MULTI-SCALE MODELS FOR TRANSPORTATION SYSTEMS UNDER EMERGENCY

FINAL REPORT

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16. Abstract

The purpose of this study is to investigate human behavior in emergencies. More specifically, agent-based simulation and social force models were developed to examine the impact of various human and environmental factors on the efficiency of the evacuation process, through a series of case studies. The independent variables of the case studies include the number of exits, the number of passengers, the evacuation policies, and instructions, as well as the queue configuration and wall separators. The results revealed the location of the exits, number of exits, evacuation strategies, and group behaviors all significantly impact the total time of the evacuation. For the queue configuration, short aisles lower infection spread when rope separators were used. The findings provide new insights in designing layout, planning, practice, and training strategies for improving the effectiveness of the pedestrian evacuation process under emergency.

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Executive Summary

Researchers primarily use queuing networks and social force model to simulate the movement of people through transportation hubs such as airports. Social force models are inspired by molecular dynamics approach where pedestrian particles evolve in time by interacting with other pedestrians and objects like walls and chairs. The force-field inputs for pedestrian movement models are challenging to estimate because of inherent uncertainties in human behavior. A critical consideration in determining human behavior is anxiety, which directs attention to threat stimuli. Specifically stated, anxiety is a transient, episodic condition engendered by specific situations, such as emergency events. Researchers used a novel approach that parameterizes the sources of uncertainty and estimated a range of valid model parameters by comparing them with experimental data.

In this study, the researchers expanded this modeling framework and integrated it with queuing-based models to investigate the effect of panic on human behavior in the pedestrian dynamics during emergencies. The larger-scale transportation network model determines when the transportation system closure is to be implemented. The researchers incorporated this as a parameter into our model to investigate the effect of resulting congestion and evaluated the transportation policies that need to be followed at transportation hubs (e.g., airports) in the event of an emergency.

Through the Case studies, this study developed a model to investigate the effect of the number of exits, the number of passengers, the evacuation policies, and instructions on evacuation efficiency. Further, this study also investigated the effects of queue configuration and quantified the effectiveness of wall separators in suppressing the disease spread compared to rope separators. Results concluded that; 1. A higher number of passengers increased the duration of the evacuation process, 2. Greater number of exit doors reduced the duration of the evacuation process, 3. The evacuation time for equal distribution policy significantly took longer than the shortest queue policy, 4. Instructions increase the efficiency of evacuation, and 5. Configurations with short aisles lower infection spread when rope separators are used. At the end of this paper, the limitations of the study and recommendations for future studies are discussed.

Background Information

Emergency Evacuation Overview

Emergencies can easily happen in our lives, with or without warnings. No matter how serious an emergency is, we always need to deviate from what we were planning to do initially and prioritize the emergency. If an emergency is not dealt with properly, harmful consequences may happen. Numerous studies were conducted to manage an emergency, reduce the impact, sometimes save people's lives, and protect property damages. The initial step of any emergency studies should include the study of types, causes, and characteristics of emergencies.

The primary purpose of an emergency is to protect people's lives and property losses. Thus, emergency evacuation is the most critical part of any emergency studies. Through the study of previous emergency evacuations, such as Hurricane Katrina, the British Petroleum (BP) oil spill and explosion in the Gulf of Mexico, the terrorist attack on September 11, 2001, and other aircraft or airport emergency evacuations, a summary of emergency phases and evacuations processes in each phase can be concluded. As a result, some limitations of current emergency evacuation studies are discovered.

1.1 Definition of emergency. The Oxford English Dictionary defines an emergency as "a serious, unexpected, and potentially dangerous situation requiring immediate action." (Lexico Dictionaries, n.d.). In other words, emergencies are the unpredictable situations that we are not familiar with but forced to deal with immediately. They can be natural, technological, human-made, intentional, or accidental situations that create intense feelings of stress, anxiety, and uncertainty (Van de Walle & Turoff, 2008).

Examples of such emergencies include fire, flood, airplane crash, traffic accidents, and hurricane evacuation. Usually, trained and equipped personnel will have professional response plans to emergencies based on the scale and severity. The scale and severity of an emergency also depend on the functional changes or suspension of normal operations. Most emergencies, such as an emergency landing at an airport, fire, and hurricane can be solved by routine emergency response plans and will not affect the regular operation significantly. However, some emergencies such as major incidents, natural disasters, terrorist attacks, and catastrophes are massive events that are out of the range of pre-defined routine emergency response plans (Alexander, 2013). The outcome of these events largely depends on the immediate, sometimes intuitive responses from the decision-maker and human involved.

An emergency like fire can happen as a result of cumulative processes. In this case, a fire hazard can exist for an extended period. This hazard will not lead to a fire emergency unless it passes a threshold. An emergency can also be a result of a sudden threat. For example, a terrorist attack can happen suddenly without any previous clues (Alexander, 2013). Understanding the characteristics of such events is of the utmost importance for human decision-makers to effectively dealing with these situations.

For these emergencies, no matter where it happened or how it occurred, some common characteristics are involved, understanding these factors will enable us to develop a policy to guide the evacuation process effectively. In the next section, these major characteristics are reviewed in detail.

1.2 Main characteristics of Emergencies. The significant characteristics associated with emergencies are 1. Stake can be high, threats to lives, 2. Impact can be very short or long, 3. Time pressure, 4. Uncertainty and unpredictable surroundings, 5. Fast-changing, dangerous, or life-threating environment. 6. Complexity, 7. Unclear situations, 8. Unavailable, incomplete or inaccurate information, 9. Stress, 10. Panic or panic behavior, 11. Crowd behavior, and 12. Damage can be light or significant.

Emergencies can lead to severe consequences if it is not appropriately managed and timely. Usually, an emergency can happen in our lives instantly and change our daily routine. Negative psychological feelings can easily develop due to the conflicting, incomplete, or missing information; inefficiency in decision-making; and intense time pressure. Decisions such as wayfinding need to be done in a very short-term deadline while processing the increased amount of information quickly. Depending on the types of emergency, time available for evacuees to process information and making decisions can be very short or not too short. An emergency can involve many people; an interpersonal relationship of evacuees becomes significantly essential when the emergencies are urgent and life-threatening (Purser & Bensilum, 2001). Most emergencies involve human beings and their intelligence, behavior, emotion, and previous experience can directly impact emergencies. Therefore, inappropriate human behavior can worsen the situation.

1.3 Causes of Emergencies. Emergencies can be caused by 1. Natural disasters such as floods, hurricanes, tornadoes, and fires. 2. Technological disasters such as airplane crash, boat collision, and bus accidents. 3. Hazardous materials releases such as toxic gas releases, chemical spills, radiological accidents, and explosions. 4. Terrorist attacks. 5. Pandemics. 6. Civil disturbances. 7. Workplace violence resulting in bodily harm and trauma, and so forth (Fagel, Krill, & Lawrence, 2013; United States Department of Labor, n.d.).

Disasters always lead to emergencies, but not all emergencies are disasters (Alexander, 2013). Disasters and terrorist attacks usually lead to emergencies that require an urgent response, such as evacuation. A disastrous event often causes human, material, or environmental losses and overwhelms local capacity such as overloading on the traffic system, and local shelters (Guha-Sapir, Hoyois, & Below, 2016). A disaster is unforeseen and happens suddenly; therefore, it leads to emergencies (Pine, 2009).

There are three generic categories of disaster, which are natural, technological, and human-made disasters (Guha-Sapir et al., 2016; Neria, Nandi, & Galea, 2008). According to the Center for Research on the Epidemiology of Disasters (CRED), which is an international non-profit institution focused on researching natural and human-made disasters worldwide, natural disaster includes earthquake, volcanic activity, flood, landslide, wave action, storm, extreme temperature, fog, drought, glacial lake outburst, wildfire, animal accidents, epidemic, and extra-terrestrial impact (Guha-Sapir et al., 2016). Technological disaster is the result of a failure of technical systems or mechanical design problems, for example, an airplane crash, boat collision, and bus accident (Cassidy, 2002).

In the year 2015, 376 reported natural disasters caused the deaths of 22,765 people worldwide. The damages were up to USD 70.3 billion. The United States (U.S.) is one of the top five countries impacted by natural disasters in the last decade. In the year 2015, 28 disasters caused USD 21.28 billion in damages in the U.S. (Guha-Sapir et al., 2016).

To deal with a disastrous situation or even to survive under such circumstances, humans are required to make quick decisions and act upon it promptly. When evacuees are not able to obtain enough information, negative feels such as anxiety, stress, and fear can occur immediately. Nonadaptive behavior such as panic behavior or crowd behavior sometimes is observed in evacuating crowds. The disaster itself may not cause fatal accidents. However, human behavior under emergency can lead to severe consequences such as injuries or deaths caused by stampeding, pushing, knocking, and trampling.

1.4 Examples of emergencies. Hurricane Katrina hit the Gulf of Mexico from central Florida and then made landfall in Louisiana and hit Mississippi in August 2005. Hurricane Katrina is, by far, one of the costliest hurricanes in the United States (E. S. Blake, Landsea, & Gibney, 2011; Fagel et al., 2013). In 2009, the Louisiana Department of Health published the statistics of deaths caused by Hurricane Katrina. The study identified approximately 986 to 1440 deaths of Louisiana residents directly caused by Hurricane Katrina (Brunkard, Namulanda, & Ratard, 2008). Although many kinds of research were conducted, there was no accurate storm-related death total, including all the impacted states. The property damage was up to USD 108 billion (E. S. Blake et al., 2011).

Within five hours of the landfall in the Gulf Coast areas (Alabama, Louisiana, and Mississippi), Hurricane Katrina had destroyed approximately 90,000 square miles of land.

Hundreds of thousands of people were evacuated (Dass-Brailsford, 2010). A few months before Hurricane Katrina, the Louisiana Department of Transportation and Development (LaDOTD) and the Louisiana State Police (LSP) facilitated emergency evacuation plans of southeast Louisiana, including the City of New Orleans. These two federal departments coordinated the transportation system to reduce traffic congestion and delay during the evacuations in the hurricane seasons. As a result, it was estimated that over one million people were evacuated using the highway system before Hurricane Katrina (Wolshon & McArdle, 2009). However, although the residents were notified to evacuate before the landfall, the scale and severity of Hurricane Katrina had caused massive loss of lives and damage to the city's infrastructures.

