A Social Distancing Index: Evaluating Navigational Policies on Human Proximity using Crowd Simulations

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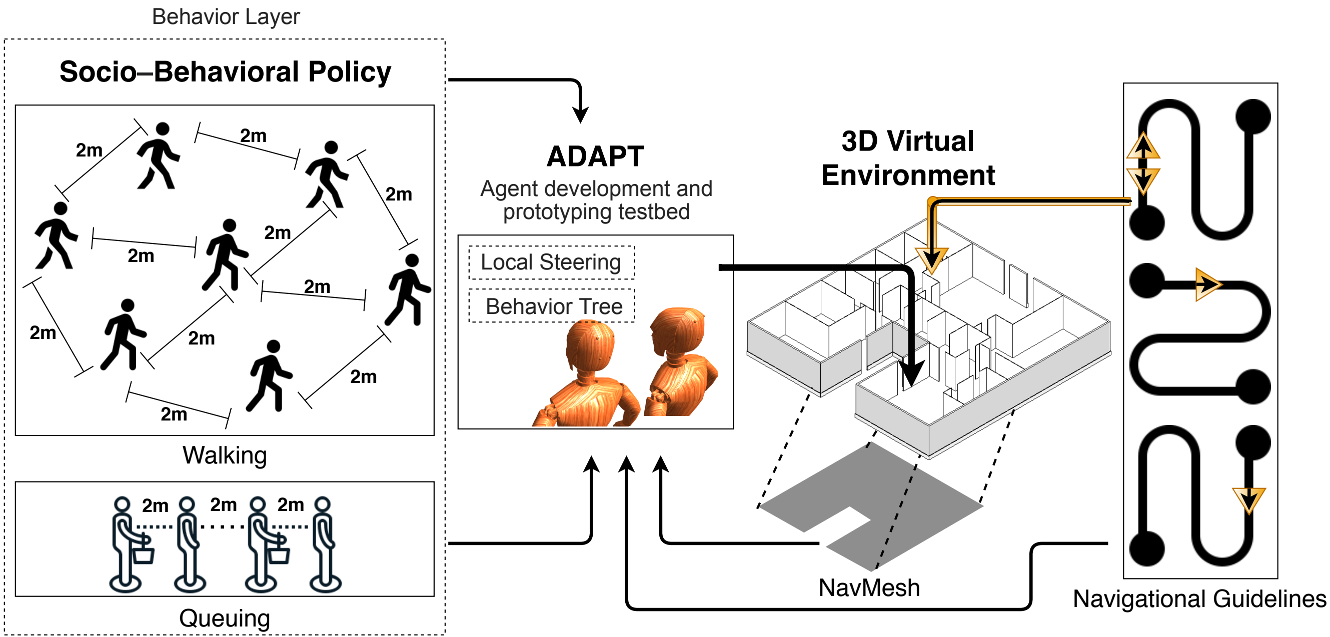

Figure 1: An integrated framework to study socio–behavioral policies and navigational guidelines in semantically rich virtual environments.

ABSTRACT

The importance of social distancing for public health is well established. However, the policies and regulations regarding occupancy rates have not been designed with this in mind. While there are analytical tools and related measures that are used in practice to evaluate how the design of a built environment serves the needs of its intended occupants, these metrics cannot directly apply to the problem of preventing the spread of infectious diseases such as COVID-19. By using a crowd-based simulator using three levels of behavior and agent control in a given environment, a novel evaluation metric for a space layout can be calculated to reflect the proclivity of maintaining a safe distance throughout the shopping experience. We refer to this metric as the Social Distancing Index (SDI), accounting for the occupancy throughput and number of distance-based violations found. Through a case study of a realistic retail store, we demonstrate the proposed platforms performance and output on multiple scenarios by changing agent-behavior, occupancy rate, and navigational guidelines.

CCS CONCEPTS

• **Human-centered computing** → *Visual analytics*; • **Computing methodologies** → *Visual analytics*; **Modeling and simulation**; • **Applied computing** → **Architecture (buildings)**; **Sociology**.

KEYWORDS

social distancing, agent-based simulation, built environment, crowd-aware analysis

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1 INTRODUCTION

The drastic impact of a pandemic on society has not been as clearly seen within the last one hundreds years as it has with COVID-19.

