Modelling the Impact of Non-Pharmaceutical Interventions on COVID-19 Exposure in Closed-Environments Using Agent-Based Modelling

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Abstract

Businesses can play a key role in reducing exposure to COVID-19 in closed environments. This is possible by assessing the impact of Non-Pharmaceutical Interventions (NPIs)—such as social distancing, wearing a mask and/or face shield, among others—in mitigating disease exposure.

This study aims to assess the impact of NPIs on COVID-19 exposure in closed environments. This is achieved by proposing an innovative COVID-19 exposure prediction framework. This framework also identifies the effect of other closed environment Operational Interventions (OIs), such as temperature measurement, on COVID-19 exposure.

The developed framework consists of three modules: Agent-Based Modelling (ABM) approach, Clustering Module (CM), and Decision Tree (DT) technique. The framework also integrates these modules considering the exposure time factor to identify the level of exposure to COVID-19 in closed environments.

A supermarket based in Jordan is considered a case study to test the applicability of the proposed framework in predicting the level of exposure and numbers.

The impact of Individual and combined NPIs application in closed environment facilities is assessed based on the exposure level along with other OIs such as opening time, measuring body temperature, and the number of people inside the supermarket.

Key results show that wearing Mask, Face Shield and leaving Social Distance guarantee no exposure to COVID-19 and increase the safety level to 61.9% in a closed environment such as supermarkets with a potential exposure rate up to 28.5% if otherwise.

Keywords

Agent-Based Modelling; Decision Tree; COVID-19 Exposure Prediction Framework; Non-Pharmaceutical Interventions; Closed Environment Facilities

1. Introduction

The emergence and outbreak of COVID-19 came as a test of the existing health policies. It defiled many used policies, resulting in the need for other approaches and plans, such as Non-Pharmaceutical Interventions (NPIs) in the global health emergency[1]. According to WHO, this need is because COVID-19 is a novel virus with unanticipated strains [2]. In most countries affected by COVID-19, the advocacy of the government healthcare bodies on NPIs for virus exposure came as a new health policy to help control the transmission [3].

The NPIs policy on COVID-19 exposure advises the public to stop the spread [4]. It advocates policies such as stay-at-home measures, hand-washing guidelines, population-wide testing strategies and limits on outdoor and in-doors gatherings, among others [5]. NPI policies may also offer a reliable alternative to pharmaceutical interventions, especially when supply chain challenges are in effect [6]–[8]. Although innovative vaccine supply chain networks are introduced [6]–[8], implementation of such models comes with its challenges, restoring to lower cost NPIs in the meantime. In countries like the United Kingdom, the NPIs policy was declared to minimise the transmission and spread of the virus [9]. In New York City, NPIs for COVID-19 were introduced to prevent and control virus transmission, reducing infections by 72% and decreasing COVID-19 cases by 76% by the end of 2020 [10].

Public adhesion to COVID-19 policies still needs to be improved, despite the ongoing effort of local governments to implement NPIs. This happens mainly in closed environment facilities such as supermarkets, cinemas, restaurants, universities, and gyms. Such facilities are limited in space with a high density of virus particles, causing a higher transmission rate [11]. Furthermore, closed environments are prone to poor open-air ventilation, which keeps the virus strands active for longer [12], [13].

Many investigators studied the impact of applying NPIs on COVID-19 exposure in closed environments. For example, the COVID T.I. team (2020) developed a deterministic SEIR (Susceptible, Exposed, Infectious and Recovered) compartmental framework to model possible trajectories of COVID-19 infections, considering the effect of non-social distancing and face masks [14]. Hoertel et al. (2020) developed an agent-based model to identify the potential impact of post-lockdown measures, including physical distancing, mask-wearing, and shielding individuals who are the most vulnerable to severe COVID-19 infection [15]. Novakovic and Marshall (2022) used a Change Point detection in an Agent-Based Model (CP-ABM) approach to capture the disease dynamics of COVID-19 [16]. Masks and regional and national lockdowns were simulated to identify their effectiveness in preventing an even more extreme outbreak. Iyaniwura et al. (2021) developed an SEIR model to assess the impact of adherence to NPIs, such as hand washing, physical distancing, wearing face masks, and avoiding large gatherings to reduce their susceptibility, transmissibility and infectiousness [17]. In a similar work, Ejigu et al. (2021) proposed a modified SEIR model to predict the number of COVID-19 cases under the implementation of NPIs at different adherence levels, including combined implementation of three public health measures: wearing of face masks, social distancing and hygiene [18].

Moreover, Operational Interventions (OIs) were investigated by Cuevas (2020), who proposed an agent-based model to evaluate COVID-19 transmission risks within facilities and to simulate the spatiotemporal transmission process [19]. Spatial patterns and infection conditions for reducing the transmission risks of COVID-19 within the facilities were simulated. Similarly, Ma et al. (2022) used spatial autocorrelation analysis, the Ordinary Least Squares (OLS) model, the Multiscale Geographically Weighted Regression (MGWR) model, and dominance analysis to explore the spatial patterns and influencing factors such as supermarket density, elderly population density, hotel density, business land proportion, and park density to investigate COVID-19 exposure [20]. Castro and Ford (2021) presented a new geospatial agent-based simulation model to explore the transmission of COVID-19 among students living in university accommodations and to simulate the efficiency of restrictions such as facemasks, lockdown, and self-isolation on the infection [21]. Alzu'bi et al. (2021) used agent-based modelling in a real wedding event that occurred at the beginning of the spread of the pandemic in Jordan [22]. NPIs, including ages, occupations, and population movements at the community level following social gatherings, were investigated. A combination of NPIs and OIs scenarios was investigated by Ying and O'Clery (2021), who developed an agent-based model of customer movement in a supermarket to estimate exposure time and the number of infections [23]. The applied scenarios include implementing a face mask policy, restricting the number of customers in the store, reducing the rate at which customers enter the store, and a one-way aisle store layout.

Although few works, including Castro and Ford (2021)[21] and Hoertel et al. (2020)[15], investigated the impact of NPIs and other OIs strategies to reduce COVID-19 exposure in closed environment facilities, the impact of applying different NPI combinations, including mask-wearing, face shield, and social distance (considering exposure time), on COVID-19 exposure, has not been considered yet, especially in closed environments. Hence, the main aim of this work is to estimate different levels and rates of COVID-19 exposure in closed environments following NPI measures.

The main contributions of this study can be summarised as follows:

(1) Identifying the impact of applying NPIs (combined/individual) and other OIs on COVID-19 exposure.
(2) Introducing an innovative framework to predict exposure to COVID-19 in closed environment facilities.
(3) Proposing a new methodology consists of an Agent-Based Modelling (ABM) approach integrated with the Decision Tree (DT) technique to simulate people's movement and identify the impact (individual/combined) of applying NPIs on COVID-19 exposure along with a new Clustering Module (CM) that is introduced to model the social distancing intervention.

The benefits of this framework are that it will assist businesses, employers and health and safety departments at closed environment facilities to predict people's exposure to COVID-19. This prediction includes analysing the impact of NPIs and deciding whether other OIs are required to control the exposure level.

The rest of the paper is organised as follows: Section 2 presents the proposed exposure prediction framework. Section 3 demonstrates a real-life case study, followed by a scenario analysis to justify the behaviour of the proposed framework. The last section will address the main findings of this study and recommendations for future work. A web link to the developed model video is also included.

2. The Proposed COVID-19 Exposure Prediction Framework

This section presents the proposed framework to predict different levels of exposure to COVID-19, including Safe, Potentially Exposed and Exposed cases in closed environments. These levels of exposure are estimated based on people's adherence to different combinations of NPIs applied in closed environment facilities. See Figure 1 for the proposed COVID-19 exposure prediction framework.