Hurricane Katrina was a massive evacuation case that involved a large number of evacuees within a relatively long period than other types of emergencies. The British Petroleum (BP) oil spill and explosion in the Gulf of Mexico in April 2010 is another type of evacuation that required an urgent response within a matter of minutes but involving fewer people than natural disasters such as Hurricane Katrina. The BP oil spill was one of the most massive ecological disasters in the U.S. (Perrow, 2011). It was a human-generated disaster and led to long-term environmental damage (Mitsch, 2010). An explosion at the Deepwater Horizon oil platform had caused fatality of 11 workers (Shultz, Walsh, Garfin, Wilson, & Neria, 2015). Immediately, the surviving workers started to evacuate the rig. Two lifeboats first evacuated, but 11 workers were left behind. Later, a life raft was launched, and seven more workers were evacuated. The remaining four workers jumped into the water and survived. Human factors played an essential role in this urgent evacuation: the workers had a high level of coordination to help each other escape during the evacuation. They were familiar with the surrounding environment; thus, they were able to choose the fastest route and alternative routes or exits. The equipment also provided necessary information such as pressure and fire warning to the evacuees. Their knowledge and experience helped them to leave the rig safely (Skogdalen, Khorsandi, & Vinnem, 2012).

In the aviation industry, aircraft evacuations occur due to various kinds of emergencies. For example, in October 2016, an American Airlines Boeing 767's right engine caught on fire during takeoff and made an emergency evacuation on a runway at Chicago O'Hare International Airport. In total, 161 passengers and nine crewmembers evacuated via slides, and 20 people received different levels of injuries (Hradecky, 2016). A United Bombardier CRJ-700 had an emergency evacuation on the runway at Denver International Airport due to left engine fire in July 2017. In total, 59 passengers and four crewmembers evacuated via aircraft stairs, and no injuries were reported (Hradecky, 2017a). On July 11, 2017, a Delta Airbus A320 made an emergency landing at Daytona Beach International Airport because of the cracked windshield after hail strike (Sandoval, 2017). In total, 132 people on board were evacuated safely (Hradecky, 2017b). The Federal Aviation Administration (FAA) adopted a 90 seconds aircraft evacuation rule for airworthiness certification (Federal Aviation Administration [FAA], 2017). This "90s rule" is required for the manufacturers and the airlines that the airplane needs to be fully evacuated within 90 seconds, with its maximum seating capacity and less than half exits available. Numerous studies were conducted in response to 90 seconds rule to simulate aircraft evacuation to increase evacuation efficiency so that the passengers could survive an aircraft accident (Miyoshi, Nakayasu, Ueno & Patterson, 2012).

Aircraft evacuation usually is conducted in a manner under the guidance of crewmembers, unless under severe conditions such as a crew-fatal crash in which passengers would need to self-evacuate. Another type of common evacuation situation in the aviation industry is airport evacuation when an emergency occurs. Airport evacuation often involves additional factors such as diverse populations of evacuees and more complicated and unpredictable factors. Although airport evacuation is similar to building evacuation at certain circumstances, there are still some unique factors associated with airport evacuation that need to be considered when planning for emergency evacuations, including human factors and policy factors. Airport evacuations also happen more often than aircraft evacuations for a variety of reasons. During the April 4, 2010, Baja California earthquake which shook the Mexico–United States border at southern California over a minute (Steinhauer, 2010), San Diego International Airport (SAN) Terminal 2 was evacuated after a water leak and potential natural gas leak (Hall & Baker, 2010). Based on the closest historical data, SAN had 1,361,558 passengers in April 2011, with approximately 45,000 passengers per operational day in April (San Diego International Airport, 2012). The evacuation in the major terminal, Terminal 2, was estimated to affect thousands of passengers according to the historical data potentially. On November 11, 2016, SAN was evacuated for about 15 minutes due to a faulty smoke alarm near Gates 3-10 at Terminal 1. Passengers were observed to be frustrated and rushed to catch the flight because thousands of passengers had to go back through security lines after the situation was cleared (Zabala & Garske, 2016).

On January 4, 2010, Newark Liberty International Airport (EWR) Terminal C was evacuated after a man walked the wrong way past a security checkpoint without security screening until noticed by another passenger (Barron, 2010). On January 16, 2010, John F. Kennedy International Airport Terminal 8 was evacuated because a passenger opened a restricted door and walked through the door. In both cases, the airports had to evacuate the secure areas, which resulted in massive delays ("JFK Terminal is Evacuated," 2010).

On October 24, 2016, London City Airport (LCY) was evacuated due to chemical concerns. Around 500 passengers were evacuated after several people became ill and were coughing violently because of chlorobenzylidene (CS) gas, which is used for crowd control ("London City Airport Declared Safe" 2016).

In addition to natural disasters, technological disasters, and hazardous materials releases, terrorist attacks become an urgent issue in contemporary security for modern aviation. On January 6, 2017, a gun shooting happened at Fort Lauderdale-Hollywood International Airport (FLL) at the Terminal 2 baggage claim area in the lower level. The shooter killed five passengers and wounded six passengers. Dozens of travelers were injured during the evacuation of Terminal 2. Miscommunication regarding a possible second shooter in Terminal 1 led to another mass evacuation and airport closure for inspection (Gomez, 2017; Vielma, 2017).

The terrorist attack on September 11, 2001, resulted in a large-scale evacuation of mixed-ability populations in and near the two collapsed high-rise World Trade Center (WTC) buildings. The massive explosions and fires urged the residents in lower Manhattan to evacuate their houses, and the subsequent damages disrupted their lives for months and even years (Farfel et al., 2008). The Department of Homeland Security was established in 2002 in response to the 9/11 attack (Fagel et al., 2013).

The impact on the WTC Tower one occurred at 8:46:30 a.m., the next impact on the WTC Tower two occurred at 9:02:59 a.m. Firefighters and trained personnel were assisting the evacuation after impact. Full-scale building evacuation on Tower one began immediately after the first impact. Although no evacuation order was issued for Tower two after the first impact, some occupants in Tower two decided to evacuate. The 16 minutes gap between the impacts on Tower one and Tower two contributed to the higher survival rate in Tower two. Within one hour, the WTC Tower two collapsed at 9:58:59 a.m., later WTC Tower one collapsed at 10:28:22 a.m. (Averill et al., 2005; Shields, Boyce & McConnell, 2009). The National Institute of Standards and Technology (NIST) estimated the total populations inside both towers when the first impact happened was 17,400 ± 1,180 occupants, and 2,146 to 2,163 perished (Averill et al., 2005).

1.5 Emergency phases and evacuation processes. Vorst (2010) suggested measuring psychological parameters based on John Leach's Dynamic Disaster Model. This disaster model describes a disaster in three phases and five stages. In each phase and stage, people will have different psychological reactions; therefore, different human behavior can be observed. The first phase is the pre-impact phase, which contains the threat stage and warning stage. The second phase is the impact phase. The third phase is a post-impact phase, which includes the recoil stage, rescue stage, and post-traumatic stage. Evacuation can happen in all three phases and four stages except for the post-traumatic stage in the third phase.

Similarly, Alexander (2013) suggested that an emergency has five phases: 1. initial emergency, 2. consolidation, 3. recovery, 4. investigation, and 5. stand down. In the first phase, external help and assistance usually are not available. Evacuees need to evaluate the situation and respond based on the information available. This first phase is when the pre-evacuation and self-evacuation happens. In the second phase, external forces will come to the affected area and start working, including guiding the evacuation, rescuing people who are trapped or injured, controlling the scene, and eliminating the emergency event (Alexander, 2013). In this phase, guided evacuation happens. The third, fourth, and fifth phases involve restoring the situation, collecting information, and returning to normality. This paper simulated human behavior and evacuees' psychological response under emergencies; therefore, the researchers focused on the human factors in the first two phases, which are the initial emergency phase and consolidation phase. Because in these two phases are where pre-evacuation, self-evacuation, and guided evacuation is happening. Total evacuation time includes these three evacuation processes.

There are also many studies that focus on evacuation processes. According to the International Organization for Standardization (ISO) technical report ISO/TR13387-8 (International Organization for Standardization [ISO], 1999), the evacuation process consists of pre-movement and movement processes. During the pre-movement process, occupants receive warnings such as alarm or cue of fire that urge evacuation. This process has two components, which are recognition and response. Recognition time is after an alarm goes off or a signal of fire is given before occupants respond to the warnings. During the recognition time, occupants remain to do pre-alarm activities (e.g., eating, sleeping, working, and watching TV). This period ends as soon as occupants realize the necessity to respond. Response time is after occupants realize they need to respond before occupants begin to evacuate. During the response time, occupants stop pre-alarm activities and prepare to evacuate (e.g., terminating machinery, securing important items that cannot be carried, collecting light and essential belongings, gathering family members, investigating the risks, planning escape routes, deciding exits if inside a building, and altering others).

The second process is the movement process. This process is after occupants start to evacuate until they have reached a safe place. Movement can occur during the pre-movement process; therefore, the term "movement process" is strictly for occupants that start to evacuate towards exits or escape routes to leave the building or reach a safe place (ISO, 1999; Purser & Bensilum, 2001). According to Purser & Bensilum (2001), pre-movement time usually determines the total evacuation time. If occupants respond slowly in the pre-movement process, the difficulty of escaping during the movement process may increase. In a crowded environment such as stadium or shopping mall, evacuation time is depending upon the pre-movement time of the first occupant who recognizes the emergency to the movement time of the last occupant to leave the hazard zone (Purser & Bensilum, 2001).

In the next section of the literature review, studies related to human behavior change and psychological change under emergencies, crowd behavior, panic behavior, and factors affect human behavior change are reviewed. In section 2.1., Leach's Dynamic Disaster Model and Alexander's emergency phases will further be discussed. Based on the reviewed literature, three categories of factors that impact human behavior change (i.e., human factors and policy factors) are concluded.

Human Behavior Changes Under Emergency

Human behavior changes in response to emergencies are complex. Human behavior varies as a function of different psychological changes during different emergency phases. These human behaviors may negatively or positively affect the efficiency of an emergency evacuation. In this section, studies related to human behavior changes and psychological change under emergency such as crowd behavior and panic behavior as well as human factors that affect human behavior is reviewed.

2.1 Human factors and psychological parameters. Vorst (2010) stated that to replicate emergencies accurately, human behavior needs to be considered when simulating an evacuation. For example, stress can be a negative impact that evacuees develop, and, human behavior, such as walking speed, will consequently change.

Human factors have been studied extensively in the field of disaster psychology. Vorst (2010) explained disaster psychology as the psychological changes people experience before or during the disaster; therefore, affect human behavior. Vorst (2010) used the evacuation rate before and after a hurricane to explain this field of psychology. For example, Vorst (2010) stated that before a hurricane makes landfall, 30% of all residents refuse to evacuate; after a hurricane makes landfall when the specific emergencies changes to be more urgent, 5% of all residents refuse to evacuate. Another example of a behavioral parameter difference is that women need 20% longer evacuation time than men due to the higher stress level (Vorst, 2010).

As mentioned in 1.5., Vorst (2010) provided suggestions on how to measure psychological parameters based on Leach's Dynamic Disaster Model. This disaster model describes a disaster in three phases and five stages. In each phase and stage, people have different psychological reactions; therefore, different human behavior can be observed. The first phase is the pre-impact phase, which contains a threat stage and warning stage. The pre-impact phase can be very short, for example, in traffic accidents, in which there is typically minimal warning time before impact. This phase can also be very long, in the scenario of a volcano eruption where there is generally ample time before impact. When the disasters have longer pre-impact phase are anticipated to happen, the risk of the upcoming event can be underestimated because the disaster has not happened yet in the pre-impact phase. Therefore, evacuation progress usually is slow. Typical human behavior in this phase is ignoring or denying the emergency and being apathetic to the imminent danger (Vorst, 2010).