However, there have been multiple instances in recent times that have caused drastic harm and concern (H1N1 [18], MERS [16]), suggesting that the need for future consideration is well deserved. While the events and protocols required in society bring to question the way environments are designed and laid out for the future, a much harder and immediate requirement is to modify the behavior of people. Social norms dictate which side to walk on, while compact and ill-defined scenarios such as shopping in a store present significant challenges in small-crowd management and proximity mitigation. When considering the limited ability to expand buildings immediately, and likely only temporarily, the ability to quickly intervene in the normative social behavior practices in non-destructive ways is essential. Rather than purely rely on self-modifications of behavior; we propose a simulation and evaluation framework for defining directionality in walkable areas of the built-environment with a user-defined social distancing parameter driving crowd behavior, to mitigate the likelihood of dangerous human proximity. Eight different scenarios are simulated to evaluate the impact of social-distancing and environment-policies, both in isolation and collectively, for two different levels of environment occupancies.

Contributions. We introduce a parameterizable human behavior simulator to flexibly study policies imposed on the environment in different ways. Our system allows a user to synthesize plausible behaviors in semantically meaningful environments using BIM-based models. Through this framework, the paper contributes a new evaluative tool for quantifying environments referred to as the Social Distancing Index (SDI).

More specifically, this paper contributes: (1) a platform for simulating the impacts of navigational policies and environment layouts on social distancing violations, and (2) a new evaluation metric for the design of the built environment. We demonstrate the effectiveness of our platform on a preliminary case study conducted in a retail store and a complex shopping mall environment. .

2 RELATED WORK

2.1 Human-Behavior Simulations

Human-behavior simulations (or "crowd simulations") is a well studied topic which uses autonomous virtual agents to provide the temporal dynamics of human-like behavior in the environment [12, 23, 29]. Early work on the simulation of behaviors showed the dynamics of a flock of birds [26], establishing the groundwork for how simple rules defining attraction/repulsion between individuals create a natural recreation of real-world behaviors.

Other developments have been to a velocity obstacle, which is a set of velocity values representing the bounds at which objects would collide. This has been generalized to reciprocal movement (reciprocity between modelled agents in their collision avoidance) [33] and to optimal reciprocal movement among an arbitrary number of agents [32]. Some approaches have used physical forces (e.g., attraction and repulsion) to push and pull the agents toward their goals and away from collisions. A notable approach using physical forces is the Social Forces model [10], later extended to simulate humans under distress [9, 14]. Kapadia et. al, uses an egocentric approach calculate space-time planning for individual agents [13]. More recently, machine learning techniques (e.g., reinforcement learning and deep learning) have been used to simulate the complexities of human-behaviors for more realistic results [24, 34].

2.2 Human-Aware Building Design

Spatial analysis and evaluation is an integral part of building design. Quantitative metrics leveraging computing power have long been desired to aide in environmental planning tasks. *Body Motion Envelopes* are some of the earliest work in this area, in which video recordings of peoples motions are used to generate a probability index of space needed by an occupant to perform a task [15]. The *Indoor Walkability Index* provides a metric for circulation routes afforded by the environments design [27]. Using a grid-based graph, [20] designated weighted areas of interest to score an environment by the common nodes used when path-finding, calculating the higher trafficked areas and referred to as the *Buzz Metric*.

While graph-focused works [20, 27] rely on the intrinsic values the graph-representation of the environment encompasses, an alternative evaluation method is to leverage the simulations described in Section 2.1. One common application of this is the prediction of occupant movement in emergency situations (e.g., egress) where the simulations provide a method for optimizing the routes [2]. The attributes of crowd dynamics during high-stress evacuations has been studied in past experiments using virtual environments [19], helping to improve how agents should move. Simulations are also used for informing the placement of environment elements (e.g., pillars and other obstacles) based on the movement flow in hallways [1, 6, 7]. The work presented in [31] presented a comprehensive comparison of sequential and joint environment–crowd parameter exploration processes to generate efficient environments. In one of recent works [8], a gamification approach is adopted to showcase the potential of community-driven design of environment layouts with respect to crowd simulations using games and networking.

2.3 Socio–Behavioral Policies in Crowds

Socio–Behavioral characteristics are the changes in human behaviors which have a direct impact on their movements. There has been a growing focus to study and measure the impact of different socio–behavioral policies in limiting, for instance, spread of the disease [35]. It is becoming essential to account for socio–behavioral characteristics of potential users in pedestrian dynamics [28]. Usually these characteristics are the changes in human behaviors – directly impacting their movements.