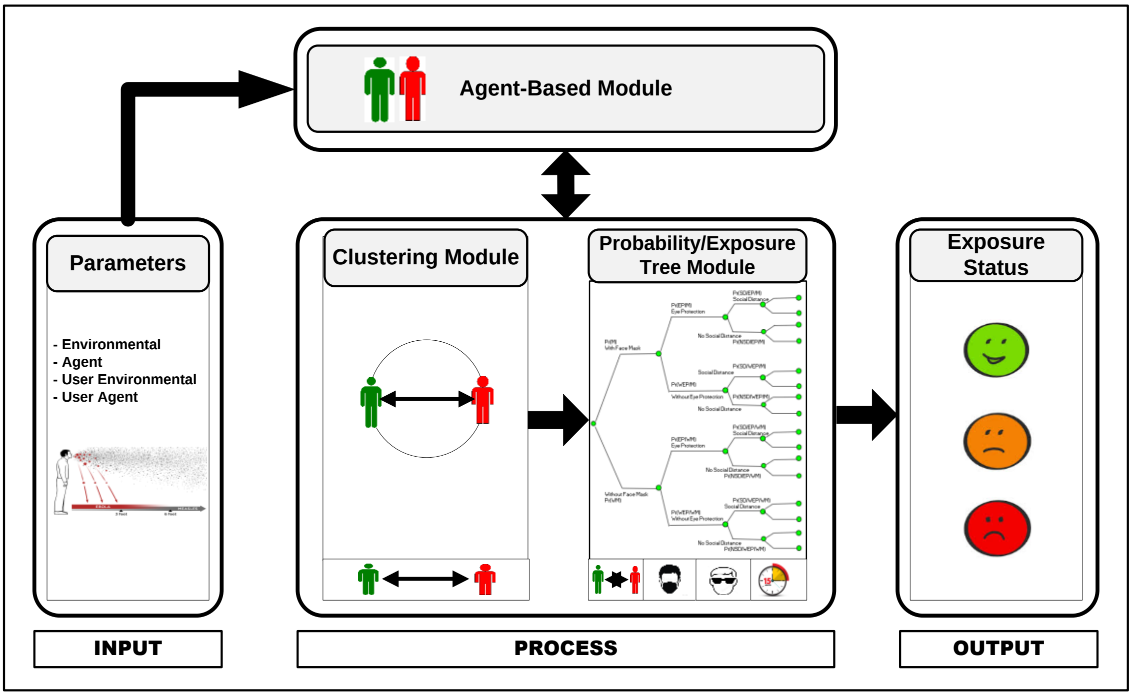


Figure 1: The proposed COVID-19 exposure prediction framework.

In this framework, three main components are proposed and integrated. The first component provides input parameters such as environmental, user environment and user agent. The second component consists of three processing modules: ABM, CM and DT. These modules are introduced and integrated to predict different levels of exposure. The last output component involves a set of Safe/Exposure/Possible Exposure rates.

The first ABM module was developed to generate and mimic the movement of a population of people, including their health status (infected/safe), mask/not, face shield/not, and social distance/not attributes. The second CM module is used to model the social distancing intervention by grouping people in different clusters, and each cluster radius equals 2 meters (6 feet). Each cluster should involve at least one infected person regardless of how many safe people are around. The third DT module estimates the chance of virus exposure in terms of rates/probabilities depending on the customer's level of adherence to different combinations of NPIs.

These modules will be discussed in more detail as follows:

2.1 The Agent-Based Module

ABM is a computational approach to modelling systems comprised of autonomous (self-control) and heterogeneous agents with different attributes interacting within an environment [24]. Through this approach, agents, for example, people, can interact with and influence each other, learn from their experiences, adapt their behaviours to suit their environment better and achieve the best behavioural decision-making practice. This advantage is the reason for selecting such an approach, which is used to model and predict COVID-19 exposure among people interacting with and influencing each other inside a closed environment facility. In addition, this approach was selected amongst other modelling approaches due to its capability of mimicking/simulating the movement of agent/people's interaction inside closed environment facilities.

This module consists of two agents: temporary entities represented by the population of people (customers) and permeant entities (resources) used to serve people in closed environment facilities. This module mainly generates a population of people and decides/mimics their movement trajectories and other attributes. These attributes include health status (infected/not), mask/not, face shield/not, and social distance/not.

The inputs are the environmental parameters, such as the dimensions of the closed facility space, the number of sections, and the facility's entrance and checkout location. The agent parameters include the agent's type, speed, temperature, and initial x and y locations. The user environmental and agent parameters are the user's inputs before or during the model's run. Figure 2 shows the input and output of the model.

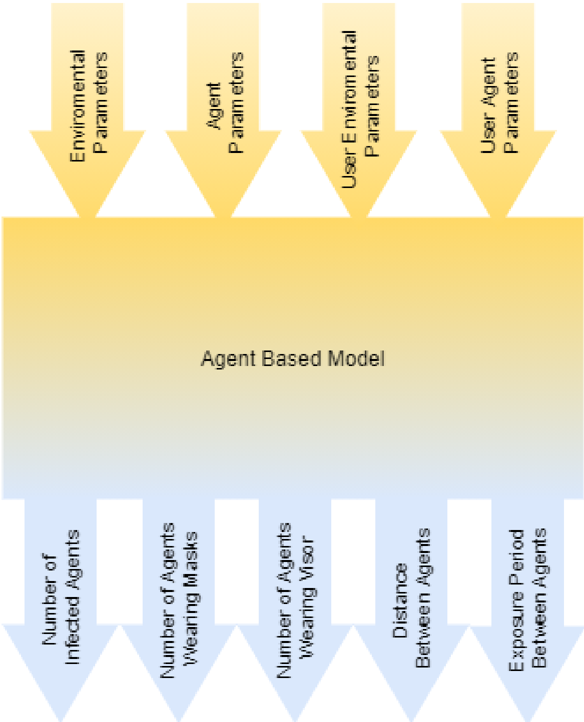


Figure 2: Agent-Based Module Inputs and Outputs.

The model outputs are the total number of infected agents, agents wearing a mask, agents wearing face shields, the distance between neighbouring agents and the exposure period between those agents. These outputs will be considered inputs to the core modules of the second (clustering) and third (decision tree). Once this module generates a population of people, the CM is applied. This agent-based module also mimics the layout of the closed environment facility, exposure time between agents, etc.

2.2 Clustering Module

This module is developed to mimic the social distance intervention, in which clusters are applied when infected people (at least one) are identified, and other safe people are around within 2 meters of social distance or less. Each cluster should involve at least one infected person covering as many as possible people with potential risk status and/or safe ones. Agents adhere to 2 meters of social distance or are classified as safe, and the exposure time will not be an issue. Any violation of social distance with different adherence levels to NPIs, including Mask and/or Face Shield, leads to exposure or possible exposure statuses. See Figure 3 for the proposed CM.

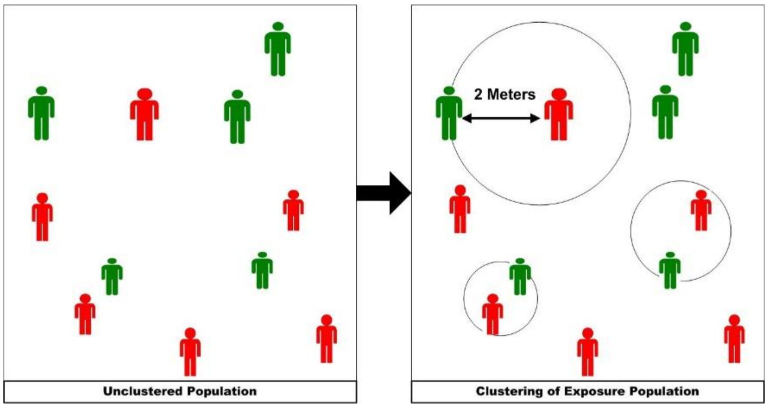


Figure 3: The proposed Clustering Module.

In Figure 3, nested clusters could be created depending on the number of infected and safe people within 2 meters (6 feet). These clusters dynamically change in response to peoples' movements and changes in infected peoples' places and positions. The number of clusters increases depending on the intensity of the infected people and the number of people who violate the social distance intervention.