The second phase is the impact phase. In this phase, evacuation is carried out immediately because of heavy stress and avoidance of life-threatening events. The length of the impact phase depends on the type of the events involved. When the impact phase is relatively short, evacuees are often confused and hampered with excessive information and may be upset or emotional. Under these time pressures, human behavior becomes reflexive, automatic, and mechanical (Vorst, 2010). According to the data stated by Vorst (2010), most of the evacuees (more than 75%) show apathetic and nervous behavior during the impact phase. Some people (about 15%) are overactive and lose emotional control. Ineffective behavior is commonly seen. Only a small portion of the population (about 10%) can remain calm and potentially lead the evacuation (Vorst, 2010).

The third phase is the post-impact phase, which contains a recoil stage, rescue stage, and post-traumatic stage. In this phase, the damage of the impact is visible, but evacuees may suppress realities, show irrational emotions, or develop emotional disorders. Especially in the recoil stage, human behaviors such as inactivity, simple behavior, apathy, and childlike dependency on others often can be observed (Vorst, 2010).

In each phase and stage, human behaviors, as well as evacuees' emotional and cognitive states, are significantly different. Evacuation can happen in all three phases (i.e., pre-impact phase, impact phase, and post-impact phase) and four stages (i.e., threat stage, warning stage, recoil stage and rescue stage; Vorst, 2010). Evacuation will stop in the last stage of the last phase, the post-traumatic stage. In this stage, survivors try to rebuild their lives. No more urgent evacuation from the life-threatening event will occur anymore. To represent the entire evacuation process, a comprehensive simulation model should include human behaviors and evacuees' psychological responses during each of the three phases and four stages, except the post-traumatic stage (Vorst, 2010).

The main purpose for Vorst (2010) to introduce Leach's Dynamic Disaster Model was to provide a grouping method of psychological variables so that the psychological behavior parameters can be implemented in the evacuation models. The first step of the grouping method is based on the evacuees' characteristics, which could include commitment to ongoing tasks, temporary status (i.e., the effects of disease, sleep, alcohol, drugs), personal effectiveness (i.e., problem-solving style, achievement motivation), intelligence, preferred moving speed, and so on (Abolghasemzadeh, 2013; Cassidy, 2002; Mu et al., 2013; Purser & Bensilum, 2001). The inclusion of such parameters in a simulation is scenario-specific. This way, the second step is to identify the phase and stage of the emergency. Many previous literatures studied human behavior under emergency during the pre-movement process and movement process. Vorst (2010) also describes procedures to estimate the psychological behavior parameters such as collecting empirical data from national research centers, referring to previous literature, and making smart guesses when developing models. Many of these grouping methods and model development procedures are discussed later in this review.

As mentioned in section 1.5, there are other variations in classifying the different phases of the emergency in addition to Leach's Disaster Model. Alexander (2013) described an emergency in five phases: 1. initial emergency, 2. consolidation, 3. recovery, 4. investigation, and 5. stand down. Evacuation can happen in the first two phases. According to ISO (1999), the evacuation phase consists of pre-movement and movement processes. Separating the evacuation phase into two processes can help build a simulation model that can quantify human behavior and measure psychological parameters, and therefore, accurately measure evacuation time. In the following two sections, previous literature regarding human behavior under emergency is reviewed based on the pre-movement and movement processes of evacuation.

Combining the Dynamic Disaster Model and current comprehensive studies on fire evacuation (Knuth, Kehl, Hulse, & Schmidt, 2013; Mu et al., 2013; Purse & Bensilum, 2001), a fire scenario is used as an example to demonstrate human behavior change under emergency. These behaviors are consistent and transferable across different kinds of emergencies (Vorst, 2010). It is worthwhile to note that the same theories and concepts can be applied to building evacuation, airport evacuation, traffic accident evacuation, natural disaster evacuation, and so forth.

Human behavior in the pre-movement process. Both the pre-impact phase and impact phase can be viewed as a pre-movement process. Vorst (2010) stated human behavior such as ignoring or denying the emergencies and being apathetic to the imminent danger is common in the first pre-impact phase in an emergency. Ineffective behavior is commonly seen in the impact phase. Some widely observed human behavior in the pre-movement process involves the response to warnings, which is sometimes slow because the event usually is not life threating yet to urge people to run for life immediately (Purser & Bensilum, 2001). According to Mu et al. (2013), human behavior such as confirming information regarding the fire, extinguishing the fire, and alerting other people can be observed in the pre-movement process. Purser & Bensilum (2001) observed human behavior such as collecting information about the emergency, collecting important belongings, and choosing an optimal exit to escape in the subsequent pre-egress time.

In Purser's studies in 1994 and 1998 (as cited in Purser & Bensilum, 2001), the author studied a fire evacuation in a department store using video analyses approach. At the time of the fire, the department store had a sales area and a restaurant full of retired people and young mothers with children. Behaviors such as warning the staff, shouting at other shoppers, activating the fire alarm, calling the fire department, trying to fight the fire, and gathering or waiting for other family members to leave was observed in the pre-movement process. For example, a retired couple had split up in the restaurant, and the husband searched around the store for his wife before he evacuated. Purse & Bensilum (2001) concluded that people need strong cues regarding an emergency (e.g., fire, smoke) to recognize the importance of evacuation, cease their normal activities, and change their behavior to evacuating. Some emergencies (e.g., fires, hurricane, flooding, or the situation in WTC Tower Two after the impact of WTC Tower One) may not threaten the occupants initially; however, once the risk or danger become visible, it can grow rapidly thus leave a very short period to evacuate. In this case, occupants whose responses are delayed for a long period during the pre-movement process may become trapped in a dangerous situation. Incident analyses have shown that there is a connection between a delayed evacuation and a high number of fire deaths or injuries, particularly in residential and hotel buildings (Purser & Bensilum, 2001). Therefore, the process in the pre-movement phase is believed to be more decisive to survival than the actual movement process (Kobes et al., 2010).

Human behavior in the movement process. During the egress time, human behavior such as wayfinding, choosing an escape route and alternatives if necessary, and movement towards the selected exit is observed (Purser & Bensilum, 2001). Sime (1994; as cited in Cassenti, 2018) stated that for evacuees who are not familiar with the environment, wayfinding or choosing an escape route usually depends upon the way the evacuees entered the building, and other escape routes or emergency exits may be easily overlooked. In Purser's studies of a fire evacuation in a department store in 1994 and 1998 (as cited in Purser & Bensilum, 2001), when the store was utterly smoke-logged, people sought the fastest ways to exit the store, including climbing out of the front windows onto a first-floor ledge. Because of the elderly population in the restaurant, some families were moving slowly to accommodate their elderly family members, although most family members were young and could move quickly.

2.2 The decision-making process. The above section discussed human behaviors under emergencies; however, before human beings act, they first undergo the decision-making process. According to Mu et al. (2013), risk perception and decision-making are the two of the most critical determinants of human behavior. Evacuation is just one of the behaviors evacuees may choose during the pre-movement process of an evacuation. People first will perceive, recall, and think about emergencies, which can be viewed as their perceptions of risks. Next, people process the information and make decisions before behaving. The output of this process is the actions that they execute during an emergency. In this section, literature regarding the decision-making process of evacuees, as well as the factors impacting decision-making is reviewed.

According to Gantt & Gantt (2012), decision-making is a process that individuals use to identify a proper response to emergencies. Human behavior under emergency is thus a reflection of the human decision-making process (Gwynne, Galea, Lawrence, & Filippidis, 2001). Ozel (2001) stated that human behavior under emergency is a decision-making process. There are three stages in the decision-making process, which are risk identification, risk assessment, and risk reduction. Risk identification involves noting the risk signals, for example, the presence of smoke or the increasing sea level during a hurricane. Once the existence of risks is identified, individuals make decisions by assessing the likelihood and severity of the risks. After evaluating the risks, individuals determine protective measures to reduce potential dangers (Gantt & Gantt, 2012).

To accurately predict and measure the change in human behavior, numerous studies have been carried out to determine the factors affecting decision-making. In an evacuation, evacuees use environmental cues to process information to promote the selection of an escape route. Limited time pressure and stress from physical threats (e.g., fire, smoke, and flood) are some of the environmental cues that affect evacuees' information processing. Different environmental cues provide different information for decision-making, ultimately resulting in variations in evacuees' behaviors. As human beings have limited information processing capacity, they tend to seek the most beneficial information to optimize decisions (Ben Zur & Breznitz, 1981; as cited in Ozel, 2001). Other than environmental cues, people also rely on warning messages from governmental authorities, information from others, and previous experience with similar scenarios to correctly identify and assess risks, make optimal decisions, and take appropriate actions (Gantt & Gantt, 2012).

Situation Awareness is the primary basis for subsequent decision making and performance in the operation of complex and dynamic systems. Endsley (1988) defines Situation Awareness as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future." This formal definition of Situation awareness breaks the idea down into three levels; Level 1 is the *perception* of the elements in a dynamic environment, level 2 is the *comprehension* of the current situation, and level 3 is the *projection* of future status (Endsley, 1988). Pedestrians with good Situation Awareness would know where to evacuate and which is the most efficient way to evacuate by retrieving appropriate information, understand what the information means regarding relevant goals, and then by predicting what will happen in the near future. However, pedestrians with poor Situation Awareness would easily get lost and often miss the best evacuating opportunity by failing to receive the information they need, or even though they receive the information but not interpreting it properly. The reason for incorrect interpretation could span from; workload, panic, and lack of knowledge.

Prior experiences also shape evacuee decision-making. According to Abolghasemzadeh (2013), in dangerous situations, decision-making is influenced by previous experiences with similar cases and psychological state, and physiological abilities determine behavior. Gwynne et al. (2001) listed factors such as familiarity with the environment, availability of external cues (i.e., warnings, signage, indications, presence of other evacuees or staff), and personal experience usually affect evacuees' decisions. Noticeably, familiarity with the environment and personal experience may not promote optimal decision-making. It may also promote a selective knowledge of the environment and lead to ignorance of alternative exit routes. Evacuees may try to escape from the further exits with which they have had previous experienced, instead of moving towards the closest exit of which they may have no prior knowledge. Bode & Codling (2013) reported that evacuees preferred to use exit routes they were familiar with; even if the route was jammed, evacuees were less able or willing to change their decisions and choose alternative routes under the motivational messages given during the experimental evacuations. As stated by Turner and Killian (1957; as cited in Gwynne et al., 2001), the familiarity with the environment may limit the number of escape options perceived as available. In a pressured environment, decision-making can defer to the familiar mode in mind; instead of making rational decisions based on environmental cues and feasible methods (Kahnemen & Tversky, 1979).

