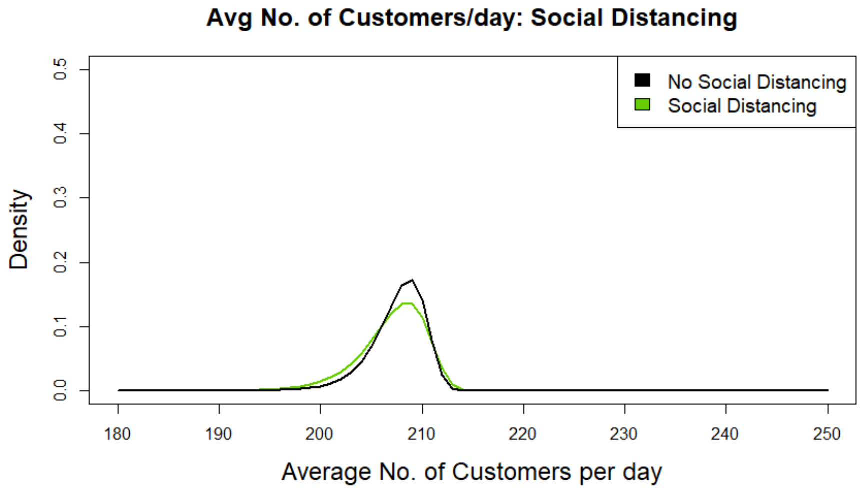

Figure 9.21: Distribution Plots showing the Change in Average No. of Customers per day resulting from the Implementation of Social Distancing Control Measures

Customers Lost:Customers Processed

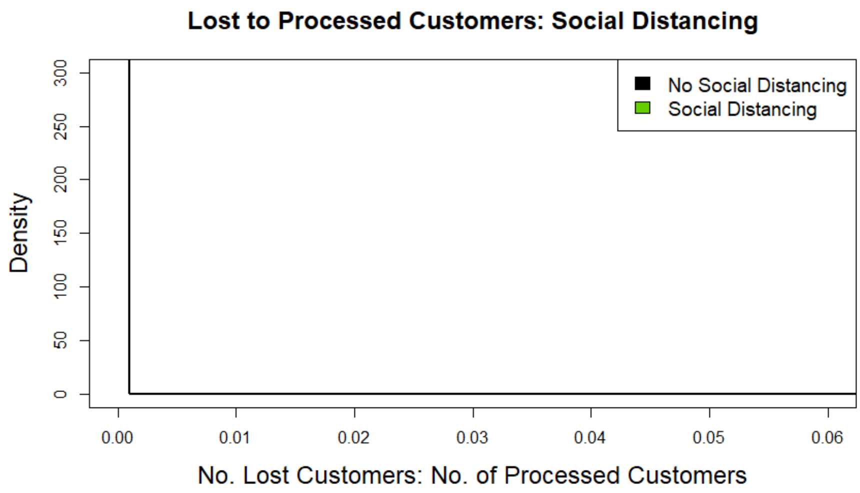

Figure 9.22: Distribution Plots showing the Change in Customers Lost:Customers Processed resulting from the Implementation of Social Distancing Control Measures

Maximum Shop Queue Time

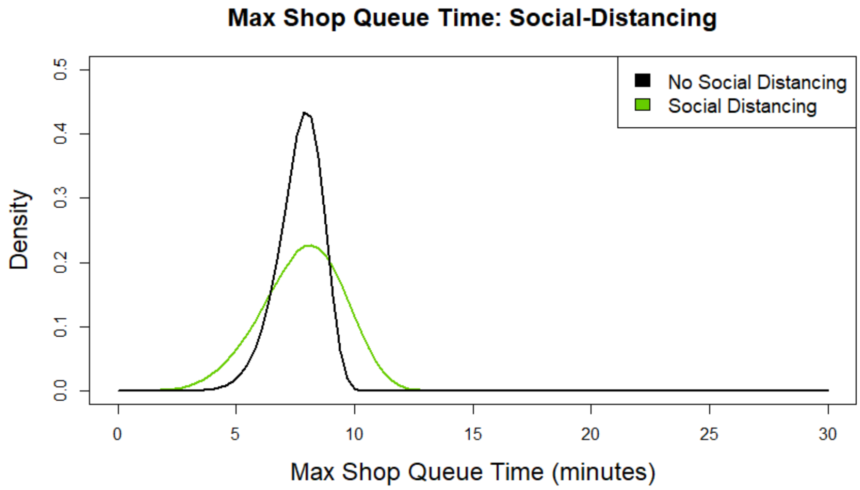

Figure 9.23: Distribution Plots showing the Change in Maximum Shop Queue Time resulting from the Implementation of Social Distancing Control Measures