It is worth mentioning that in previous studies related to COVID-19 transmission, different equations for transmission rules based on the crowd flow modelling were proposed to estimate the chance of infecting the uninfected people [25]. Different exposure mechanisms were used with microscopic crowd models to estimate occupant exposure in confined spaces [26]. Two different uniform distributions (within pre-specified limits) to randomly set the decision of infection and the contact (or mobility) rate were used [19]. The infection risk using accumulated functions based on the exposure time and pre-defined exposure rates was investigated, considering the effectiveness of exposure time per agent [27]. *However, none of these studies used the clustering concept to estimate the exposure rate of people who violate the social distancing intervention in closed environments; hence, this module was proposed*.

2.3 Decision/Exposure Tree Module

This module uses the DT technique to identify the impact of NPIs on COVID-19 exposure in closed environments. The calculated conditional probability value (rate) for each tree branch of the entire decision tree represents the impact of customers' adherence towards different NPIs. For example, a high exposure chance occurs when a safe person is exposed to an infected one without adhering to any NPIs, including social distancing.

The decision tree involves a series of independent events (NPIs in this case), showing the chance of that event occurring after the parent event, for example, the chance of a person not wearing a mask, given that their status is infected. The chance that a series of events leading to a node will occur is equal to the product of that node and its parents' probabilities. See Figure 4 for the decision/exposure tree diagram.

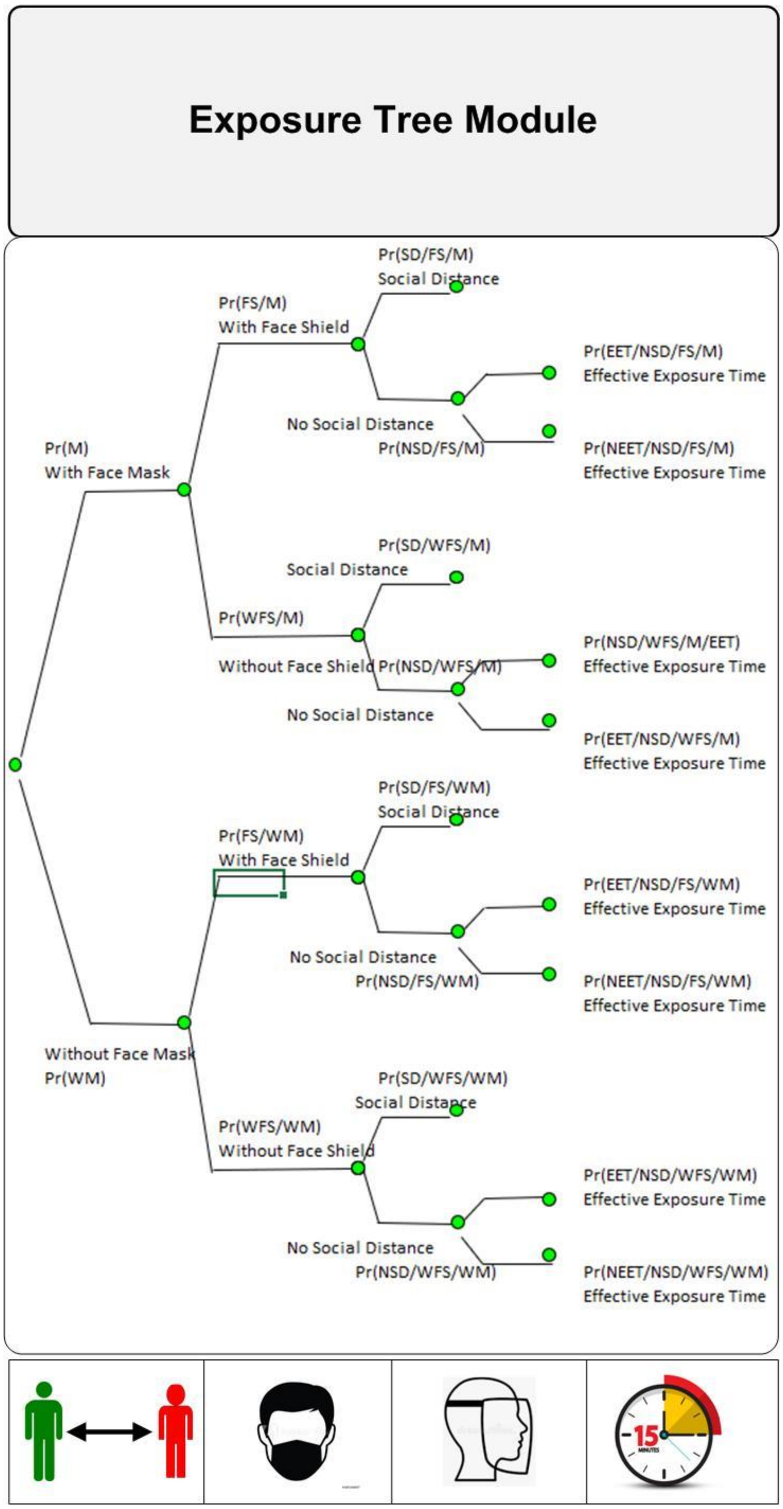


Figure 4: Decision tree diagram-based NPIs.

Figure 4 shows the chances of infected and safe people applying different combinations of NPIs in a decision tree diagram. Different levels of exposure are identified and expressed in conditional probability forms, as shown in Table 1.

Table 1 Different exposure risk levels

Risk Level	Exposure Risk Probability/ Non-Pharmaceutical Interventions Impact	Academic Reference/Source
Safe	Pr(M ∩ FS ∩ SD)	[2], [28]–[31].
Safe	Pr(M ∩ WFS ∩ SD)	[2], [28]–[31].
Safe	Pr(WM ∩ FS ∩ SD)	[2], [28], [32].
Safe	Pr(WM ∩ WFS ∩ SD)	[33], [34].
Probably Exposed	Pr(M ∩ WFS ∩ NSD ∩ NEET)	[29], [35]–[38].
Probably Exposed	Pr(M ∩ FS ∩ NSD ∩ NEET)	[29], [34]–[38].
Probably Exposed	Pr(WM ∩ WFS ∩ NSD ∩ NEET)	[35].
Probably Exposed	Pr(WM ∩ FS ∩ NSD ∩ NEET)	[35].
Probably Exposed	Pr(M ∩ FS ∩ NSD ∩ EET)	[29], [34]–[38].
Exposed	Pr(WM ∩ FS ∩ NSD ∩ EET)	[35], [38].
Exposed	Pr(M ∩ WFS ∩ NSD ∩ EET)	[35].
Exposed	Pr(WM ∩ WFS ∩ NSD ∩ EET)	[28], [29], [31], [35].

M: Mask; FS: Face Shield; SD: Social Distance (within 6 feet); EET: Enough Exposure Time (greater than 15 min)
WM: Without Mask; WFS: Without Face Shield; NSD: Non-Social Distance (less than 6 feet); NEET: Not Enough Exposure Time (less than or equal to 15 min).

In Table 1, three levels of exposure to COVID-19, including Safe, Probably Exposed, and Exposed levels, are presented. The highest chances of exposure to COVID-19 violate social distance and at least one NPI with enough exposure time to the infected person. Adherence to social distance could prevent COVID-19 exposure and define the level as safe. In contrast, different levels of adherence to masks and/or Face Shields, social distance violation, and mainly, enough exposure time is applied could reduce the chance of Safety to Probably Exposed.