Emergencies demand decision-making under time pressure (Knuth et al., 2013). According to Staw, Sandelands, & Dutton (1981), stress, anxiety, and arousal are the immediate consequences of threat, and may individuals undergoing such states tend to make decisions based on internal hypotheses and dominant cues. The inappropriate dominant response, however, can impair decision-making because it results in the neglect of processing unusual information or by reinterpreting the unusual information to fit previous experience or their expectations (Rice, 1990). For example, after the initial attack of WTC Tower One on September 11, 2001, the emergency operators did not evacuate the people in WTC Tower Two immediately because they did not expect Tower Two to be jeopardized, which had worsened the situation (Van de Walle & Turoff, 2008).

In the worst case, when evacuees start to feel hopeless about escaping from the danger, they may enter the highest level of stress for the decision-making phase, which is hypervigilance. Aldag (1980) stated that human decision-making pattern could be vigilance, which referred to thorough information search and unbiased assimilation of new information. The authors also stated that human beings have four defective decision-making patterns. First was adherence to the current course of action. Second was adherence to changes to a new course of action. The third was defensive avoidance of decision-making, for example, procrastinating, shifting responsibility, or bolstering the preferred alternative. Four was hypervigilance, the highest level of stress and most extreme form of presence, for example, panic emotion and panic behavior as a consequence (Aldag, 1980). Such a high level of stress can lead to errors in decision-making under emergency (Ozel, 2001).

Successful decision-making depends on the extent to which the information available and the time available for processing the information are limited (Heliovaara, Kuusinen, Rinne, Korhonen, & Ehtamo, 2012). In an emergency, decision-making is like a choice-between-gambles task because the time pressure and stress from time constraint and other physical life-threating cues affect the intention of optimizing decisions (Ben Zur & Breznitz, 1981; as cited in Ozel, 2001). When an emergency happens, decision-making requires immediate and effective action under the pressures of incomplete, unacceptable and invalid information (Yoon, Velasquez, Partridge, & Nof, 2008) during very intense periods with very short-term deadlines. Therefore, an adequate amount of information provided to the evacuees can promote decision-making behavior (Proulx & Sime, 1991; Proulx, 1993). Evacuees continuously review their decisions during evacuation by assessing the surroundings and processing additional information to determine if they need to change their decisions. However, it is also possible that evacuees may attend to the same information differently under stress, and if the stress level becomes intense, evacuees may experience distortions in the decision-making capacity to the extent that they cannot process all the information or develop false risk perception (Mu et al., 2013; Ozel, 2001). Evacuees may end up attending to the threatening aspects of the situation and ignoring the positive aspects of alternative routes or abandoning decision-making in favor of following group behaviors (Ozel, 2001).

Hasan & Ukkusuri (2011) also pointed out that the complexity of social networks could also affect decision-making. During a hurricane evacuation, evacuees need to decide if they are going to evacuate, when, where and how to evacuate, and these decisions are determined by risk level perception, resource availability, individual characteristics, and social influence. Particularly, there are three different levels of social influence, which are individual, household, and community. The researchers investigated the social contagion processes in different communities and found faster information flow in the community of individuals living close to each other. Also, large social networks act as a single community when the connections among communities are strong; in other words, the information flow is faster among these communities. Conversely, the community of individuals having fewer connections with others requires additional interventions to ensure successful evacuation.

2.3 Policy factors. The emergency response plan and emergency management strategy of the company, as well as rescue response from governmental organizations, can also impact human behavior during an evacuation (ISO, 1999). There are numerous policies, regulations, and laws existing to deal with the egress and evacuation of individuals (Abolghasemzadeh, 2013). For example, the Robert T. Stafford Disaster Relief and Emergency Assistance Act (Stafford Act) is a national level regulation for emergency management. It authorizes the delivery of federal emergency technical, financial, logistical, and other assistance to states and localities for devastating events with the coordination of the Federal Emergency Management Agency (FEMA; Association of State and Territorial Health Officials, n.d.). For example, the Occupational Safety and Health Administration (OSHA) sets standards and guides evacuation policies, evacuation procedures, emergency escape procedures, and route assignments, as well as rescue and medical duties for designated workers in workplaces. OSHA indicates that the best emergency response plan should include employees' roles and duties, provide general training, and should be reviewed with them regularly (United States Department of Labor, n.d.). OSHA standards for evacuation plans and procedures such as Emergency Action Plans, Fire Prevention Plans, and standards for fire detection systems, employee alarm systems, fixed extinguishing systems and portable fire extinguishers, the Occupational Safety and Health Act are the main guidance for emergency planning (United States Department of Labor, n.d.). Also, general policies, standards, procedures such as fire alarm evacuation policy, emergency procedures, safety management system, and emergency response plan are enforced by any public venues, residential buildings, and so forth. Most of the policies, regulations, and laws are based on simplified application rules because of the difficulties of including human factors such as demographic factors, physical ability, and behavioral changes in evacuation research (Abolghasemzadeh, 2013).

To achieve an emergency response and recovery effectiveness, first responders such as firefighters, police, etc. need to be prepared and trained for various emergencies and decision support systems. Often in a large-scale disaster, people who work together have no history of doing so and as a result, do not have a basis for trusting in the abilities of others. Human beings factor their emotions, decision-making, intelligence, and experience into emergencies, which could have a direct impact on the emergency response. Confusion, injury, and property damage are mostly caused by disorganized evacuation. Some policies (rules and regulations) are used by organizations to coordinate employer and employee actions during workplace emergencies. In developing an emergency action plan; it is important to use properly designed policies that consider human factors which are critical parameters in policy development and have mutual influences on each other (Abolghasemzadeh, 2013).

The following chart summarized the human factors and policy factors that affect human behavior change, as mentioned in this section.

Human Factors	**Policy Factors**

The ability of evacuees (mental & physical) (Helbing et al., 2002; Cassidy, 2002; Purser & Bensilum, 2001)	Assignment of employees' roles & duties under emergency (United States Department of Labor, 2001)
Age (young or old) (Vorst, 2010; Helbing et al., 2002; Purser & Bensilum, 2001; Mu et al., 2013)	Construction standard (Abolghasemzadeh, 2013; United States Department of Labor, 2001)
Anxiety (Staw et al., 1981; Knuth et al., 2013)	Emergency response plan (United States Department of Labor, 2001)
Body size (Schneider & Kirchberger, 2006; Proulx, 2008)	Emergency management strategy (United States Department of Labor, 2001)
Commitment to ongoing tasks (Vorst, 2010)	Evacuation drill
Density (number of evacuees, crowd) (Purser & Bensilum, 2001;	Evacuation policy (United States Department of Labor, 2001)
Distribution of evacuees within the building (Purser & Bensilum, 2001;	Evacuation procedures (United States Department of Labor, 2001)
Educational level (Purser & Bensilum, 2001; Mu et al., 2013	Evacuation training for employees (United States Department of Labor, 2001)
Effectiveness (Problem-solving style, achievement motivation) (Cassidy, 2002)	Evaluation of policies (United States Department of Labor, 2001)

Engagement in work at the time of emergency onset (Purser & Bensilum, 2001)	Laws (United States Department of Labor, 2001; Abolghasemzadeh, 2013)
Familiarity with the environment (Vorst, 2010; Schneider & Kirchberger, 2006; Proulx, 2008; Purser & Bensilum, 2001;	OSHA policy and standards (United States Department of Labor, 2001)
Fear (Knuth et al., 2013)	Rescue response from governmental organizations
Gender (Vorst, 2010; Helbing et al., 2002; Purser & Bensilum, 2001; Mu et al., 2013	Regulations (United States Department of Labor, 2001)
Income **(**Benight & Harper, 2002)	Route management guidance (Abolghasemzadeh, 2013)
Individual or group (Ozel, 2001; Pan, 2006; Aveni, 1977; McPhail, 1991; McPhail, 1986; Nilsson & Johansson, 2009; Cocking et al., 2009; Vorst, 2010; Sime, 1983; Yang et al., 2005)	
Intelligence (evacuation strategies) (Vorst, 2010)	
Interaction with others (Purser & Bensilum, 2001;	
Knowledge (Vorst, 2010)	

Mobility (healthy or disabled) (Vorst, 2010; Helbing et al., 2002; Purser & Bensilum, 2001; Mu et al., 2013	
Panic (Miyoshi et al., 2012; Cocking et al., 2009; Helbing et al., 2002; Saloma et al., 2003**;** Gantt & Gantt, 2012; Abolghasemzadeh, 2013; Hu et al., 2014; Zakaria & Yusof , 2016; Schneider, 2008; Helbing et al, 2000; Hu et al., 2014)	
Personality trait (Xin et al., 2013)	
Preferred moving speed (Schneider & Kirchberger, 2006; Proulx, 2008)	
Preferred personal space (Schneider & Kirchberger, 2006; Proulx, 2008)	
Pre-movement time (recognition and response to the initial situation)	
Pressure (Helbing et al, 2000; Hu et al., 2014)	
Profession (Purser & Bensilum, 2001; Mu et al., 2013)	
Purpose of the trip (Helbing et al., 2002)	

Relationship to others in the group (if evacuating in the group)	
Roles in the group (if evacuating in the group) (Helbing et al., 2000)	
Relevant experience of evacuation (Vorst, 2010; Purser & Bensilum, 2001; Mu et al., 2013	
Scenario (Helbing et al., 2002)	
Step length (Schneider & Kirchberger, 2006; Proulx, 2008)	
Stress level	
Surrounding (Helbing et al., 2002)	
Time of the day (Helbing et al., 2002)	
Training of emergency situations	
Temporary status (physical health, sleep, alcohol/drug ingestion) (Purser & Bensilum, 2001; Mu et al., 2013	
The velocity of egress movement (Vorst, 2010)	

2.4 Crowd behavior. When people are stuck in a crowded environment, negative emotions can lead to serious consequences. Negative psychological reactions such as insecurity, anxiety, worry, or fear experienced during an emergency can lead to distress and worsen a threatening or harmful situation (Knuth et al., 2013). Helbing, Farkas, Molnar, & Vicsek (2002) described this phenomenon as "herding behavior," a type of irrational behavior that often leads to dangerous overcrowding and impaired escape. Helbing et al. (2002) viewed herding behavior as the result of social contagion, which is the transition of experience from individual psychology to mass psychology. Conformity in behavior can be observed, in which individuals tend to follow others' actions. According to Pan, Han, Dauber, & Law (2006), people dissolve their identities, motivations, and rationalities into a collective mind when being in crowds; therefore, behavior including decision-making differs in crowds in comparison to being alone or in a small group.