The use of human behavior for emergency and disease spread studies in agents has appeared in past literature for various cases. With respect to the built environment, [22] uses a multi-agent system to simulate competitive queuing and herding behaviors in crowds during emergency egress. In [5], a targeted social distancing design is presented to mitigate the pandemic influenza for local community social contact networks. Others have considered the spread of disease relating to social distancing through differential-games [25] and multi-agent simulations in urban environments accounting for social structures in crowds [3].

With an ongoing pandemic [21] around the world, several questions about our current social and environment setups have been raised. For example: "*What is a maximum afforded social distance?*", "*Does the current environment layouts facilitate to maintain a desired social distance?*", "*Is current level of social distancing enough to contain the spread* [4]?". By using behavioral crowd simulations, many of these questions can be computationally explored.

2.4 Our Approach

We present a parameterized workflow to measure the affordances of environment layouts for facilitating a desired human proximity. The affordance of an environment is measured using a new environment performance metric called the Social Distancing Index (SDI). Our approach allows modelling of navigational guidelines for the environment, define socio–behavioral policies for crowds, and simulate their respective impact on social distancing violations for individual occupants. While we use the crowd steering mechanism from ADAPT [11], the evaluation method of the environment is applicable to any past, or future, steering algorithms as well.

3 FRAMEWORK

The presented framework encompasses the following steps: (a) importing a semantically rich 3D virtual environment (e.g., a Building Information Modeling (BIM) model); (b) setting crowd occupancy specifications including occupancy distribution within the environment, behavioral characteristics (e.g., walking speed), and activities the crowd will engage in (e.g., egress, gather in a meeting room, shopping in a mall, doing groceries, etc.); (c) defining socio–behavioral policies for crowds (e.g., maintaining a social distance of $2m$ with other occupants while moving or standing in a queue); (d) defining navigational guidelines in the environment (e.g., one-way aisles and corridors, no–go areas, etc.) to assist socio–behavioral polices; and (e) information parsing, simulation, and animation in real-time using a 3D simulation and gaming engine (Figure 1).

3.1 Navigational Guidelines and Environment Graph

Two components are necessary for driving the crowd simulation in our framework; 1) a navigable space in the 3D environment and 2) a graph representation of the environment. The navigable space is defined by a NavMesh which enables the ADAPT framework to perform localized steering behaviors and account for social distancing parameters (see Section 3.2 for details). At a larger scale, the environment graph enables a user of our framework to determine navigational guidelines which are then represented by the directions of edges in the graph.

We represent the environment graph using a Visibility Graph Analysis (VGA) [30]. The visibility graph is constructed by decomposing the environment space and sampling it with a fixed grid. All the locations in the environment are the nodes or vertices in the visibility graph. We then compute the line-of-sight between these nodes. Two nodes are connected to each other in the visibility graph (e.g., have an edge between them) if they have an unobstructed line of view between them. In other words, if the line of view between the two nodes is obstructed by an object (e.g., a wall), then these two nodes will not have an edge between them in the visibility graph.

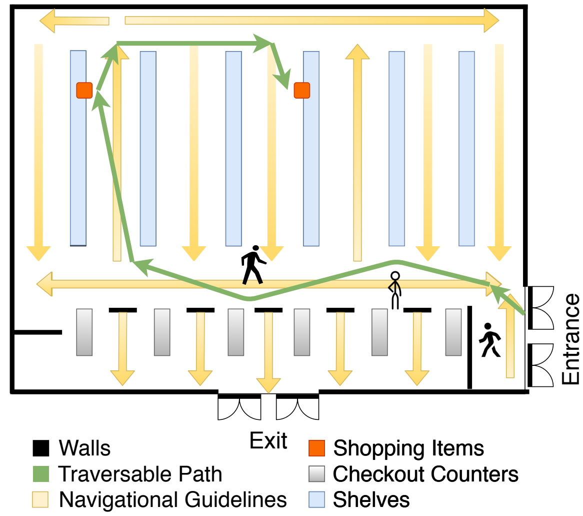


Figure 2: A sample pathway of a virtual agent to shop two items from the facility. Navigational guidelines are in effect in the environment. Shortest path to items is used with directed graph while local steering avoids agents.

The abovementioned graph representation is used to implement the navigational guidelines in the environment. The environment graph ($G_{env} = \langle N, E \rangle$) where nodes ($N$) are defined by key navigational waypoints such as exits, checkout counters, and ends of hallways. Edges are defined by ordered pairs of nodes such that $(n_i, n_j) \in E$, and for each (n_i, n_j), there is a line of sight connecting the two nodes. Additional edges can be defined by adding nodes at points of interest (e.g., shopping items on shelves) and connecting them with the initial graph G_{env}, following the navigational guidelines. A sample navigation policy can be seen in Figure 2 (represented as yellow arrows).