2.4 Modelling Assumptions

a) Exposure occurs in-store main level (only one floor) with a multiple-ways aisle layout.
b) Social distance is considered at 2 meters (6 feet) at least.
c) Exposure occurs when social distance is violated with effective exposure time applied.
d) Probably Exposed case occurs when social distance is violated, and possibly one of the NPIs is violated.
e) Safety is a guarantee when social distance adheres.
f) Five cases, including infected (arriving at the store) and non-infected (arriving at the store), safe (leaving the store), probably exposed (leaving the store), and exposed (leaving the store) agents, have been considered.
g) Individual customers (not bulks) arrive at the store.
h) Three NPIs are considered: Mask, Face Shield and Social Distancing.
i) Exposure time between 5-20 minutes is applied to each cluster of people. The effective/enough exposure time is greater than 15 minutes.
j) Exposure time is cumulative (enough exposure time in one cluster is equivalent to accumulating it in different clusters at different times.

k) Conditional probability formulation is applied to model conditional safety procedures.

l) The probability of Safe, Probably Exposed, and Exposed giving safety procedures (individually and/or combined) is calculated (for example) by the following formula:

Pr(A∩B) = P(B/A) . P(A)

Pr(Exposure) = Pr(No Mask ∩ No Face Shield ∩ No Social Distance)

Pr(Exposure) = Pr(No Social Distance/ No Face Shield/ No Mask) x Pr(No Face Shield/ No Mask) x Pr(No Mask)

2.5 The Proposed COVID-19 Exposure Prediction Algorithm

The proposed COVID-19 exposure prediction framework mechanism is summarised as follows:

Step 1- Identify infected people (set by the ABM as the agent's attribute),
Step 2- Set inspection cluster(s) of Radius=2 meters around the infected people(s),
Step 3- Calculate the exposure time per cluster (at least 15 minutes is an effective exposure time),
Step 4- Implement the exposure tree on each cluster and estimate Safe, Probably Exposed and Exposed,
Step 4- Update statistics related to the number and status of Safe, Probably Exposed (can be exposed), and Exposed (already exposed and will not be at risk of exposure again),
Step 5- Exclude Exposed people from any further statistics investigation and update their numbers accordingly,
Step 6- Apply Steps 1-5 for different people movement scenarios to update the probability tree(s) until all people have left the closed environment facility or the simulation termination condition is reached,
Step 7- Communicate all the tree diagrams together for a final update, including their conditional branches and update the probability of each branch accordingly,
Step 8- Calculate the conditional probability value for each tree branch,
Step 9- End.

3. Case Study

3.1 Description

Sultan Stores, one of the busiest supermarkets located in Amman, Jordan, was considered as a platform to test the efficiency and applicability of the proposed COVID-19 exposure prediction framework. This store consists of four main sections: Veggies, Groceries, Bakery and Clothing. Each section has three aisles separated by four shelves. Every shelf has a unique set of items the customer might want to select. The main customer entrance leads into the central aisle between sections starting with the Veggies section on the right and the Clothes section on the left. On the other deep side of the store, the Bakery section is on the left, and the Groceries section is on the right. Each section has one worker allocated to guide customers. In the checkout area, three cashiers were allocated to receive payments. This area is located near the main store entrance. The store's opening hours are from 6:00 AM until 10:00 PM, seven days a week. On average, customers are expected to arrive daily at the store every 2 minutes, with a maximum of 1000 customers. See Table 2 for the model parameters and their sources.

Table 2: Model parameters

Parameter	Value	Source
Average Number of customers/ days	1000 customer	Sultan stores/ business development department
Opening Times	6:00 am-10:00 pm	Sultan stores/ business development department
Interarrival time (Average)	2 min	Measured by the researcher
Probability of infected people (Average)	20% or less	National Centre for Security and Crisis Management – Jordan
Probability of customers wearing Mask (Average)	Up to 90%	By Inspection
Probability of customers wearing Face Shield (Average)	Up to 30%	By Inspection
Minimum Social Distance	2 meters (6 feet)	[28]
Effective Exposure Time	Minimum 15 min	[35].

Table 2 shows that secondary data, including the infection probability, were collected from the National Centre for Security and Crisis Management – Jordan records. The researcher measured the interarrival time of customers by averaging up the interarrival time readings collected by a sensor set at the shop entrance. The inspection was used to identify the number of people wearing a mask and/or shields with respect to the total number of customers. Academic references were used to justify some parameters, including minimum social distance and effective exposure time.

It is worth mentioning that a customer's path within the store is based on the shopping list of that customer. It was challenging to obtain individual information about each customer's shopping list. However, a list of shopping items per customer is randomly generated with a random number and different items.

3.2 Model Development

NetLogo software is a multi-agent programmable modelling environment for simulating natural and social phenomena. It is particularly well suited for modelling complex systems developing over time. This software was used to simulate people's movement in the supermarket, each with different attributes and behaviour. The model link on YouTube is https://youtu.be/wv12lgEzKB0.

In this model, the agent enters the store space, starts looking (searching) for the top items of the shopping list, and adjusts its direction towards it until all items (based on availability) have been collected. The customer will then head to the checkout area to pay and leave the supermarket. The agent's attribute/property value does not change during the agent's lifetime. It affects the neighbouring agents at the meeting time throughout the supermarket sections. Those attributes/properties are presented with agents' colours, as shown in Figure 5. In this figure, the blue represents an agent wearing a mask and face shield. The Yellow colour presents an agent wearing a mask and not wearing a face shield. The Orange colour presents an infected agent wearing a mask and face shield. Red presents an infected agent without a mask and a face shield. See Figure 5 for the agents' properties represented in colours. The worker agent is presented with the worker costume and does not impact customer agents.

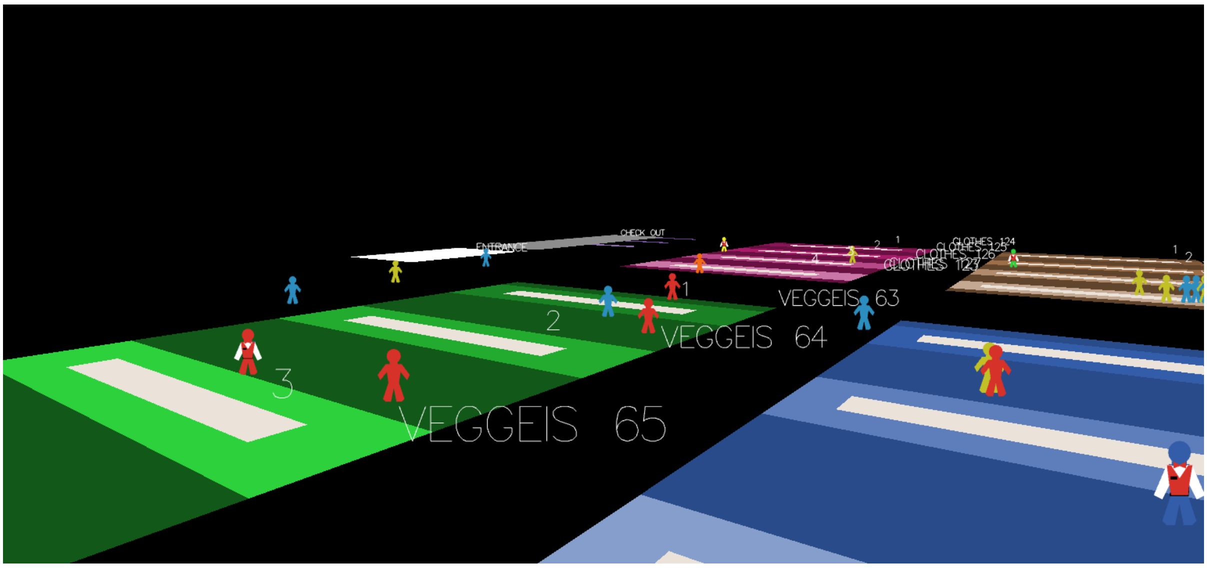


Figure 5: Agent properties presented in colours

The cluster size is set at the beginning when the model is run. Every agent within a cluster spends different times and departs once that period ends. This period is determined by a randomly generated value between 0 and the exposure period variable. This period applies between a healthy agent and an infected agent in an extended meeting, as discussed in Section 2.2, while progressing through the aisles. The chance of that happening is also random and would affect the exposure time of the healthy agent when it takes place.

Figure 6 shows the overall model, including the dashboard and other setting features.