Maximum Till Queue Time

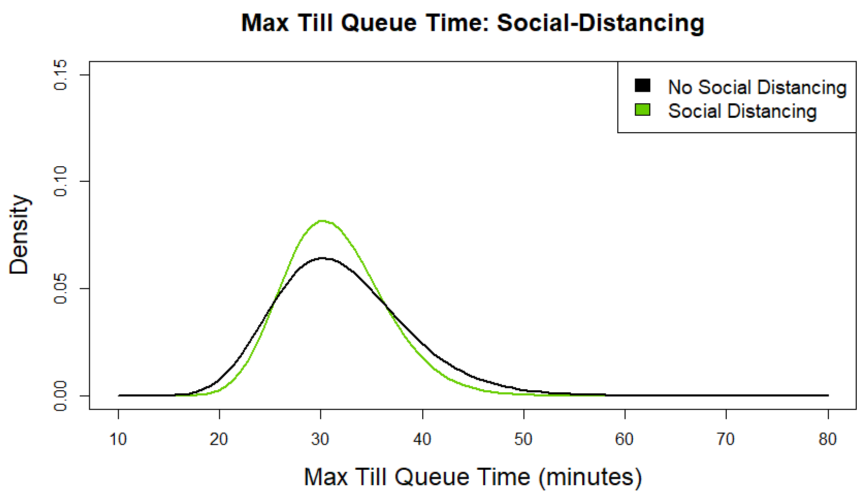

Figure 9.24: Distribution Plots showing the Change in Maximum Till Queue Time resulting from the Implementation of Social Distancing Control Measures

Capacity Limiting

Total Transmissions : Infectious Arrivals

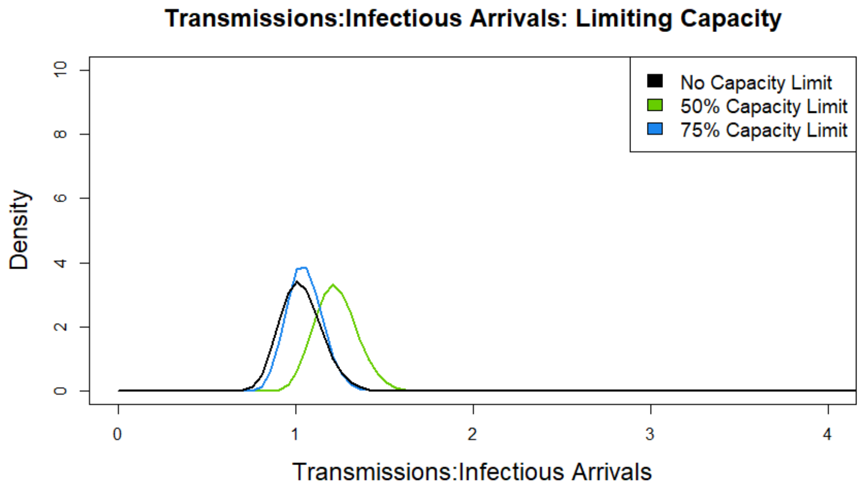

Figure 9.25: Distribution Plots showing the Change in Total Transmissions : Infectious Arrivals resulting from the Implementation of Capacity Limiting Control Measures

Total Transmissions

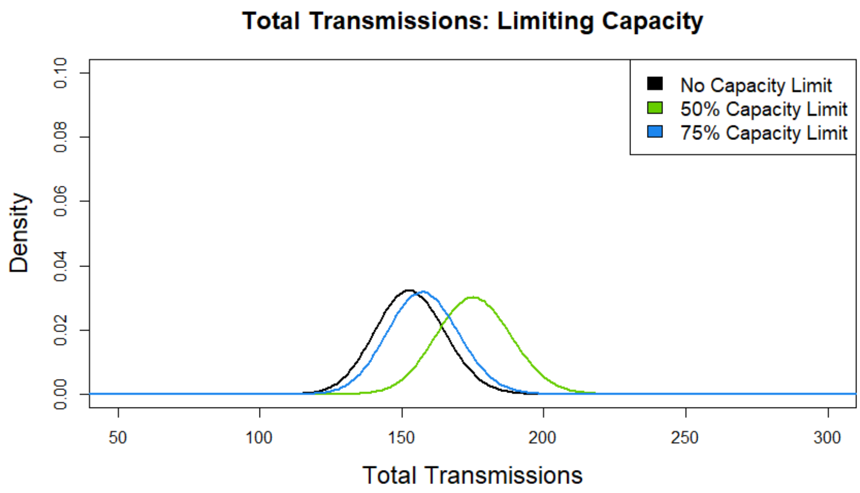

Figure 9.26: Distribution Plots showing the Change in Total Transmissions resulting from the Implementation of Capacity Limiting Control Measures