3.2 Human Behavior Simulator

The behavior simulator $Simulator = f(G_{env}, B)$ accounts for an environment graph (G_{env}) and parameterizable virtual occupants (B) by connecting three layers: 1) Behavior Layer 2) Behavior Tree Layer 3) Local Steering Layer.

Behavior Layer. Manages the allowable actions agents can perform during the simulation (e.g., walking, queuing, social distancing, etc.) and defines simulation-level behaviors (e.g., generating shopping lists, assigning shopping items to the agents, etc.). Table 1 shows a complete list of behaviors implemented in this layer.

Behavior Tree Layer. Represents a sequence of actions that define a behavior of an agent across the course of a simulation. It takes the defined behaviors as input from the behavior layer, schedules the order in which the behaviors will be carried out, defines which and how many agents will be participating, and controls the execution of these behaviors. In this layer, parameters for crowd occucpancy (i.e., max. number of occupants allowed in the environment) are set for B. More complex behavior trees including selector branches, repeating loops and additional logical operator can also be modeled in our framework, although a simple example

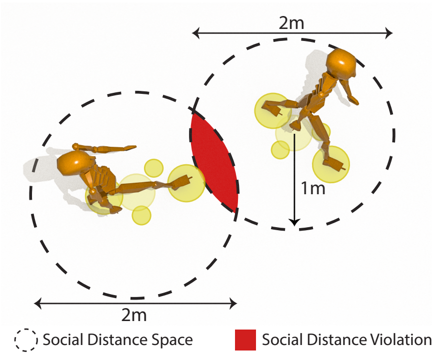


Figure 3: A snapshot of agent's social space and social-space violation.

is given below. Listing 1 shows a sample behavior execution order for shopping.

Listing 1: Behavior tree for shopping

```
Generate_Shopping_List()
Loop: (Has More Items)
        Walk_To(item)
        Item_Pickup()
To_Checkout()
```

Local Steering Layer. Controls the navigation of the agents in the environment. It communicates with the behavior tree layer to identify schedules of the behaviors and the participating agents. It then queries the environment graph G_{env} to determine the appropriate sequence of nodes to be traversed by the participating agents in order to carry out a particular behavior. In this layer, the parameterized values of B for walking speed (i.e., how fast the agents can walk) and social distancing (e.g., if parameterized, agents will be encouraged to maintain a set social distance with other agents while walking) are set. Social distancing is parameterized by defining a proxy velocity obstacle around each agent during the simulation [17]. The exact movement of an agent is determined by the agents movement from one node to the next, using Reciprocal Velocity Obstacles for steering and Unity's Navmesh for path planning.

The Simulator. Once these layers are defined, the Simulator then runs the simulation for the environment and population parameters and generates crowd trajectories, where each trajectory is a set of spatial points in the environment space walked by the agent during the course of the simulation. This trajectory is defined as $Trajectory_{A_i} = (step_t, step_{t+1}, step_{t+2}, ..., step_{t+n})$, where $step_t$ is the position of an agent in the environment in world coordinates at the simulation timestep t (corresponding the simulated real timescale value), represented as: $step_t = WorldPos(Agent_i)$. In Sec. 4, we use $Trajectory$ to synthesize a meaningful outcome between the environment graph, policies, and occupancy rate.

4 SOCIAL DISTANCING INDEX

The Social Distancing Index (SDI) is an environment performance measure which represents the proclivity of an environment design to afford the desired human proximities of the occupants. To compute this metric we discretize the environment to a fixed-size grid of cells with a given spacing λ for recording location-specific data. The set of cells are a spatially significant structure for storing data collected during simulation. We represent these cells in an array C.

Using the framework in Section 3, data on the rate and location of social distancing violations (M) are recorded and mapped to a given cell. This is done by analyzing crowd trajectories in space every 1 second of real-world time in the simulation. If trajectories of two or more agents come in proximity such that their distance is less than a desired social distancing threshold (e.g., 2 meters or 6 feet, as shown in Fig. 3), these agents are found in violation of each other's social space, with the location mapping to a cell $(x, y) \mapsto i$. The violation count of that cell is then incremented, $c_i = c_i + 1$. Once a violation between agents is recorded in a given cell c_i, it is excluded from future increments of violations until at least one agent moves to a position located above a different cell (e.g., c_{i+1}). If a violation is not between the same agents, we increment c_i (the social violation count of the underneath grid cell for that location).