Further, behaviors like stampeding, pushing, knocking, and trampling on others, are commonly seen in crowds. These destructive actions are described as nonadaptive crowd behaviors and may result from an individual's high-stress level, inability to make decisions, social identity within a group, loss of personal space, high crowd density, severe external crises or emergencies, and high emotional arousal (Pan et al., 2006). Tragically, in human-made, technological and natural disasters, many injuries and deaths are the results of nonadaptive crowd behaviors or crowd panic rather than the actual cause of the emergency (Pan et al., 2006; Shiwakoti & Sarvi, 2013). Given the global trends of mass urbanization, terrorist attacks, natural disasters and mega-events, crowd control, especially nonadaptive crown behavior control, is becoming increasingly important (Shiwakoti & Sarvi, 2013).

On a macroscopic level, social structures of interaction also affect human behaviors in crowds. Pre-existing structures (e.g., family or friends) and structures formed at the time of emergency (e.g., queues) are the two social structures of interaction to be considered when studying crowd behavior (Tucker, Schweingruber, & McPhail, 1999). Previous studies have demonstrated that pre-existing social structures of interaction play a significant role in human behavior in crowds (Aveni, 1977; McPhail, 1991; McPhail & Wohlstein, 1986), specifically, people who come together to a location as a group also tend to move together, orient toward each other, and leave the location together. The closer the relationship among individuals is within a group, the more likely it is that they will behave as a single entity. Nilsson & Johansson (2009) also suggested that social structures of interaction increase with decreasing distance between people. Family, friends, or colleagues tend to influence evacuees more than groups formed by strangers. This behavior could potentially slow down the flow of the crowd if a large group with a strong relationship between people try to move together or move slowly to wait or look for other group members (Pan et al., 2006). Researches have also supported that the evacuation time generally increases as the density of the pedestrian group travel increases (Cheng, Reddy, Fookes, & Yarlagadda, 2014; Lu, Chan, Wang, & Wang, 2017; Zhao, Sun, Yao, Cui & Zhang, 2017).

According to Cocking, Drury, and Reicher's (2009) study of social attachment model in crowd behavior, in times of emergency, people normally display affiliative behaviors. Affiliative behaviors include moving from unfamiliar situations towards familiar people and places. When people need to escape from an urgent situation immediately, the time they spend to seek familiar people or move towards familiar place could slow down the evacuation process. After the reunion with the familiar group, the chance of individual escape is decreased. The larger the group one is in; the longer people take to evacuate. In other words, social attachment model delays egress.

Vorst (2010) stated that in evacuations, most evacuees will refuse to evacuate without their families or will not be able to evacuate without help from their families. Sime (1983) also concluded that groups of individuals who have a very close relationship with would exhibit group evacuation behavior at great personal risk. Highly attached group first search for other group members before attempting to exit. For instance, evacuees would search for their family members before exiting, although the situation could be very dangerous. A parent would refuse to leave a burning building without his/her child. Sime's study in 1983 showed that some evacuees that were not together with their families when an emergency occurred would still find each other and were grouped at their exit. Family is the closest relationship, so that they are more likely to stay together. Close friends or colleagues somewhat less and casual acquaintances (e.g., hotel guests) were unlikely to stay together if not necessary (Sime, 1983).

Other than the social structures of interaction that affects evacuees' decision-making to move as a group, evacuees sometimes experience the phenomenon called *going with the crowd* when they abandon their thinking and adopt actions by following others (Yang, Zhao, Li, & Fang, 2005). For example, when the visibility is very low due to smoke in a fire, evacuees who are prone to the phenomenon of going with the crowd may be easily affected by other evacuees and follow the crowd movement. Although following the crowd is not always harmful, doing so irrationally can reduce the efficiency of using exits, lead to wrong route choices, and result in jamming. Sometimes evacuees follow the crowd movement due to limited information (Sime, 1983). For example, evacuees may crowd together in hopes of finding an exit due to limited visibility; in this case, following other evacuees in front of them may lead to moving towards an exit safely or unsafely (Sime, 1983).

2.5 Panic behavior. Panic-related emotions and panic behavior also influence decision-making and consequent human behavior changes. Armfield (2006) found that the risk level of disasters affects the severity and distribution of panic. Cocking et al. (2009) believed social attachment model of crowd behavior is a better description of human behavior under emergencies than a panic model. Under panic situations, people prefer to move towards the desired walking direction, even if the direction they are heading to is jammed. People prefer not to take detours or move opposite to desired walking direction (Helbing et al., 2002).

Saloma, Perez, Tapang, Lim, & Palmes-Saloma (2003) studied the dynamics of escape panic in mice as an analog to the escape panic of human evacuees. Saloma et al. (2003) concluded that human panic behavior was influenced by the architecture of the space to which they are confined. The experiment showed that exit with larger and wider door resulted in a higher escape rate. However, more exit number did not result in a higher escape rate. It is because mice are (also known as) allelomimetic, therefore they all tried to escape from one exit door. Herding prevented the full utilization of the two exit doors in the experiment. Pedestrians are not allelomimetic, thus, the second result does not apply to human evacuation (Saloma et al., 2003). Gantt & Gantt (2012) identified environmental and situational cues that may generate and facilitate panic behavior: 1. Perception of an urgent and immediate threat to him/herself and/or loved ones, 2. The belief that escape from the emergencies is possible, however, the escape routes are becoming inaccessible and time to escape is rapidly decreasing, and 3. Feelings of helplessness, especially when others are not willing or not able to help.

Panic-related emotions, which can influence decision-making behavior and therefore, actions, can spread to others easily. Because of the ethical difficulties associated with measuring panic, the consequent human behaviors are thusly, somewhat unpredictable (Abolghasemzadeh, 2013; Hu, Sheu, & Xiao, 2014). According to Zakaria & Yusof (2016), previous studies equated panic with fear and anxiety because it was believed that these three conditions would transform into the same emotion eventually. Anxiety refers to vigilance regarding a possible threat, evaluating whether the situations are certain or uncertain, and attempting to survive amid a threat. Fear is similar to anxiety, but with greater intensity. Panic is a more intense extension of the fear and arises when an individual is overwhelmed by physical and mental feelings, such as in a sudden life-threatening threat. The human body will turn to an optimum state for survival when panic emotion arises (Zakaria & Yusof, 2016).

Panic occurs when fear becomes the dominant emotional motive or dominant psychological entity of a group. Panic is the internal state of human beings under collective phenomena (Keating, 1982; Schneider, 2008). Schneider (2008) concluded that strong fear disables an individual's conscious and planned behavior, reduces rational behavioral patterns, and increases instinct-guided behavior and rigidity. When an individual is exposed to great danger, the usual conscious personality is replaced by the unconscious personality that produces irrational actions unless there is a presence of a strong positive social (e.g., a leader) influence.

In addition to fear, according to Schneider (2008), the bodily sensation of physical pressure caused by contact with other bodies confined in space also has the potential to cause panic. Under emergencies, aggressive human behavior may happen due to the competition for resources like space or escape opportunity. If the pressure is not managed properly, panic behavior, which is associated with being thoughtless, instinctive, and rigid, can easily worsen emergencies and claim lives. Schneider (2008) also indicated that crowding is another factor that leads to fear.

Panic behavior can lead to a faster-is-slower movement trend, in which individuals attempt to move faster but cause slower flow through a bottleneck in the exit route (Helbing, Farkas, & Vicsek, 2000; Hu et al., 2014). The harder the evacuees push towards an exit, the more pressure and interpersonal friction forces will occur in the crowd. In a crowded environment, physical pressure, fear, and anxiety, as well as panic develop quickly. Evacuees sometimes tend to develop blind activism and start pushing, and interactions among evacuees become physical. Increased physical interactions can easily cause evacuees to fall or to be injured; become obstacles on the escape route and slow down the evacuation process. The bottleneck usually is the resulting clogging, arching, and the jammed crowd builds up in front of the exit. Unavoidably, moving, or passing a bottleneck frequently becomes uncoordinated (Helbing et al., 2000). Panic stampede is a kind of collective behavior that may cause the death of people who are either crushed or trampled by others.

In contrast to the literature reviewed above, other studies have suggested that egocentric, adverse or non-adaptive panic behavior is not necessarily common during emergencies (Aguirre, 2005; S. J. Blake, Galea, Westeng, & Dixon, 2004; Bohannon 2005; Cocking et al., 2009; Mawson 2005) and some studies have critiqued the overuse of the term "panic" when describing behaviors during disasters. Cocking et al. (2009) conducted two interview-based studies on two groups of survivors from different emergencies and found that most evacuees denied that panic or non-adaptive behaviors occurred; instead, evacuees reporting coordinated and humane treatment towards others at the time of egress. The authors indicated that not enough evidence could be used to support the occurrence of mass panic in crowds; instead, the findings reflected a genuine sense of common identity that develops as an emergency unfolds. S. J. Blake et al.'s (2004) study of human behavior of evacuees in the WTC Towers One and Two during the 9/11 attack showed that during the pre-evacuation phase, only 0.8% of the evacuees were noted to exhibit egocentric or irrational behaviors. S. J. Blake et al. (2004) concluded after conducting a qualitative research analysis of the database developed by the Fire Safety Engineering Group (FSEG) of the University of Greenwich. This database contains most human behavior records during the WTC evacuation. The data was collected from the literature published in the public domain including books, journals, and the electronic media; survivor accounts printed in newspapers and newspaper web sites, interviews in the electronic media, survivor web sites and books.

2.6 Leadership. Leadership is a factor that had been addressed in the evacuation studies. The proportion of leaders in the overall population size was investigated to influence the evacuation efficiencies. Ma, Yuen, and Lee (2016) researched that a smaller percentage of leaders in large size of the crowd and a larger percentage of leaders in a small size of crowd tend to achieve higher satisfactory guidance for evacuees. However, they also suggested that leadership may not always improve the evacuation. Instead, it can affect the evacuation in a negative way when the achieved visibility range of a group of evacuees of the environment was high enough (Ma et al., 2015). Dyer et al. (2008) conducted several real-life experiments to test the effects of the number of leaders at an emergency on the group dynamics. They found that just one leader would be capable of guiding a whole group to a destination without obvious signaling or verbal communication.

The number of leaders was also considered in different scenarios regarding the number of exits. Hou, Liu, Pan, and Wang (2014) used a social force evacuation model to demonstrate how emergency leadership could influence an evacuation. To maximize the efficiency in an emergency, they suggested to match the number of leaders with the number of exits and make each leader head to different exits in case of an emergency. From the research, they suggested that the evacuation process was tested not to be significantly faster when the number of leaders was higher than the number of exits.

Identified guiders, who were known by the evacuees as a leader, were tested to have more conductive instructions on evacuees than unidentified guiders. As for the guidance given by the leaders, Cao, Song, & Lv (2016) supported that dynamic guidance acts more effectively than static guidance. Dynamic guidance is when the leaders move around the environment, while the static guidance is when the leaders keep staying at the same spot during the evacuation process.