Average Shop Time

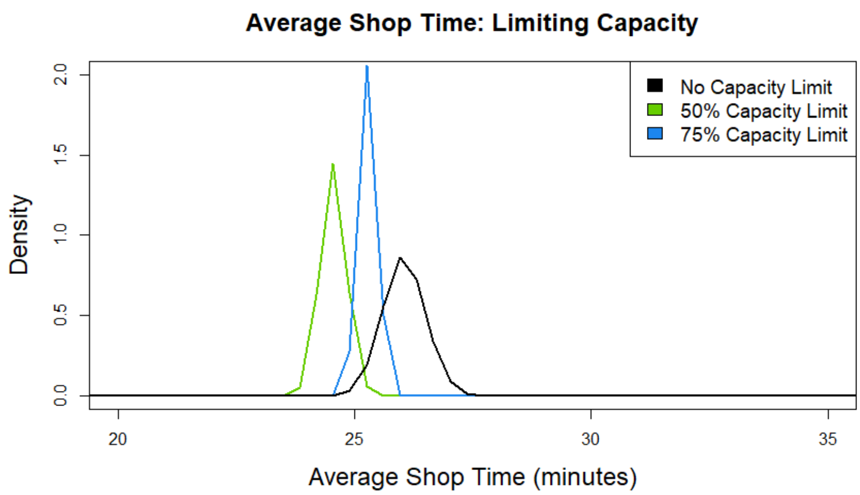

Figure 9.27: Distribution Plots showing the Change in Average Shop Time resulting from the Implementation of Capacity Limiting Control Measures

Average No. of Customers per day

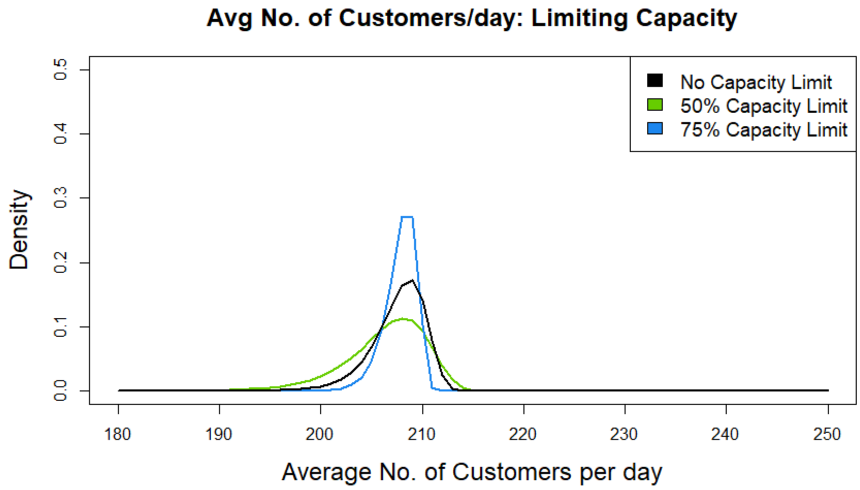

Figure 9.28: Distribution Plots showing the Change in Average No. of Customers per day resulting from the Implementation of Capacity Limiting Control Measures

Customers Lost:Customers Processed

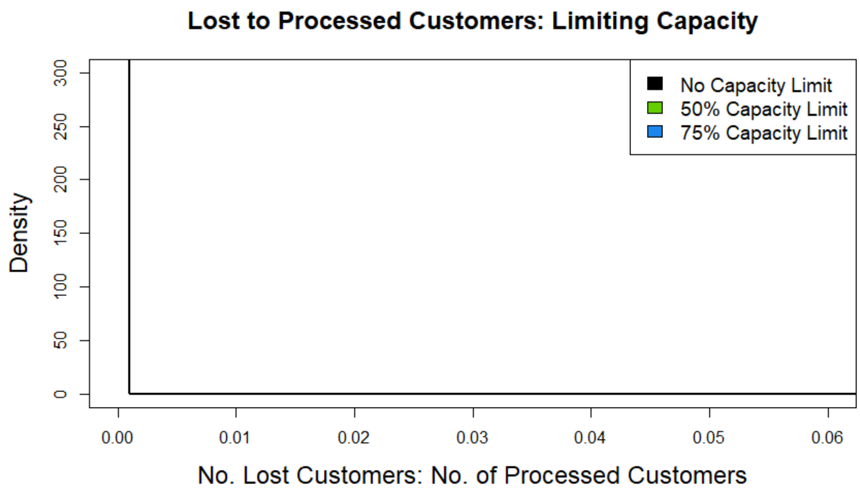

Figure 9.29: Distribution Plots showing the Change in Customers Lost:Customers Processed resulting from the Implementation of Capacity Limiting Control Measures