This maintains a record of sensitive and critical areas in the environment which are more vulnerable to human proximity violations. Once the social violations are recorded for the course of the simulation, we then extract four values from M:

(1) Total Violations $M_t = \sum_{s \in C} s$
(2) Cell Violations $M_m = \max(C)$ (Max violations of any single cell)
(3) Unique violations $M_u = |M_{uv}|$ where $M_{uv} = \{c_i \,\forall\, C \mid c_i > 0\}$
(4) Average Cell Violations $M_{avg} = \frac{M_t}{M_u}$

Finally, we compute SDI by dividing the number of unique social distance violations (M_u) in space by the average number of agents served in the facility (A_s) (i.e., facility throughput). $SDI = \frac{M_u}{A_s}$, where the number of people served are the agents who have left the facility already (i.e., they have completed their shopping).

5 CASE STUDY

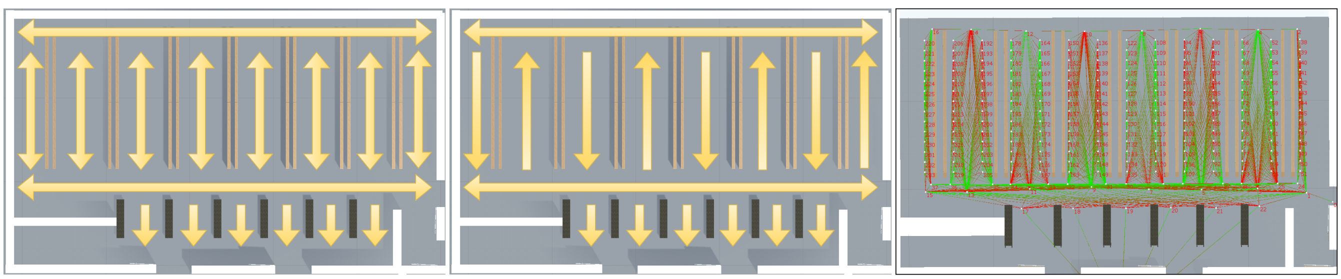
We conduct a series of experiments using the presented framework to demonstrate the outcomes and reflected SDI values on different occupant and environmental policies. The combination of these policies demonstrates the efficacy of our platform to provide meaningful insights into the impact policies have on social distancing violations for a given environment layout and design.

A real-scale 3D store environment (BIM model) is designed using a mainstream architecture design tool (Autodesk Revit) and brought into Unity in the FBX format. We simulate eight different scenarios to evaluate the impact of environmental and crowd behavioral policies, both in isolation and collectively, for two different levels of agent occupancies. For the violation data collection, we set λ to 0.5m. Note that the presented experiments in the case study are the proof-of-concept to showcase the preliminary efficacy of the proposed framework. More complex scenarios with additional socio–behavioral parameters will be considered in future studies.

Independent Variables. We allowed a maximum of 150 agents in the facility in one time during the course of simulation. Each simulation is run for about 8 hours. Two different behavioral policies are considered for agents' walking: (1) normal-walking – agents may enter each other's social space; and (2) social-distancing – the proxy velocity obstacle is set to $2m$. Similarly, two different environment policies are considered: (1) normal-navigation — agents may move

Behavior	**Description**
Initiate_Crowds	Initiate group of occupants at the entrance of the environment facility at random times.
Shopping_List	Generate a list of randomly selected shopping items for the agents.
Walk_To	Move to a given point of interest in space.
Item_Pickup	Turn towards the desired item and pick it up.
To_Queue	Line up and wait for the turn.
To_Shop	Collect the given list of items from their placements in the facility.
To_Checkout	Look around to identify least crowded active counter, perform the queuing behavior, pay the bill for the shopped items, and exit the facility.
Social_Distancing	Maintain a social distance (e.g., $2m$) with other occupants while walking or waiting in a queue.
Navigation_Guides	Follow the navigational guidelines enforced in the environment facility (e.g., walking in directed pathway).

Table 1: A list of agent-level and simulation-level behaviors defined in the simulator.



Normal-Navigation *Directed-Navigation* *Directed-Navigation Graph*

Figure 4: Left & Middle: Environment navigation guidelines used as independent variable in the case study. Right: a sample navigation graph constructed using our environment–graph representation, to model directed-navigation guidelines where the edges in the graph are directed from *Green* to *Red*.