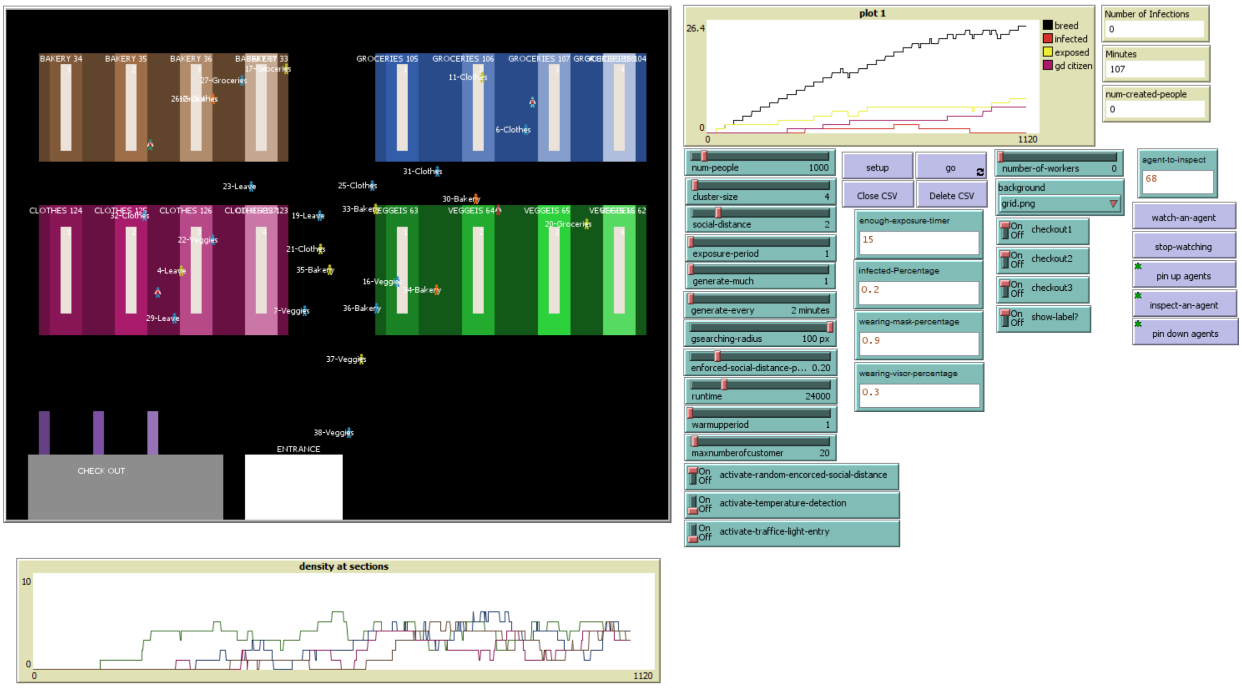


Figure 6: Model dashboard and other setting features.

Additionally, the model performs an enforced social distancing of meters between a selected agent and other agents. The selected agent must have the infection and has met the pre-defined probability of 'enforced-social-distance-percentage.' The model will enforce this behaviour on the agent from the time of the agent creation until it leaves the store through the checkout area. The infected agents are excluded from the final exposure statistics.

Further operational improvement scenarios could be applied using this model, such as the traffic light policy allowing a certain number of people to be inside the store, restricting the supermarket's opening times, and temperature measurement at the store's entrance. If the temperature were above 36 degrees, the agent (doorman) would not let that agent (customer) enter the supermarket.

4. Experimental Study

In this section, a number of scenarios were suggested to reduce the exposure level of COVID-19 inside the supermarket. These scenarios include both NPIs and other OIs. See Table 3 for the supermarket's scenarios, including NPIs and other OI ones.

Table 3: All scenarios suggested by the supermarket management

Scenario No.	Scenario (by Supermarket)
As-Is	Mask not mandatory, Face Shield not mandatory, SD not mandatory
Scenario 1	Mask mandatory, Face Shield not mandatory, SD not mandatory
Scenario 2	Mask not mandatory, Face Shield mandatory, SD not mandatory
Scenario 3	Mask mandatory, Face Shield mandatory, SD not mandatory
Scenario 4	Mask mandatory, Face Shield not mandatory, SD Advised
Scenario 5	Mask not mandatory, Face Shield mandatory, SD Advised
Scenario 6	Mask mandatory, Face Shield mandatory, SD Advised
Scenario 7	Mask mandatory, Face Shield not mandatory, SD Advised. TEMPERATURE MEASUREMENT
Scenario 8	Mask mandatory, Face Shield not mandatory, SD Advised. TRAFFIC LIGHT
Scenario 9	Mask mandatory, Face Shield not mandatory, SD is Advised. LIMIT OPENING TIMES

In Table 3, Scenario 1, the supermarket suggests that a mask is mandatory. This means that all customers should wear Masks. At the same time, Face Shield is not mandatory means that it is optional and based on the customer preference (randomness by the model is applied in this case). Other not mandatory interventions could be applied in which customers are free to respond to them based on their preferences.

The impact of applying the NPIs (individually or combined) is investigated and analysed. The probability of a customer being exposed depends on their actions of selecting NPI measures. See Table 4 for possible NPI actions taken by customers and the subsequent risk of these actions.

Table 4: Customer's action and the subsequent risk

Actual Action (by Customer)	Risk Level	Risk Level Probability
S1	Safe	Pr(M ∩ FS ∩ SD)
S2	Safe	Pr(M ∩ WFS ∩ SD)
S3	Safe	Pr(WM ∩ FS ∩ SD)
S4	Safe	Pr(WM ∩ WFS ∩ SD)
PE1	Probably Exposed	Pr(M ∩ WFS ∩ NSD ∩ NEET)
PE2	Probably Exposed	Pr(M ∩ FS ∩ NSD ∩ NEET)
PE3	Probably Exposed	Pr(WM ∩ WFS ∩ NSD ∩ NEET)
PE4	Probably Exposed	Pr(WM ∩ FS ∩ NSD ∩ NEET)
PE5	Probably Exposed	Pr(M ∩ FS ∩ NSD ∩ EET)
E1	Exposed	Pr(WM ∩ FS ∩ NSD ∩ EET)
E2	Exposed	Pr(M ∩ WFS ∩ NSD ∩ EET)
E3	Exposed	Pr(WM ∩ WFS ∩ NSD ∩ EET)

In Table 4, four safe levels are guaranteed if customers adhere to specific NPI settings, as highlighted in green in the third column. Each NPIs scenario includes 12 possible actions the customer could take if some NPIs are optional in the supermarket. Once a particular scenario is run, different people adhering to different combinations of NPIs in mandatory, non-mandatory, or advised levels could be populated under each action in terms of a probability value. For example, customers could (Probably) be exposed if some of them adhered to the PE2 action, where masks and face shields are mandatory, social distancing is not mandatory, and customers have not been exposed enough to infected customers.

4.1 Results Analysis and Discussion

After running the developed agent-based decision tree model, results are generated for each proposed Scenario 1-9. These results include the percentage level of Safe, Probably Exposed, and Exposed, which are classified as Safe (actions S1-S4), Probably Exposed (actions PE1-PE5), and Exposed (actions E1-E3).

Figure 8 presents, at a high level, results for all the NPIs and OIs suggested by the supermarket management, as discussed in Table 3, and their impact on different customer exposure rates.