Maximum Shop Queue Time

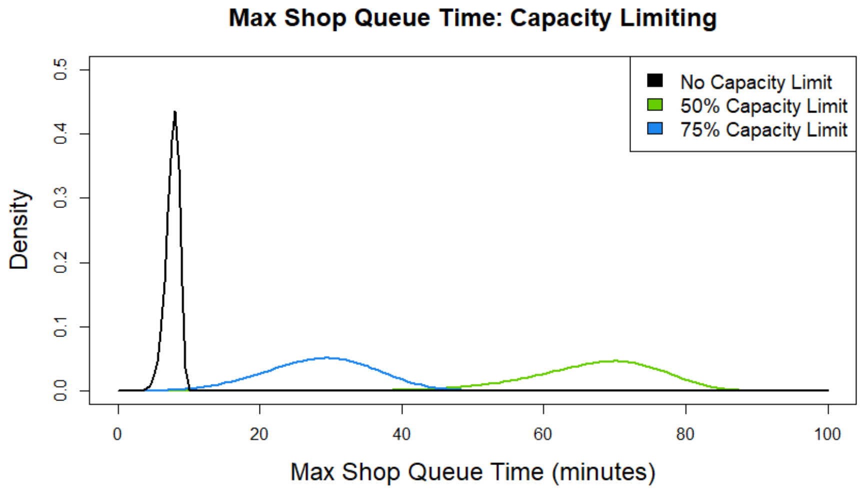

Figure 9.30: Distribution Plots showing the Change in Maximum Shop Queue Time resulting from the Implementation of Capacity Limiting Control Measures

Maximum Till Queue Time

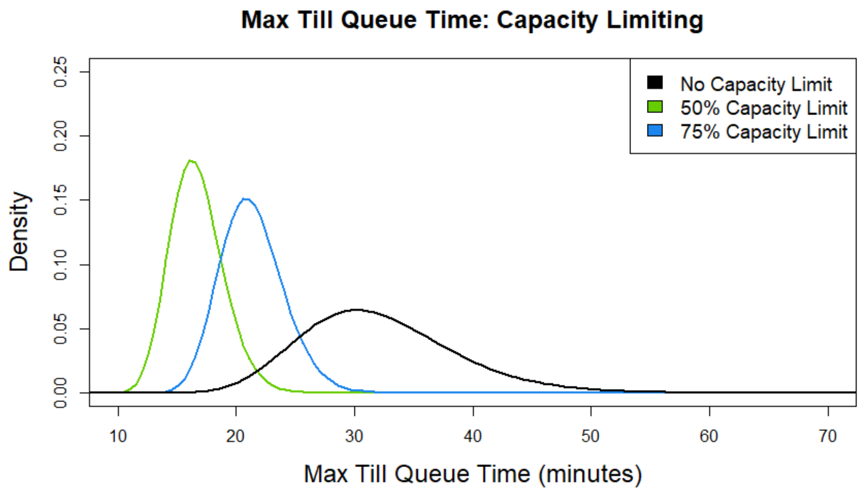

Figure 9.31: Distribution Plots showing the Change in Maximum Till Queue Time resulting from the Implementation of Capacity Limiting Control Measures

Staff COVID Testing

Total Transmissions : Infectious Arrivals

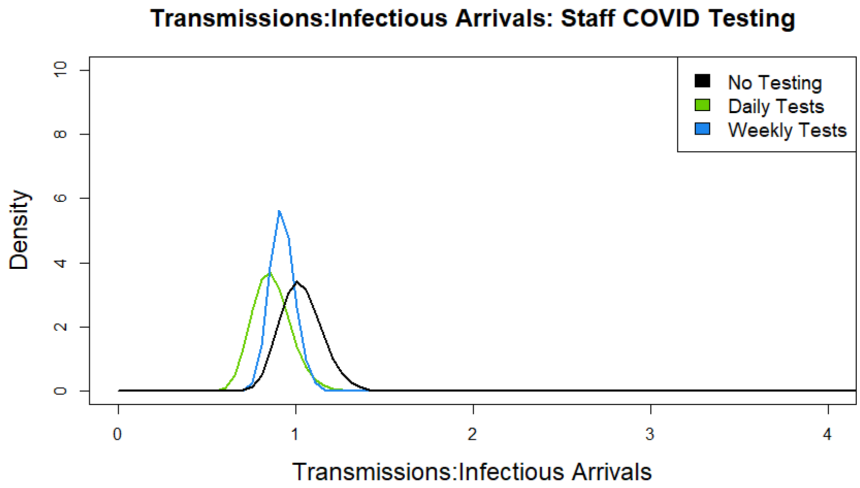

Figure 9.32: Distribution Plots showing the Change in Total Transmissions : Infectious Arrivals resulting from the Implementation of Staff COVID Testing Control Measures