Occupancy	**Behavior P.**	**Environment P.**	**M_{av}**	**M_u**	**A_s**	**SDI**
100%	Normal	Normal	68.5	2936	90	32.62
100%	Normal	Directed Navigation	55.68	2717	50	54.34
100%	Social Distancing	Normal	60.22	2223	75	29.64
100%	Social Distancing	Directed Navigation	56.28	2781	71	39.17
50%	Normal	Normal	14.85	2159	57	37.88
50%	Normal	Directed Navigation	13.64	1996	41	48.68
50%	Social Distancing	Normal	17.33	1657	49	33.81
50%	Social Distancing	Directed Navigation	12.77	2038	42	48.52

Table 2: Summary statistics from the experiments. Light-Gray (baseline: normal scenario), Gray (highest SDI: less favorable policies) and Dark-Gray (lowest SDI: more favorable policies).

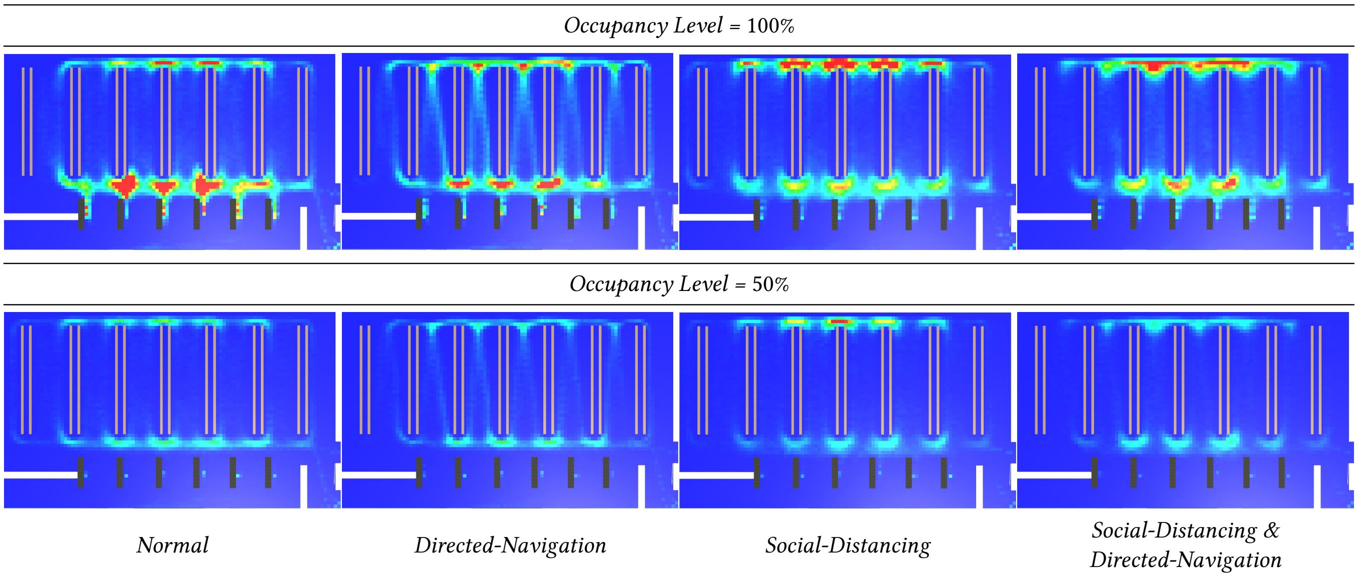


Figure 5: Qualitative results from the experiments. The top row shows the results for 100% agent occupancy, whereas the bottom row shows for 50% occupancy. Heatmaps show the aggregated social distance violations which are occurred during the course of simulation in the environment space. Areas where higher social violations occurred are shown in *Red* compared to *Blue* ones with fewer to none violations. Results are normalized among all images.

in any direction in the environment; and (2) directed-navigation – agents are required to follow given environment navigational guidelines.

Dependent Variables. A number of variables are dependent on the simulations including M_{avg} (average cell violations), M_u (unique violations), A_s (agents served in the facility), and *SDI* (social distancing index).

Design. The study has a 2 x 2 x 2 factorial design with agent occupancies (2) x behavioral policies (2) x environment policies (2).

Simulation Setup. At the start of the simulation, agents are given a shopping list of randomly selected items ($1 \leq n \geq 30$). Agents are tasked to shop the given list of items, perform the check-out, and exit the facility. The walking speed of agents is set to an average adult walking speed of 1.3 m/s. Agents are scheduled to enter the facility every 4^{th} second in a group of 1 to 5 (randomly picked) until the set maximum environment capacity is hit (e.g, 150 agents). Afterwards, a new agent will only enter the facility when an existing agent leaves.