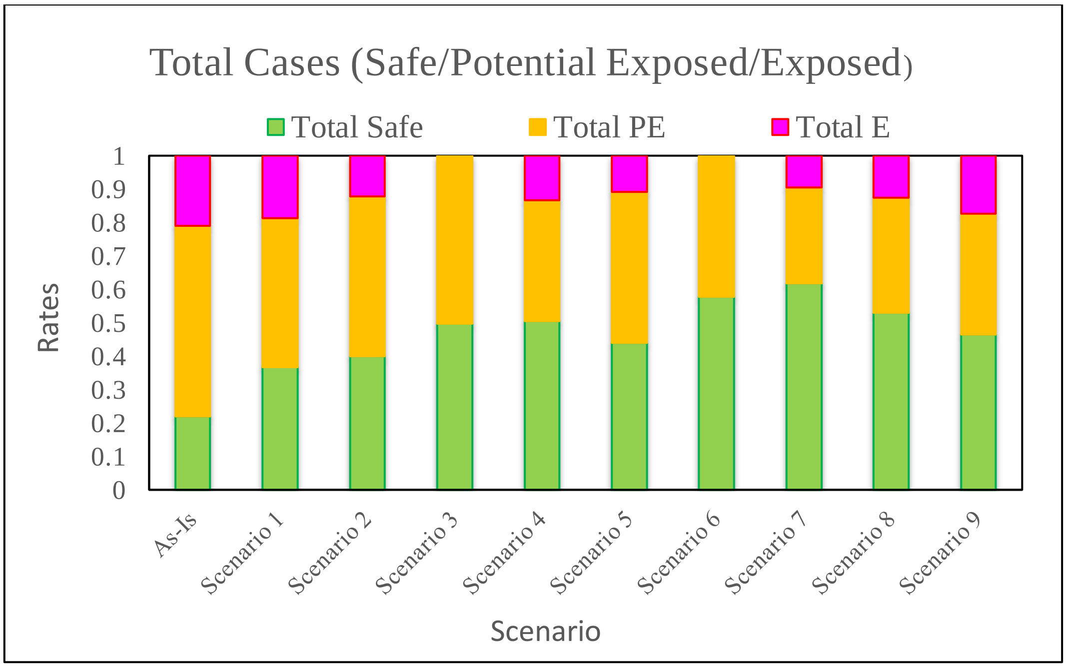


Figure 8: Safety levels of the As-Is vs Scenarios 1-9 presented as percentages. PE indicates Partially Exposed; E, Exposed.

For the As-Is scenario, the lowest percent of safe customers (21.9%) was obtained, where customers selected the Safety actions (S1-S4), while the selection of any of the less strict Safety actions (PE1-PE5) led to a 57.2% of customers to be classified as Probably Exposed. The highest exposure rate of 21% was noticed due to customers violating most of the Safety interventions and choosing the risk actions (E1-E3), putting themselves at high risk of exposure to COVID-19.

For the NPIs, Scenarios 1-6, the highest safety level was achieved in Scenario 6 (Mask and Face Shield mandatory, SD advised), in which 57.8% of customers stayed Safe, and 42.2% of customers were Probably Exposed. This shows a 62.2% increase in the Safe cases and a reduction of 35.4% in the Probably Exposed rates compared with the As-Is scenario. The lowest safety level was achieved in Scenario 1 (Mask mandatory and Face Shield and SD not mandatory), in which 36.8% stayed safe, and 44.5% were Probably Exposed. The safety rates of Scenarios 3 (49.7%) and 4 (50.5%) are almost similar as mask wearing is mandatory and any one of the other NPIs is not mandatory. The safety rates slightly decrease when at least a face shield is mandatory, as in Scenarios 5 (43.9%) and 2 (40%) or when wearing a mask is the only mandatory NPI, as in Scenario 1 (36.8%).

For the OIs, Scenarios 7-9, the highest safety level (61.9%) was achieved by applying Scenario 7, in which customers' temperature should be measured. In addition, less Probably Exposure rate (28.5%) was noticed in this scenario compared with all scenarios, including Scenario 8 (34.59%) and Scenario 9 (36.27%). Different levels of the Exposed case were noticed in some scenarios depending on the selected customer's action.

Amongst all Scenarios 1-9, the percentage level of Safe customers was increased by 64.6% when Scenario 7 was applied compared to the As-Is situation. The mandate application of masks and social distance (NPIs) and temperature measurement (OI) increased the Safety level.

See Figures 9-14 for the analysis of the individual impact of each scenario on different levels of customer exposure to COVID-19.

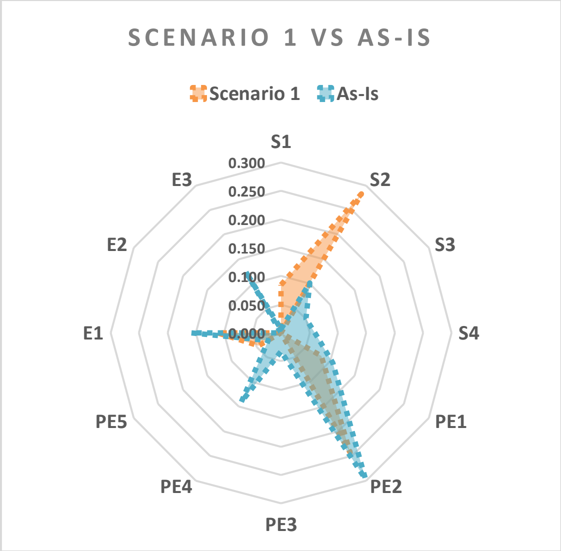


Figure 9: Scenario 1 Mask mandatory, Face Shield not mandatory, Social Distancing not mandatory.

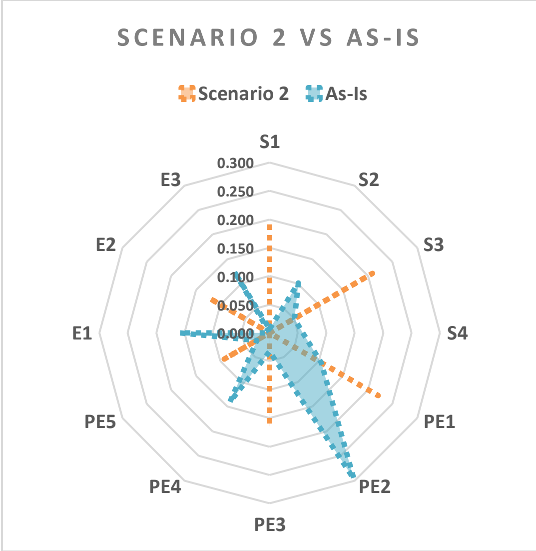


Figure 10: Scenario 2 Mask is not mandatory, Face Shield mandatory, Social Distancing not mandatory.

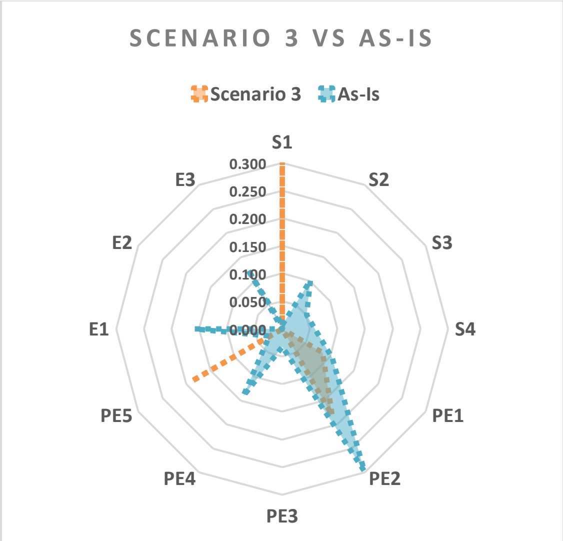


Figure 11: Scenario 3 Mask mandatory, Face Shield mandatory, Social Distancing not mandatory.