Total Transmissions

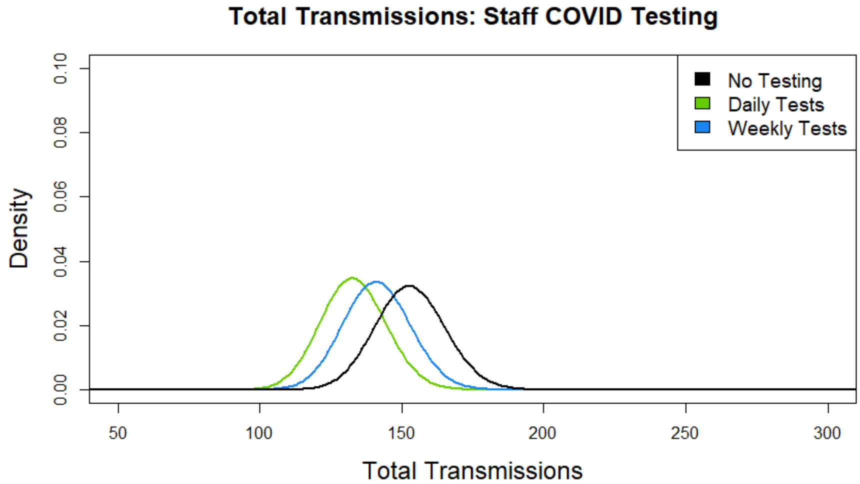

Figure 9.33: Distribution Plots showing the Change in Total Transmissions resulting from the Implementation of Staff COVID Testing Control Measures

Average Shop Time

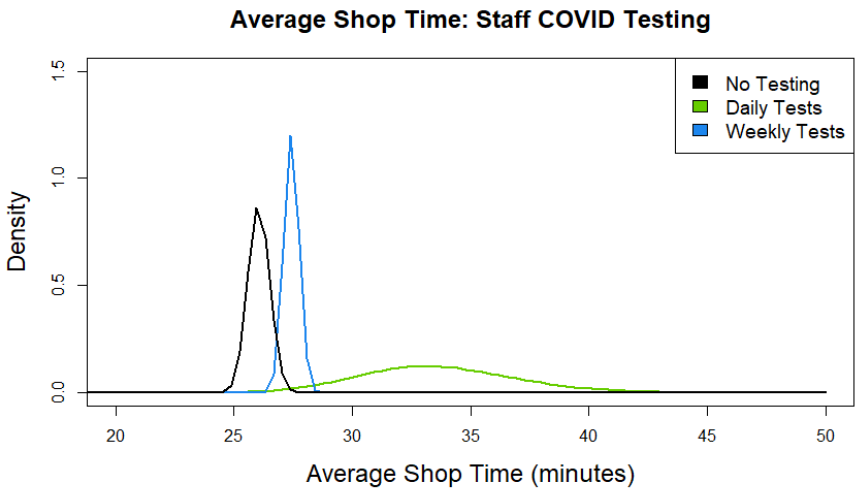

Figure 9.34: Distribution Plots showing the Change in Average Shop Time resulting from the Implementation of Staff COVID Testing Control Measures

Average No. of Customers per day

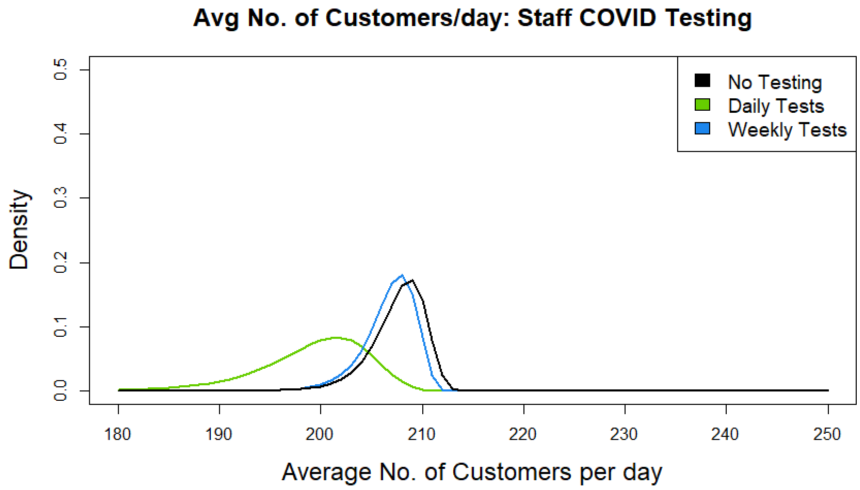

Figure 9.35: Distribution Plots showing the Change in Average No. of Customers per day resulting from the Implementation of Staff COVID Testing Control Measures

Customers Lost:Customers Processed

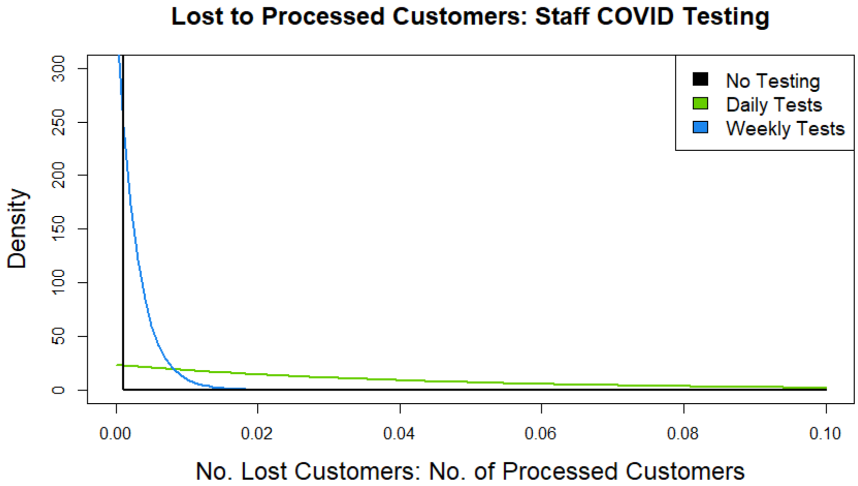

Figure 9.36: Distribution Plots showing the Change in Customers Lost:Customers Processed resulting from the Implementation of Staff COVID Testing Control Measures