Results. Table 2 shows a summary of the findings from the experiments. Rows (1) and (5) are baselines (normal scenarios) as no environment or behavioural policies are enforced. Rows (3) and (7) produced best, whereas rows (2) and (6) produced worst social distancing index for occupancy levels 100% and 50% respectively.

Behavioral policy to maintain a social distance of $2m$ yielded closest facility throughput to baseline for both agent occupancies. This, however, is not valid for the scenarios where behavioral policy was enforced in combination with environment policy. The average social distance violations are minimum when environment policies (e.g., directed-navigation) are enforced. This case, however, has a tradeoff with lower facility throughput as agents had to travel longer distances, and therefore, took more time to complete the shopping list. Enforcing both social-distancing and directed-navigation produced somewhat reasonable facility throughput but with a tradeoff of higher unique social violations. Imposing social-distancing alone produced a moderate balance of higher throughput and fewer unique social violations. Therefore, yielding the best SDI values. Qualitative results of the experiments are shown in Figure 5. A lot many violations happen around the checkout counters with 100% capacity during normal policies. This region has significantly less violations when applying social-distancing behaviors, however, a large portion of the SDI is shifted to the upper boundary wall of the environment. Through this visualization we can understand how the environments design (and in this case, restricted space), impacts the likelihood and amount of social distancing violations.

Note that, it can be a possibility where we do not get similar trends for some other environment as it might have different architectural and physical components in it or they may be oriented or placed in different way. The same is applicable to crowd behavior simulator. Our approach is not bound to only use ADAPT [11] and other steering algorithms can also be adopted. However, doing so, might result in a different set of findings depending on behavioral characteristics of the agents in that steering approach.

Additional Results. To demonstrate the scalability and flexibility of the presented framework, we also tested it for a complex real environment called *Nexus Shopping Mall*, located in Mumbai, India. We designed two different simulation scenario and ran it with our framework: (1) normal walking behavior with normal navigation (baseline); and (2) social distancing behavior with normal navigation. Like for the retail facility, all the agents were assigned a shopping list with randomly selected items. We simulated 1000