In addition to the number of leaders in an evacuation, the position of the leaders was found significant in the evacuation process (Hou et al., 2014). In terms of the distribution of the leaders, leaders in a uniform distribution were suggested to make a more positive effect in evacuation than leaders in other distributions by covering the largest area and the number of evacuees (Cao et al., 2016). In contrast, Hou et al. (2014) suggested that the center distribution is more effective than the other distributions. The four types of distributions are shown below in Figure 1.

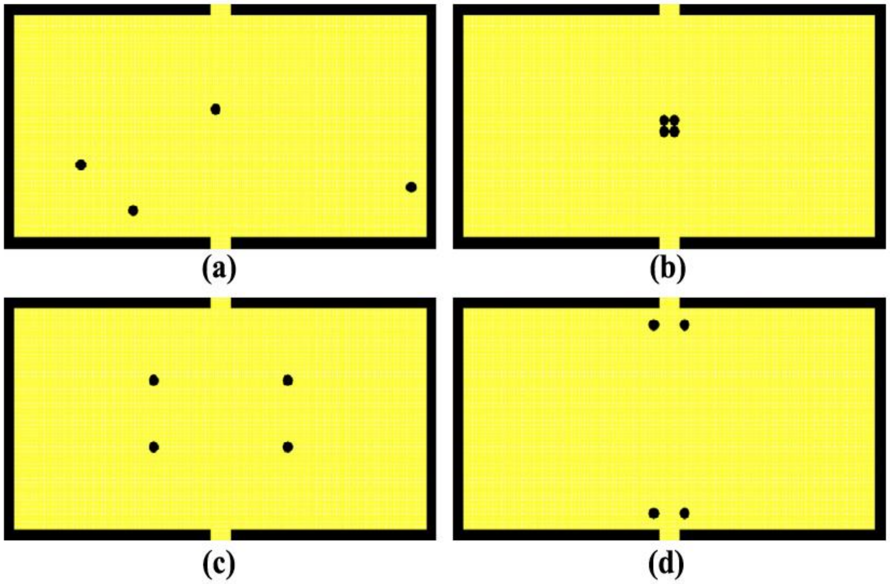


Figure 1. The black circles represent guiders' positions in the room. (a) Random distribution, (b) center distribution, (3) uniform distribution, (4) exit distribution., by Cao, Song, and Lv, 2016.

Previous Studies and Simulations

As previously mentioned, emergencies could impair individuals' lives and health. Therefore, collecting, studying, and analyzing various emergencies would be an optimal approach to prepare for emergencies. Due to emergencies have specialties, which are unpredictability and abruptness, data measurement of human behavior changes are generally difficult to collect. As a result, an experiment of emergencies is a suitable strategy for gathering these missing yet necessary data.

3.1 Studies with human participants. A fire accident is one of the most common emergencies in daily life. Fire accident can extremely endanger people' life and can occur everywhere at any time. The U.S. Fire Administration (USFA) reported a total of 1,298,000 fires that had happened in 2014 (U.S. Fire Administration, n.d.). These fire accidents caused 3,275 deaths, 15,775 injuries, and total loss of USD 11.6 billion (U.S. Fire Administration, n.d.). To prevent people from unnecessary injuries and life loss in similar emergencies, researchers had to understand people's reactions throughout an entire emergency process.

To investigate how the spatial factor can influence human, researchers had experimented fire emergency evacuation in certain narrow configurations, such as in an airplane cabin. In 1991, for instance, an experimental study of how fast passengers could be evacuated from a McDonnell Douglas MD-11 when an emergency like fire situation was carried out (Gow & Clark, 2006). The result of the study showed that 421 participants spent a total of 132 seconds to evacuate from the airplane, but 28 of them were injured in the simulation (Gow & Clark, 2006). On March 26th, 2006, another airplane manufacturer, Airbus, did an evacuation test for its aircraft A380-800, which has a maximum capacity of 853 passengers and 20 crew members ("A380 successful evacuation trial", 2006). The simulation test only spent 78 seconds to evacuate all the 873 individuals on board ("A380 successful evacuation trial", 2006). Despite one of the participants fractured the leg, and another 32 participants were suffered minor injuries during the evacuation, the result was entirely successful as well as undeniably under FAA's 90 seconds aircraft evacuation rules (Gow & Clark, 2006; "A380 successful evacuation trial", 2006).

Participants, nevertheless, could be injured easily, even in fully prepared emergency simulations (Marcus, 1994). To ensure participants' safety, any simulation studies that involve human participants must be initially approved by the Institutional Review Board (IRB) nowadays (Office for Human Research Protections, 2016; Penslar, 1933). According to Title 45 Code of Federal Regulations (CFR) Part 46, IRB is a committee that has been formally designated to approve, monitor, and review biomedical and behavioral research with human participants in research (Office for Human Research Protections, 2016). It means that the IRB conducts forms of risk-benefit analysis to determine whether human participants should join the research studies or simulations (Privitera, 2014). As a result, the IRB would bring inconvenience for simulation studies with hazardous situations.

3.2 Studies with animals. To better study emergencies while being approved by IRB, numerous studies began to use animals in emergency experimental studies rather than human participants. In medical simulation studies of clinical trials, researchers regularly use mice instead of human beings. This is due to the high similarity of both biology and sequence between human and mouse (Battey, Jordan, Cox, & Dove, 1999; Wasserman, Palumbo, Thompson, Fickett, & Lawrence, 2000). Therefore, mice became a primary animal species in various simulation studies (Battey et al., 1999).

As early as the 1970s, there had already been studies used mice in emergency experiments (Shiwakoti & Sarvi, 2013). For example, Saloma et al. (2013) studied how the mice are evacuating with different width exits to replicate panic conditions during the evacuation. This study demonstrated that the width of the exit and the mice body sizes had power-law distribution relationships (Saloma et al., 2013). Moreover, Lin et al. (2016) did an emergency evacuation study by using mice to investigate the faster-is-slow effect. The study used different smoke concentrations to stimulate a varying degree of panic to the mice, and its result indicated that the mice were more eager to escape and spent longer evacuation time when the smoke density was increased (Lin et al., 2016).

Other researchers used other species of animal for similar evacuation studies. Shiwakoti, Sarvi, Rose, & Burd (2011), for instance, observed and studied Argentine ants' movement patterns in a series of experiments. They found that the ants' movement patterns were affected by the layout or the geometrical structures in the escaping areas (Shiwakoti et al., 2011). Soria, Josens, & Parisi (2012) similarly used ants to conduct an experimental evacuation study. However, the study result was not efficient to prove the faster-is-slower effect at the end of the experimental test (Soria et al., 2012). This is because the ants did not display selfish evacuation behavior during the experiment (Soria et al., 2012). Further analysis of the Soria et al.'s experimental data, Parisi, Soria, & Josens (2015) pointed out the ants had important differences that they were inadvisable for representing human behaviors. As a result, ants were not suitable creatures for replicating human behaviors, especially under emergency conditions.

Although the experimental method of substituting human participants with animals was beneficial for studying emergency situations, it also had many deficiencies. The deficiencies could summarize as animals behaved differently as human participants in the case of emergencies. As a result, computerized simulation models had become a popular method to investigate emergency situations.

3.3 Studies with simulations. Computer-based simulation is a method for studying and researching different scenarios in a real-world system. It is achieved by numerical evaluation of using software designed to simulate system operations or features. From a practical viewpoint, a computer-based simulation is a process of designing and creating a simulation model of a real or proposed system. With the continuous progress of science and technology, computer-based simulation has become a popular method that substituted experiments and applied in different research areas. This is because of computer-based simulations have the flexibility to deal with various scenarios. It means that researchers not only can use computer simulation to study simple systems but also can use it to study complicated systems. By conducting, simulating, and analyzing corresponded computer-based simulations, researchers could have a better understanding of an entire process or principle in a given set of research conditions.

Other advantages of using computer-based simulation were the significant improvement in safety, performance, and reduction in costs. For instance, Miyoshi et al. (2012) used the computer-based simulation, which was developed by the Microsoft Visual Basic, to investigate whether passengers' emotion affects evacuation efficiency from an airplane. The study used the Garuda Indonesia Airways accident happened at Japan's Fukuoka airport in June 1996 as a test object (Miyoshi et al., 2012). To be more realistic, the study simulated a DC-10-30 aircraft model, which was exactly the same as the actual airplane model in the accident (Miyoshi et al., 2012). The result of the study directly indicated that the passengers' emotion would significantly influence evacuation flow to the exits (Miyoshi et al., 2012). Also, the results indirectly implied that the passengers' emotion might lead to panic, which was another factor to delay evacuation time (Miyoshi et al., 2012). Compared with the A380 experimental evacuation mentioned previously, the computer simulation clearly demonstrated its powerful abilities, specifically in the aspects of safety, performance, and cost.

The power of computer-based simulation would become more significant when simulating sophisticated conditions. As mentioned earlier, actual emergencies are unpredictable, and they can appear randomly. However, computer-based simulation can simulate these uncontrollable or random conditions during a study. Shi, Ren, & Chen (2009), for instance, used computer-based simulation to study agent-based evacuation under large public buildings and fire conditions. During the research, researchers used the computer-based simulation simultaneously to build and run several models, including physical systems dynamical model, spatial environment model, and agent decision model (Shi et al., 2009). To randomly simulate fire locations and situations, as well as arbitrarily distribute the population in the designed area, they applied the random function when during the simulation (Shi et al., 2009). The final result of the study determined that the quantity and width of exit were an essential factor which affected an evacuation process (Shi et al., 2009). Undoubtedly, the random, or the stochastic ability of the computer-based simulation made the simulation scenario closer to actual emergencies.

Concisely, a real evacuation scenario or experiment is dangerous, expensive, and arduous to replicate. Because of these reasons, a computer-based simulation is the best alternative tool for researchers. Researchers can use simulations to study and prepare a specific emergency with special emergency conditions. More importantly, the simulations can be safely reproduced. Even the necessary procedures and principles of implementing models are relatively similar among all the simulation applications, but different simulation systems still have particular capabilities. In the next section, some commonly used simulation systems, and their abilities are reviewed.

General Purpose Simulation System (GPSS) and the airEXODUS. In the 1970s, the General Purpose Simulation System (GPSS) mode was one of the first computer-based aircraft evacuation simulation models that appeared in the open literature (Snow, Carroll, & Allgood, 1970). Due to the limitations of computer technologies at that time, this model had limited capabilities. In the 1990s, the Graphical User Interface first appeared in simulation software to present aircraft design. For example, the airEXODUS software was developed for aircraft certification purposes. AirEXODUS software had considered interactions among people, hazards, and structure in the evacuation process (Galea, Finney, Dixon, Siddiqui, & Cooney, 2006). This simulation system and model had abilities to predict the total evacuation time under certification scenarios for both narrow-body and wide-body aircraft. Moreover, it could provide a total estimated evacuation time within an average of 5.3% or 3.8-sec variation (Galea et al., 2006). Because the computer technology was limited in both hardware and software, and the realistic accident data was difficult to obtain, validating simulations for the evacuation of real aircraft accidents was extraordinarily challenging at that time.