Maximum Shop Queue Time

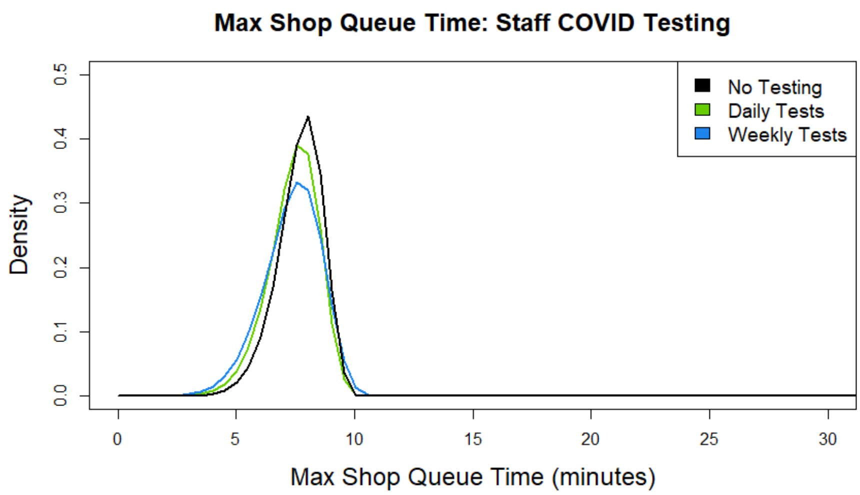

Figure 9.37: Distribution Plots showing the Change in Maximum Shop Queue Time resulting from the Implementation of Staff COVID Testing Control Measures

v

Maximum Till Queue Time

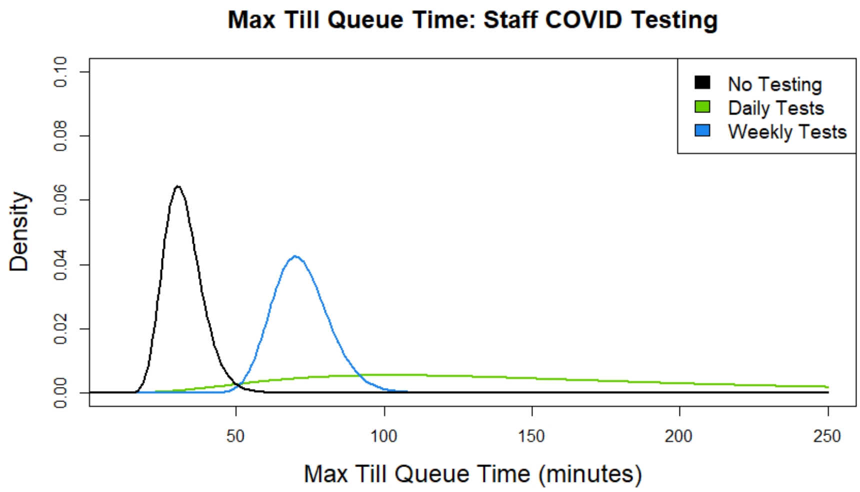

Figure 9.38: Distribution Plots showing the Change in Maximum Till Queue Time resulting from the Implementation of Staff COVID Testing Control Measures

Sanitization

Total Transmissions : Infectious Arrivals

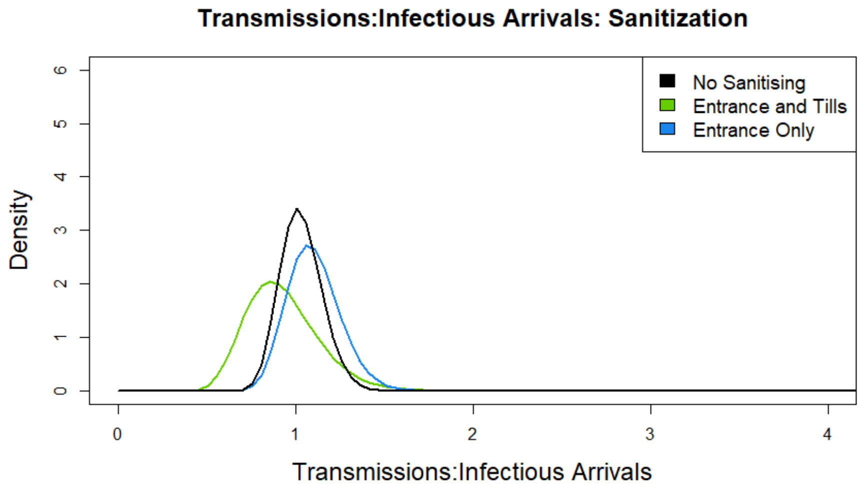

Figure 9.39: Distribution Plots showing the Change in Total Transmissions : Infectious Arrivals resulting from the Implementation of Sanitization Control Measures