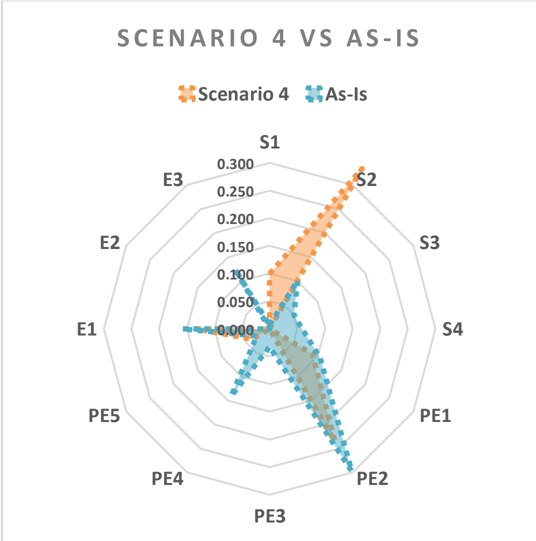
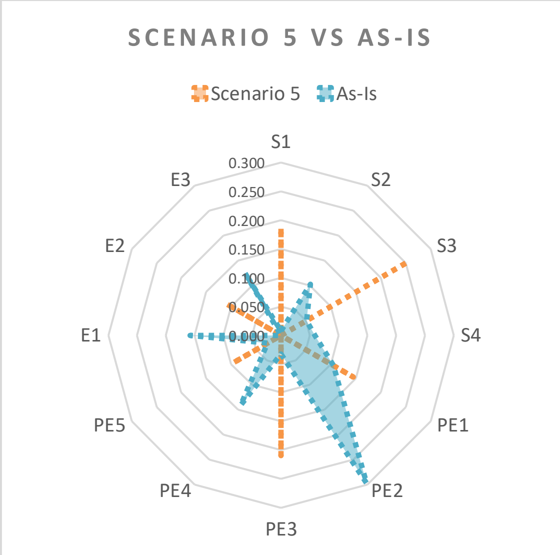


Figure 12: Scenario 4 Mask mandatory, Face Shield not mandatory, Social Distancing Advised.



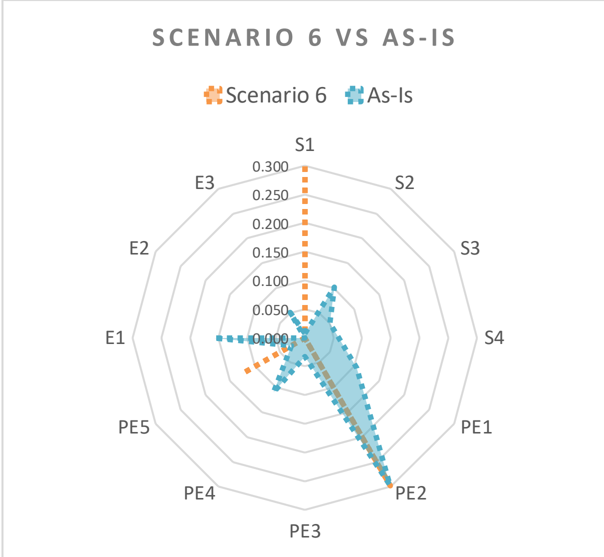


Figure 13: Scenario 5 Mask not mandatory, Face Shield mandatory, Social Distancing Advised.

Figure 14: Scenario 6 Mask mandatory, Face Shield mandatory, Social Distancing Advised.

In the As-Is scenario, where Mask, Face Shield and Social Distance are not mandatory (optional), the highest achieved Safety level was 10.2% by customers adhering to action S2, where Mask is mandatory, Face Shield is not mandatory, and Social Distance is advised. Moreover, a maximum Probably Exposed rate (29.7%) was achieved by selecting action PE2, where Mask is mandatory, Face Shield is mandatory, Social Distance is not mandatory, and Exposure Time to infected people is Not Enough. It has also been noticed that 11% of customers are Probably Exposed by applying action PE4, where Mask is not mandatory, Face Shield is mandatory, Social Distancing is not mandatory, and the Exposure Time to infected people is Not Enough. Finally, the highest exposure rate of 15.8% occurs by applying action E1, where Mask is not mandatory, Face Shield is mandatory, Social Distance is not mandatory, and Exposure Time to infected people is Enough. It is worth mentioning that other minor percentages are also calculated at each action (S1-E3).

For Scenario 1, Figure 9, the Safety level was increased to 28.3% (against 10.2% in As-Is) by applying action S2, in which masks and social distance are mandatory. Applying the PE2 action reduced the Probably Exposure rates to 24.3% (against 29.7% in As-Is) and 0% (against 11% in As-Is) by applying the PE4 action. The Exposure rate to COVID-19 was reduced to 11.2% compared with 15.8% in As-Is by applying action E1.

For Scenario 2, Figure 10, the highest Safety levels (20.9% and 19.1%) were noticed by applying action S3, where Mask is optional, Face Shield is mandatory, Social Distance is advised, and action S1, respectively. The Probably Exposed level was reduced to 0% by applying actions PE2 and PE4. However, the Probably Exposed rates increased because some customers selected other less strict Safety actions (PE1, PE3 and PE5). The exposure to COVID-19 was reduced to 0% compared with 15.8% (As-Is) and 11.2% (scenario1). However, the Exposure rate increased by 12.2% choosing action E2 because of selecting such risky action, in line with what was stated by Castro and Ford (2021), that masks could reduce the infection if worn by all people.

For Scenario 3, Figure 11, a rate of 44.9% of Safe customers was achieved by applying action S1. The Probably Exposed rate was reduced to 18.1% by applying the PE2 action. This rate was increased to 19% by adopting the PE5 action. The exposure rates to COVID-19 were 0% for all the (E1-E3) actions.

For Scenario 4, Figure 12, 33.4% of customers, by applying the S2 action, were Safe compared with the 10.2% in As-Is. A Probably Exposed rate of 23.5% was achieved by applying PE2 compared with the As-Is scenario (29.7%). A slight reduction of 13.3% in Exposure cases compared with 15.8 in As-Is was achieved by adopting the E1 action.

For Scenario 5, Figure 13, the highest Safety rates of 25.5% and 18.5% were achieved by applying the S3 and S1 actions, respectively. The Probably Exposed levels were reduced to 0% by applying less safety actions PE2 and E4. A slight increase in the Probably Exposed level of 14.5% was achieved (compared with 14.5% in As-Is) by applying the PE1 action. The Exposure rate was reduced from 15.8% (As-Is) to 0% by applying the risky action E1.

For Scenario 6, Figure 14, the highest Safety level across all Scenarios of 57.8% was achieved by applying the S1 action; this finding is justified by Ejigu et al. (2021), who stated that increasing mask-wearing increases safe cases. The Probably Exposed rates were reduced to 0% by applying less Safe action PE2 and PE4. The exposure to COVID-19 was reduced from 15.8% to 0% by the E1 action.

The impact of other OIs, including Temperature Measurement, Limit Opening Times and Traffic lights for lowering the number of customers inside the supermarket, were also analysed and discussed. See Figures 15-17 for the different levels of exposure by applying Scenarios 7-9.

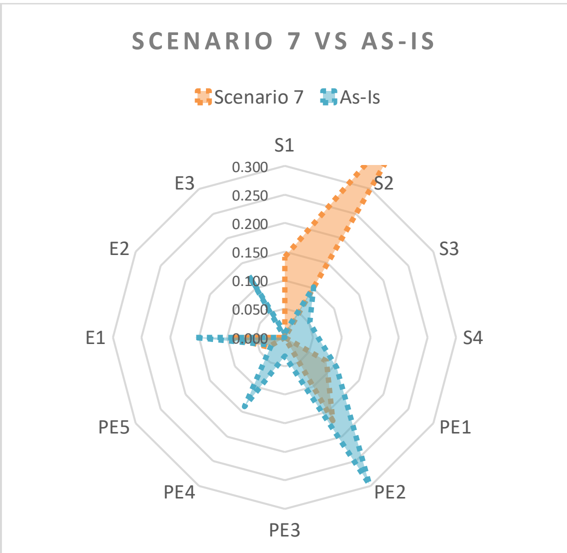


Figure 15: Scenario 7 Mask mandatory, Face Shield not mandatory, SD Advised. HIGH TEMPERATURE.