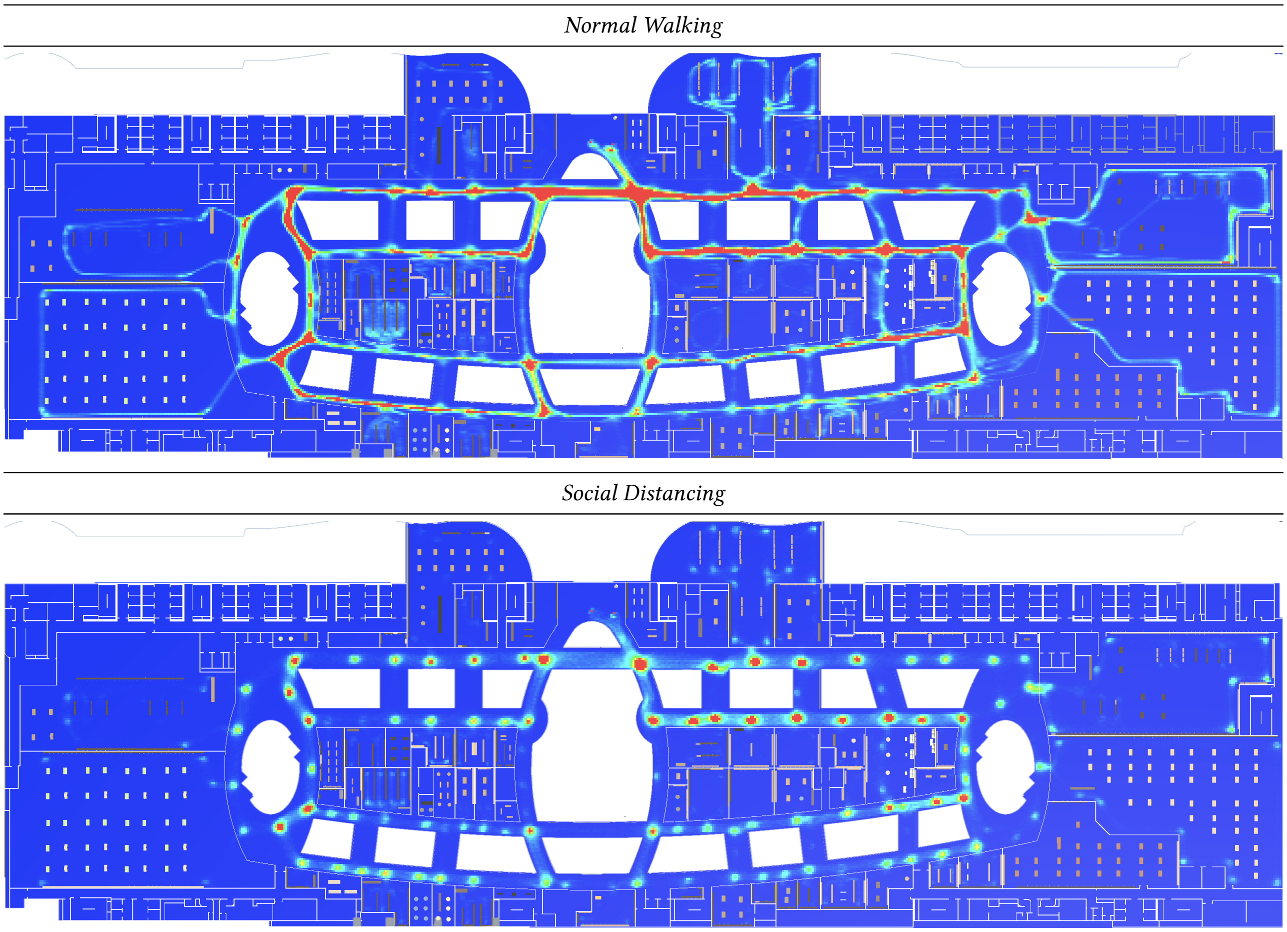


Figure 6: Qualitative results for a complex real environment located in Mumbai, India: *Nexus Shopping Mall*. The color-coded heat maps show the aggregated social distance violations occurred at different locations in space during the course of simulation. Areas with higher social distance violations are highlighted in *Red*, compared to *Blue* ones, with fewer to none social distance violations. Top: a normal walking behavior with normal navigation (e.g., no environment guidelines are enforced). Bottom: a social-distancing behavior, also with normal navigation.

agents for about 4 hours. Figure 6 shows the heat maps for aggregated social distance violations from the simulations. Results reveal significantly higher social distance violations in the hallways especially towards the top-side when agents were not maintaining any social distances while walking. However, with a $2m$ social distancing behavior, we see lot less hotspots in the heat map (Figure 6: Bottom).

Observations. In the retail facility, the reason we see many violations in the presence of social distancing is that agent behaviors are set in a way that they are encouraged to maintain a 2m social distance from other agents as a soft constraint. This is to avoid any deadlocks among the agents during the simulation. With social distancing, we still see some violations (red areas). It is because there is a boundary wall right next to the top horizontal hallway. Agents did try to maintain a 2m social distance. However, since they did not have enough room at the top side to avoid other agents and walk by around them, therefore, they end up violating the social space of others while continuing their journey towards their respective targets. The same behavior, however, is not highlighted in the complex shopping mall environment. Our platform showed that, with social distancing in the shopping mall, violations are reduced by order of magnitude.

6 CONCLUSION

The importance of social distancing for public health is well established. However, the policies and regulations regarding occupancy rates have not been designed with this in mind. To introduce a metric capable of accounting for a space layouts proclivity for maintaining a safe distance for occupants, we use a crowd-based simulator consisting of three levels for behavior and agent control in a given environment. We refer to this metric as the Social Distancing Index (SDI), accounting for the occupancy throughput and number of distance-based violations found. Through a case study of a realistic retail store, we demonstrate the proposed platforms performance and output on multiple scenarios by changing agent-behavior, occupancy rate, and navigational guidelines. It is also essential to note that the presented scenarios are only the preliminary demonstration of the effectiveness of the proposed framework. More complex scenarios (e.g., to study the causality of different design factors in the environment) will be evaluated in future work.

The SDI is a function of both environment and crowd parameters, both of which are easily modified in our flexible framework. It is also pertinent to take the case study in context of demonstrating our framework and the SDI, while not providing direct guidance on policies for retail stores as variations in the environment and agent steering may change outcomes. Future work that integrates verified agent behaviors within a social distancing-enforced environment can easily be integrated into our framework. Furthermore, additional research regarding the probability of infection by distance can be implemented as a function of agents proximity for the SDI. Future studies will also incorporate more realistic agent walkings to eliminate any deadlock situations when agent behaviors (e.g., social distancing) are set as hard constraints.

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