Total Transmissions

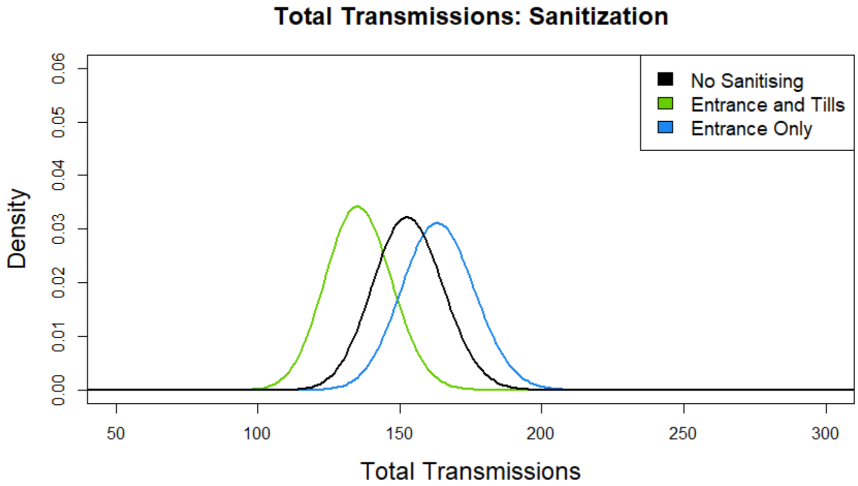

Figure 9.40: Distribution Plots showing the Change in Total Transmissions resulting from the Implementation of Sanitization Control Measures

Average Shop Time

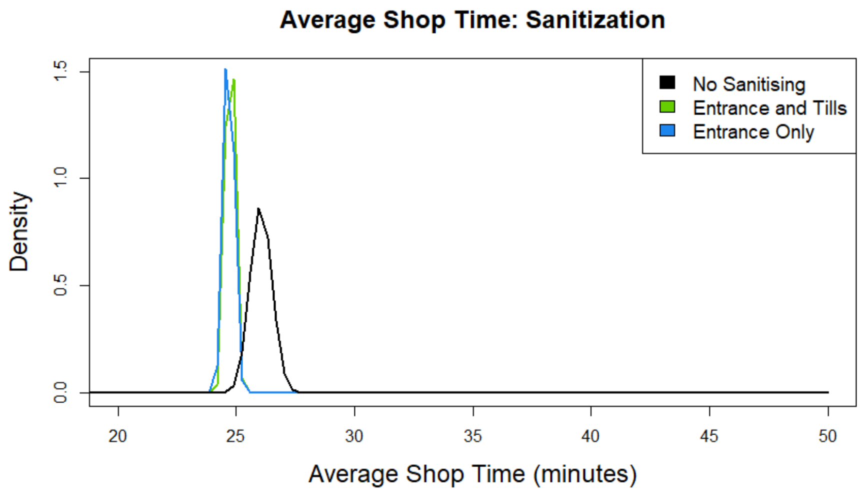

Figure 9.41: Distribution Plots showing the Change in Average Shop Time resulting from the Implementation of Sanitization Control Measures

Average No. of Customers per day

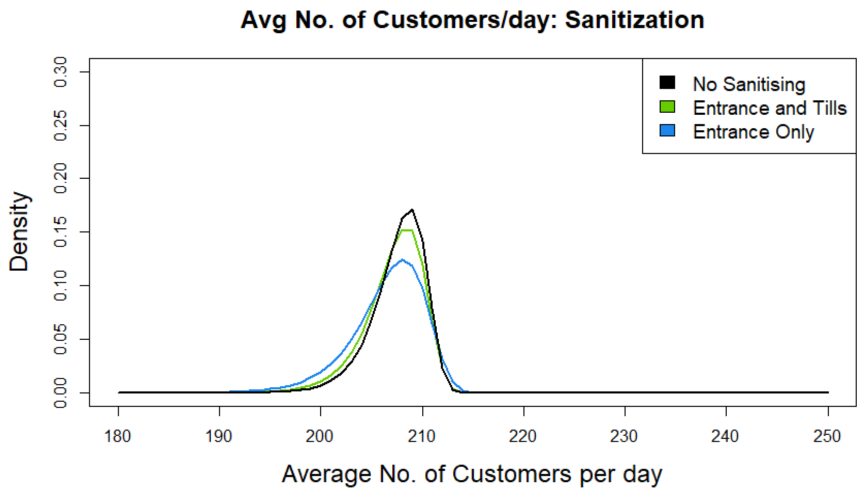

Figure 9.42: Distribution Plots showing the Change in Average No. of Customers per day resulting from the Implementation of Sanitization Control Measures