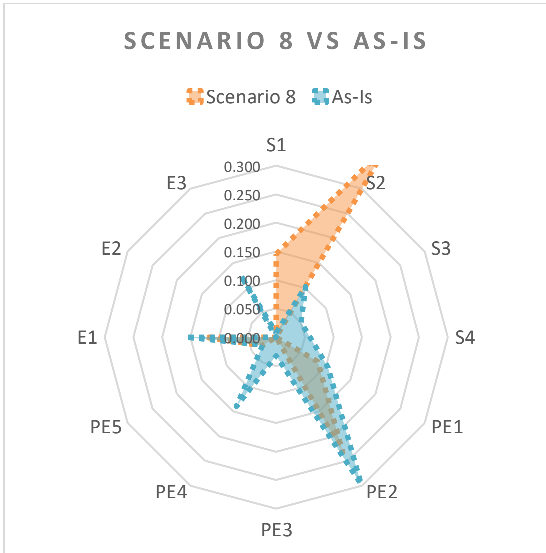


Figure 16: Mask mandatory, Face Shield not mandatory, SD Advised. TRAFFIC LIGHT.

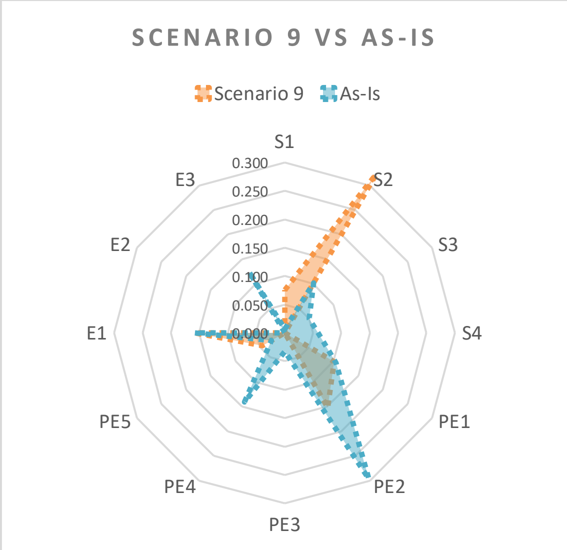


Figure 17: Mask mandatory, Face Shield not mandatory, SD is Advised. LIMIT OPENING TIMES.

For Scenario 7 (High-Temperature Measurement), Figure 15, the highest rate of Safe customers (47.7%) compared with 10.2% (As-Is) was achieved by applying the Safe action S2. The Safety rate was increased from 7% (As-Is) to 14.1% using the S1 action. The Probably Exposed cases were reduced from 29.7% (As-Is) to 16.8% by applying the PE2 action. The Exposure rate was reduced from 15.8% (As-Is) to 9.6% by applying the E2 action.

Scenario 8 (Traffic Light), Figure 16, was similar to Scenario 7 regarding Safety rates. The Exposure rate was reduced to 12.5% (from 15.8% in As-Is) because different customers preferred to apply the E1 action rather than any other action. The Probably Exposed rate was also reduced from 11% (As-Is) to 0% by applying the PE4 action. In addition, this probably exposed rate was also reduced from 29.7% (As-Is) to 23.3% by applying the action PE2. The reduction in PE4 was similar to the one achieved in Scenario 7.

For Scenario 9 (Limit Opening Time), Figure 17, the highest Safety level of 32.3% was achieved by applying the Safe action S2 (against 10.2% in As-Is). The Probably Exposed rate was reduced from 29.7% in As-Is to 15.2% by applying the PE2 action. No improvement was made regarding the Exposure level of customers as they pretty much applied similar actions to the As-Is ones.

5. Conclusion and Future Work

This paper aimed to evaluate the impact of NPIs on COVID-19 exposure in closed environments; hence, we proposed an innovative framework to predict COVID-19 exposure rates in closed environment facilities. This framework consisted of three modules: the agent-based approach, the clustering module (proposed), and the decision tree technique. An agent-based decision tree model was developed to identify the impact of NPIs on customers' exposure to COVID-19 in closed environments. The decision tree model captured customers' adherence to different NPIs and other closed facilities OIs scenarios. The clustering module modelled and identified the impact of the Social Distance intervention on different exposure rates to COVID-19, considering the exposure time factor (i.e., effective exposure time > 15 mins).

A supermarket in Amman-Jordan was used as a case study to test the proposed framework's applicability and efficiency in predicting different customer exposure rates to COVID-19. Secondary data were collected from the National Centre for Security and Crisis Management records, the store's business development department, and academic references.

The results revealed that high compliance with Masks, Face Shields, and Social Distance (optional), along with applying the temperature measurement OI led to the highest level of Safety, 61.9%. The highest level of Probably Exposed to COVID-19 (57.2%) was noticed in the As-Is scenario, where the NPIs were not mandatory. In comparison, the less Probably Exposure rate (28.5%) was achieved when high compliance to Masks, Face Shields and Social Distance and the temperature measure OI was applied. The Exposure rates were high when customers were exposed significantly to infected ones without attention to the Social Distance intervention. The Opening Times Limit Scenario was inefficient, especially in the short run when a limited number of customers were available inside the Supermarket.

At the action levels (S1-E3), it has been concluded that the highest rates of Safe customers were achieved by applying actions S1 and S2, where Mask and Social Distance are mandatory, which agrees with COVID T.I. et al. (2020) findings [14]. The highest Probably Exposed rates occurred by applying actions PE1 and PE2, where Mask is mandatory, and Social Distance is not mandatory given that exposure time is not significant/enough. Regarding the Exposure rates, customers who violated both Mask and Social Distance interventions or any of them were more Exposed to COVID-19 than others, given that they were exposed enough (timewise) to infected customers.

This study offers several managerial and theoretical implications for business in a closed facility. From a theoretical point of view, most studies on COVID-19 exposure in closed environments are limited to identifying the impact of NPIs considering geospatial and other OIs scenarios. However, this study investigated the impact of combinations of NPIs along with some related OIs on different levels of exposure. It provided a new and flexible methodology consisting of ABM and DT techniques along with a new CM (considering exposure time) to identify the impact of adhering to different levels of NPIs on the exposure process. From a managerial point of view, this study implies that stores and supermarkets should install supporting technologies to monitor, detect, and raise an alert for individuals not wearing a mask and/or face shield and advising them to do so. Floor markings should be put in place to keep everyone in the store a safe distance away from each other while they are shopping and working. Indoor body temperature detection cameras must be installed to instantly detect individuals' raised body temperatures. However, the simplest scenario could also be applied by measuring their temperature at the entrance point. Finally, a traffic light system should be imposed to count the number of people entering and leaving a shop against a fixed maximum allowed in any given situation, thereby easily controlling the maximum number of people inside a shop at any point.

The limitation of this study is that it used secondary data such as epidemiological parameters and other store and customer information collected from records of a National Centre and the store itself. Therefore, the developed model was not updated with other parameters, especially those related to the worst time of the pandemic. As a result, all findings presented in this study are from a simulation of secondary store data and should not be generalisable to other settings. In addition, studying the behaviour of different samples of customers in terms of their adherence to NPIs on different days was also risky and prohibited by the store's management. This might lead the model to suggest better/worse outcomes than the ones observed in a faced pandemic situation. Furthermore, validation of study results was impossible given the lack of real-time data on the number of exposed individuals exiting the studied supermarket.

For future work, the impact of using vaccines as a pharmaceutical intervention on different exposure levels will be identified by developing an innovative ABM methodology. In addition, the impact of having ventilation systems in such supermarkets on the different exposure levels, including Safe, Probably Exposed, and Exposed, will be investigated further. Further work could include enhanced cleaning efforts, store ventilation, hand sanitiser stations, and capacity limits.

Declaration

Competing interests

The authors have no competing interest in relation to any part of the research, including the modelling and reporting of the results.

Ethics Approval and Consent to participate

Not applicable.

Consent for publication

Not applicable.

Funding

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Code Availability

Not Applicable

Availability of supporting data

Not Applicable

Human and Animal Ethics

Not Applicable

Authors' contributions

Ammar Al-Bazi conducted the Conceptualisation, Methodology, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft. Faris Madi developed the software, Data Curation, Writing - Review & Editing. Anees Abu Monshar collected the resources, Writing – Review & Editing. Yousif Eliya conducted the Formal analysis, Writing - Review & Editing. Tunde Adediran and Khaled Al Khudir participated in obtaining the related resources.

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