AvatarSim. Under emergencies, panic could lead to nonadaptive behaviors, such as pushing each other (Helbing & Molnar, 1995). Particularly, at narrow exits, panic behaviors could increase evacuation time (Sharma, Singh, & Prakash, 2008; Helbing & Molnar, 1995). AvatarSim had the function to imitate evacuees' stress, anger, and panic behaviors. Also, it had a mixture of techniques to model various evacuation scenarios and conditions. Sharma et al. (2008) used AvatarSim to study passengers' emotion and panic behaviors during aircraft evacuations. Through the study, they used AvatarSim to incorporate fuzzy behavior characters of passengers and crew, social forces model for passenger movement speed, and geometric models for aircraft configuration and simulation construction (Sharma et al., 2008). By observing and comparing the results, they found that passengers were in a highly panicked situation when the evacuation process was delayed or evacuation time was increased (Sharma et al., 2008).

AvatarSim and airEXODUS represented two instances of the application of simulation to investigate the certification scenarios as well as the recreation of real emergency evacuations. Although both of them had been widely used to simulate evacuation in airplane configurations, they still had unique abilities to investigate particular elements in different emergency conditions and scenarios.

buildingEXODUS. buildingEXODUS is a computer-based simulation software for studying evacuation simulation, pedestrian dynamics, and pedestrian circulation analysis. For example, it could be applied to incorporate and validate the empirical crawling data (Muhdi, Gwynne, & Davis, 2009). Also, it has highly sophisticated functions to simulate complex models. Therefore, it can change the traditional engineering analysis and produce realistic human-human, human-fire, and human-structure interaction models. Gwynne et al. (2001) used the buildingEXODUS software to present the interaction relationships of people's decisions with fire conditions (Gwynne et al., 2001). In this study, the results identified that fire emergency with smoke conditions would reduce people's evacuation speed and increase evacuation time. Especially when the smoke density caused people to use the crawling posture to escape, the evacuation time would significantly increase (Gwynne et al., 2001). Later, they tried to use the same software, the buildingEXODUS, to validate the Stapelfeldt and Milburn House evacuation data. The original purpose of the study was to certify and investigate a range of factors, including occupant drive, occupant location, and exit flow capacity (Gwynne, Galea, Owen, Lawrence, & Filippidis, 2005). Unfortunately, the final simulation outcomes were not sufficient to verify all the study assumptions or factors (Gwynne et al., 2005).

AIEva. AIEva is another evacuation system that can simulate evacuation with fire scenarios. Designers can use the core functions, which includes fire information database, core analysis module, rule reasoning mechanism, graphics platform, individual person movement speed and fire conditions in the structure, to estimate and analyze the total evacuation time. This system had been widely used for the study of evacuation model in large public buildings under fire conditions (Shi et al., 2009). The Beijing Municipal Science & Technology Committee (BMSTC) of China, moreover, used this system for the "Project for Crucial Research on Gymnasiums and Stadiums for the 2008 Beijing Olympic Games".

AnyLogic. AnyLogic® is one of the most powerful simulation software. The software was developed by the AnyLogic Company to investigate discrete events and agent-based system dynamics. AnyLogic can use a graphical modeling language and Java language to build models. Additionally, it supports the most common simulation methodologies, such as system dynamics and agent-based modeling. Purdue University used this software to assist the Illinois-Indiana-Wisconsin Regional Catastrophic Planning Team for the evacuation planning and building resilience in a major city (Kirby, Dietz, Matson, Pekny, & Wojtalewicz, 2015). Other organizations and companies, such as the National Aeronautics and Space Administration (NASA), Rolls-Royce, and FedEx, also use the system to build their simulation models for different projects (AnyLogic, 2017).

ARENA. ARENA, developed by Rockwell Automation, has been widely used in various industries as an operational simulation software (Kelton, Sawdowski, & Swets, 2010). It was written in SIMAN language with functions to adopt Visual Basic and C++ code, so it provided flexibilities to people who had limited knowledge in programming (Kelton et al., 2010). Additionally, it is an event-driven simulation system. Dorton and Liu (2015) had used the software conducted a simulation model for the study about the effects of baggage volume and alarm rate on an airport security checkpoint.

3.4 Modeling and simulating pedestrian movement. Movement of passengers within an aircraft is a special case of a more general problem of pedestrian movement. This problem has been addressed using several approaches such as particle dynamics or social force models (Helbing et al., 1995; Helbing et al., 2000), models based on cellular automata (Burstedde, Klauck, Schadschneider, & Zittartz, 2001), fluid flow models (Henderson, 1971), and queuing based models (Rahman, Ghani, Kamil, Mustafa, & Chowdhury, 2013). Social force models have specific advantages for studying passenger movement and contacts in airplanes. Each passenger is modeled individually and moves continuously; this enables individual trajectory evolution and estimation of the contacts between pedestrians.

Social force models of pedestrian movement are essentially based on molecular dynamics. In molecular dynamics, atoms are treated as Newtonian particles with forces between atoms described by interatomic potentials (Allen, 1989). Social force models extend this concept to pedestrian movement. Here the forces are a measure of internal motivations of individual pedestrians to move towards their destination in the presence of obstructions like other pedestrians and objects (e.g., chairs). Social force models have been applied to crowd simulations situations in panic (Helbing et al., 2000), traffic dynamics (Treiber, Hennecke, & Helbing, 1999), evacuation (Wei-Guo, Yan-Fei, Bing-Hong, & Wei-Cheng, 2006) and animal herding (Li & Jiang, 2014). Algorithmic developments have included generation of force fields using visual analysis of crowd flows (Mehran, Oyama, & Shah, 2009), explicit collision prediction (Zanlungo, Ikeda, & Kanda, 2011), and collision avoidance (Lämmel, & Plaue, 2014). Member of Current group Namilae has used pedestrian dynamics described by the social force model in a multiscale model to study the spread of epidemics during air travel (Namilae, Derjany, Mubayi, Scotch, & Srinivasan, 2017a; Namilae, Srinivasan, Mubayi, Scotch, & Pahle, 2017b). The social force model was discussed in more detail below because it is an important part of the future work plan of this study.

From a Newtonian mechanics perspective, Helbing and Molnar (1995) developed a microscopic particle-based social force approach to mimic the behavior of foot-travelers in their milieu of locomotion. Their principle reflects the influence of the surrounding on the internal motivation of a pedestrian to reach his designated terminus. Founded on Newton's second law, repulsive and attractive forces are summated and equated to the acceleration to reach the desired velocity. The tendency to avoid collision with other individuals in high-density crowds and immobile obstacles in the walking path is represented by the repulsive term, although there are no physically subjected forces on the pedestrian itself. However, repulsive forces inhibit the walker's motion at proximity with an obstruction.

On the other hand, guided by his intention, a pedestrian self-propels to his targeted destination or one of the exits either individually or collectively by joining a formed group of walkers. A fluctuation term is added to the equality to account for the stochastic deviation in the path. Also, the alteration of free navigation speed between one individual and another is taken into consideration. The theoretical model is validated using computer simulations. Bi-directional, counter-crossing Pedestrians are modeled in the first case along a hallway, then at a single exit door. Lane formation between successive pedestrians in the same direction is noticed, enabling the pedestrian in the rear to move more freely along the way cleared by the forward individual. In addition, the crowd accumulates in an arc shape space and clogs the exit.

In continuation of their work achieved in 1995, Helbing et al. propose a theoretical model to simulate the comportment of people on a certain closed site under a life-threatening escape panic encounter. Since their previous model only applies for regular everyday condition, a modification of the repulsive forces is required to fit the current case study. In contrast to normal situation, pedestrians do not stay apart within a critical radius. Instead, they are allowed to collide, resulting in additional shear and pushing forces during their motion. A real-life experiment is impossible. Therefore, computer simulations are performed to adjust the newly induced parameters and validate the theoretical presentation.

Further, Helbing et al. (2002) establish a comparison between pedestrian behaviors in normal and evacuation situations. The social force model alters between these analyzed cases since the nervousness factor is implemented. In a normal situation, the self-organization of pedestrians is emphasized through line formation along hallways and oscillations at bottlenecks. On the other hand, panic circumstances are more chaotic. The tendency of herding, lane breakdown and clogging are observed, which in return reduces the chance of survival.

Lakoba, Kaup, & Finkelstein (2005) improve on the basic ideas of Helbing et al. (2000). Despite the accuracy of their theoretical model presented for a panic situation based on modeling pedestrians as Newtonian particles, the parameters within the repulsive terms are not realistic. They are not valid for a small crowd or a separate pedestrian. Also, the repulsive term used to model pedestrian-pedestrian and pedestrian-wall repulsion does not guarantee overlapping prevention. For this purpose, an optimized algorithm is set up to seek for the values of the adequate parameters. The density effect is also taken into consideration and implemented in the force expression derivation as it inversely affects the free speed of a pedestrian. The proposed model is simulated by monitoring the evolution of pedestrian within a closed room with a single exit.

Analyzing pedestrian motion helps planning for facilities and predicts evacuation strategies to suppress the risk of human lives loss. For instance, Makkah is a city in Saudi Arabia that receives millions of Muslims across the world for pilgrimage during the last month of the Muslim calendar. Deaths due to pushing in high-density crowds have been recorded every year. Therefore, modifications to the building have been established to facilitate the rituals. Temporary mobile floors have been inserted to organize the crowd and are held by pillars. This expands the mosque capacity and reduces the crowd density on the ground floor. Dridi (2015) simulated the pilgrimage situation using Pedflow. The software solves the differential equation of motion using a microscopic social force approach. An empirical data has been first collected using cameras and human detectors to assess the density and capacity of the site and inputted to the simulation. The pedestrian motion is circular, and the tour induces body contacts since the density ranges between 5 to 8 persons/m^2. The performed simulation shows that by addition of the mobile floor, the crowd density reduces and enables more comfortable displacement of pilgrims. The study also aimed to shed light on the important role of the social and physical force model to plan and set up evacuation strategies in emergency conditions in highly congested zones.

Mehran et al. (2009) exploit the principle of social force model to localize abnormalities in a crowd. For this aim, a data set of crowd videos are interpreted. A grid of mobile points is placed over the screen, and the floating particles are allowed to move with the stream of people. The estimation of the interactive forces between the pedestrian and his surrounding is indicative of distortions. Their method proved its capability to evaluate the crowd as a whole without the need for identifying every single individual and identify the irregularities.

Chraibi, Seyfried, & Schadschneider (2010) suggest a theoretical improvement to the repulsive term in the social force model to prevent collision between individuals. In contrast to the standard circular representation of the pedestrian, a more realistic elliptical concept is introduced. The study restricts itself to crowd enclosed in corridors, and a unique set of parameters for this investigation are chosen.