Customers Lost:Customers Processed

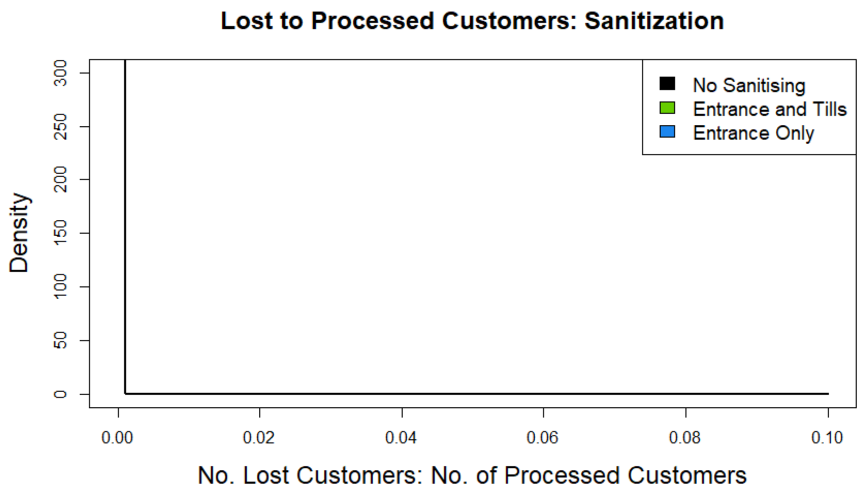

Figure 9.43: Distribution Plots showing the Change in Customers Lost:Customers Processed resulting from the Implementation of Sanitization Control Measures

Maximum Shop Queue Time

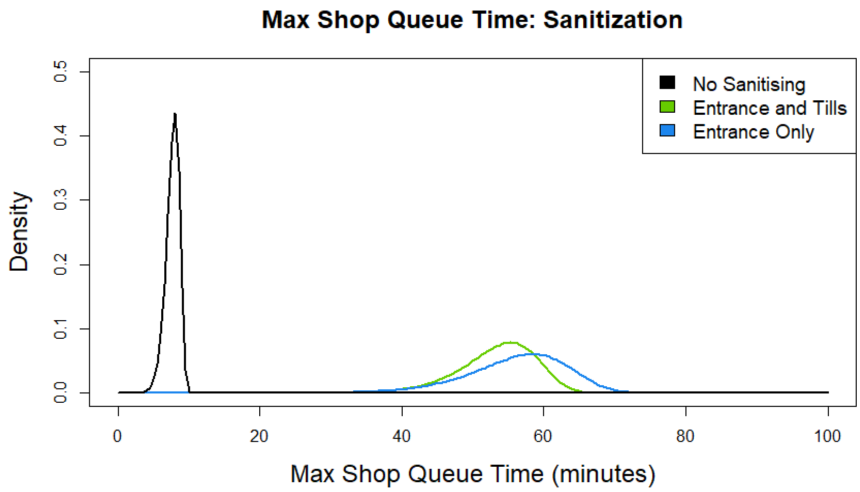

Figure 9.44: Distribution Plots showing the Change in Maximum Shop Queue Time resulting from the Implementation of Sanitization Control Measures

Maximum Till Queue Time

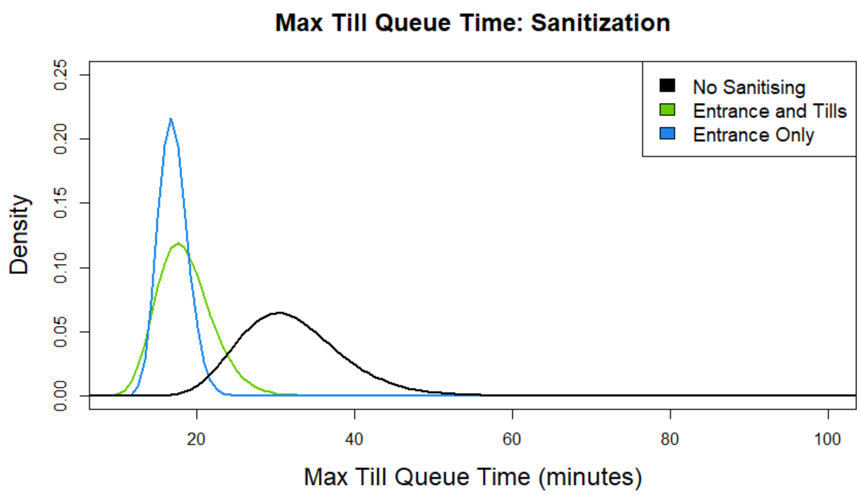

Figure 9.45: Distribution Plots showing the Change in Maximum Till Queue Time resulting from the Implementation of Sanitization Control Measures