Based on the model proposed by Helbing et al. (2000), Yang, Dong, & Yao (2017) simulated a crowd evacuation in Beijing south subway station to emphasize the role of crowd leaders, guiding the crowd to the nearest exits, in suppressing evacuation time and reduce injuries and lives loss. The microscopic social force model is extended to identify the direction of the socio-psychological force and account for the tendency of pedestrians to follow the crowd when the vision is obscure, and the exits are not acknowledged. Several computational experiments have been run, and the mean evacuation time is obtained with and without evacuation leaders. Also, the mock-ups are validated using simple evacuation simulations from a square room with a single exit. It has been concluded that the appropriate number of leaders as well as their accurate distribution near stairs, corners and bottlenecks at clogged exits plays an important role in accelerating the clearance of travelers.

Chen, Di, Liu, & Wang (2017) performed a computer simulation using the AnyLogic software to mimic the evacuation situation in case of emergency in the Xizhimen Metro station in Beijing since it is quite hard to perform actual experiments. The panic situation is manifested by a mathematical model accounting for the pedestrian's response time to an emergency, the exit distance, and the abnormal crowd density. Also, the pedestrian motion is obtained using the social force model developed by Helbing et al. their theoretical model enables the evaluation of the panic spread time and rate among the travelers.

Von Sivers et al. (2016) modeled the emergency evacuation of the London train station when bombed in 2005 using a new approach combining a locomotion model combined with social identification and self-categorization theories. The authors implement the psychological factor to mimic the real situation. The social identification reflects the situation of the pedestrians; they can be safe and evacuate without caring or supportively intervene in the rescue process. Unlike previously established analyses, this model takes into consideration the helping behavior to assist injured pedestrians to evacuate. Incapacitated travelers are either represented by low-speed moving particles or stationary obstacles if severely injured. To accurately identify the model parameters, an uncertainty quantification method is used. The range of people sharing the same social identity, the number of injured pedestrians as well as the mobility of the rescuer of an injured individual are the calibrated inputs.

Alonso-Marroquin, Busch, Chiew, Lozano, & Ramírez-Gómez (2014) investigate the occurrence of the tragic incidence that took place in the Madrid Arena Pavilion in 2012 in Spain, where five girls were a victim of a crowd stampede. In contrast to the conventional representation of pedestrians as single or three-circles for a comfortable or moderately crowded environment, the authors suggest a spheropolygons representation of pedestrians to simulate heavy crowd conditions. The social force model based on Newton's law of motion and proposed by Helbing et al. is used, although additional forces for contact, friction, and ground reactions are added. A counter-flow of pedestrians in a corridor is selected to reproduce the real incidence.

Kirkland & Maciejewski (2003) suggest introducing autonomous robots to organize a flowing crowd. A social force model based on gas kinetics and developed by Helbing et al. (2002) to animate the motion of the heterogeneous mixture of robots and human agents. The model also takes into account the visual and audible effects generated by the robots to steer the pedestrians towards them. The simulation models guided pedestrian motion by maneuvering robots along a hallway. The role of the robots is to suppress the deviation and disturbance of people movement towards the openings, generate line formation pattern, and organize jamming and bottlenecks at narrow exits.

From a computer graphics perspective, Pelechano, Allbeck, & Badler (2007) suggest an improvement to the mathematical models previously proposed by implementing a high-density autonomous crowd model relying on psychological, physiological and geometrical rules for a more realistic simulation. Unlike conventional models that generate animated, impracticable particles, this method mimics the real human movement. This technique also eliminates the fluttering of the particles during time step evolution occurring at high-density crowds. Also, the social force model enables a continuous domain of motion in contrast to the cellular automaton data, which discretizes the plane of movement and restricts the pedestrian to some specific spots. Moreover, the queuing in a normal situation and pushing in impeded crowd motion are underlined.

The researchers now describe the past work related to modeling of pedestrians during air travel in the context of the spread of contact-based diseases, such as Ebola and SARS. The researchers formulate new models of pedestrian movement in the air transportation infrastructure and integrated the model with a stochastic framework for infectious disease surveillance of populations moving within airports using social force modeling and meta-population epidemic modeling. In order to assess the effect of local transportation policies, our model simulates pedestrian trajectories and uses these to get estimates of direct and indirect contacts as people move through high-density areas in airports and airplanes. The researchers achieve this by modeling the time evolution of pedestrians, treating them as particles that interact with other pedestrians and inanimate objects like walls and chairs. The force $\bar{f}_i$ acting on i^{th} pedestrian can be defined as:

$$m_i \frac{dv_i}{dt} = \frac{m_i}{\tau}\left(\bar{v}_o^i(t) - \bar{v}^i(t)\right) + \sum_{j \neq i} \bar{f}_{ij}(t) \tag{1}$$

The pedestrian position at a given time obtained by integration with respect to time. Here $\bar{v}_o^i(t)$ is the desired velocity of a pedestrian, $\bar{v}^i(t)$ is the actual velocity, m_i is the mass, and τ is a time constant. The momentum generated by a pedestrian's intention results in a self-propulsion force that is balanced by a repulsion force $\bar{f}_{ij}(t)$. The researchers introduce location dependence to the desired velocity in the self-propulsion term as:

$$\bar{v}_o^i(t).\hat{e}_1 = \left(v_A + \gamma_i v_B\right)\left(1 - \frac{\delta}{\bar{r}_i \hat{e}_1 - \bar{r}_k \hat{e}_1}\right) \tag{2}$$

Here, $\hat{e}_1$ is the direction of desired motion, v_A and $\gamma_i v_B$ are the deterministic and stochastic components of the desired velocity, and δ is a distance constant such that at a distance δ between the i^{th} and k^{th} pedestrians the desired velocity of i^{th} pedestrian is zero.

There are several parameters in the model in equations (1) and (2). Experimental data is available for some of the parameters, such as walking speed (See Table 1). The researchers perform a massive parameter sweep of feasible ranges of parameters and correlate it with available experimental data to identify narrower parameter ranges that are realistic. We demonstrated this approach in the limited context of pedestrians exiting from airplanes (Namilae et al., 2017a). The researchers simulated several possible paths and identified parameter ranges that produce simulation results in agreement with empirically observed exit times for airplanes of different sizes. This is illustrated in Fig. 2. Also, the researchers also checked if simulations reproduced qualitative features of observed passenger exit patterns (Marelli 1998, Wald 2014).

The pedestrian trajectory information from the above model is integrated with a discrete-time stochastic susceptible-infected (SI) model for infection transmission as described in (Namilae et al., 2017b). Using this multiscale approach, the researchers the impact of different procedures for boarding, disembarkation, and seat assignment on the number of contacts and consequent spread of Ebola infection for passengers on an airplane. Our results show promise for

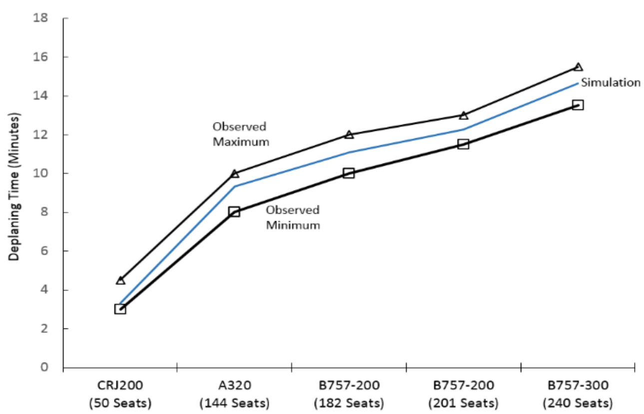


Figure 1. Validation of simulation based on empirical observations of deplaning.

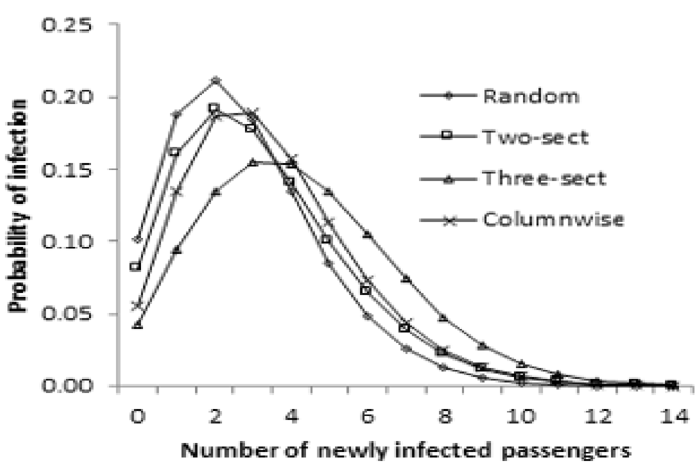


Figure 3. Infection profile with different boarding strategies for Boeing 757-200.

substantial impact. For example, Figure 2 shows that on a 182 passenger Boeing 757 aircraft, different boarding policies can lead to changes in infection transmission. The researchers have also obtained similar results showing the potential for changes in in-plane movement, deplaning procedure, seating arrangement, and plane sizes in reducing the likelihood of infection transmission.

Aggregated results of our model indicate that the probability of generating 20 infectives per month from air-travel could have been reduced from 67% to 40% using better pedestrian movement strategies during the 2014 Ebola epidemic if unrestricted air travel had been permitted at the 2013 levels. This could have been further reduced to 13% by exclusively using smaller fifty-seater airplanes (Namilae et al., 2017b).

Pedestrian density effect. Pedestrian density is one of the primary factors affecting the movement of pedestrians. This is expected to be more important during an emergency and high crowd density situations. There is significant experimental evidence for reduction of pedestrian speed with increase in pedestrian density with studies dating back from 1935 as tabulated in Table 1. The reduction in the speed of the overall pedestrian group as a function of density has been curve-fit to experimental data and is expressed either in linear or exponential forms by various researchers as tabulated. The table and corresponding notes describe the reduction in pedestrian speed when more people are in their proximity. The researchers will incorporate some of these ideas into this research plan.

Table 1

Literature survey of pedestrian density vs speed data and equation descriptions.

References	Speed-density relation	Notes
Greenshields (1935)	S = -a.D' + b *Where:* D': density, a, b: constants for the fitting line	Data collected by photographic method on a roadway section to monitor the traffic capacity.
Older (1968)	$v(k) = v_f - \theta.k$	
Navin (1969)	$v(k) = v_f - \theta.k$ *where:* v_f: free flow speed, k: density θ: parameter	
Fruin (1971)	$S = \frac{a.M-b}{M}$ *Where:* $M=1/\rho$, ρ : density, a, b: constants for the fitting curve	Uses level Of service (LOS) concept
Pushkarev (1975)	$V=-\alpha.k + \beta$	The author incorporates previous work for the various pedestrian types.
Tregenza (1976)	$v_e = v_f . \exp(-(\frac{k}{\theta})^{\gamma})$	
Polus (1983)	$V=-\alpha.k+\beta$	Video Data collected in the central business district of Haifa, Israel.
Tanaboriboon (1986)	$v(k) = v_f - \theta.k$	Bidirectional pedestrian data from sidewalks in Singapore using a photographic technique.
Tanaboriboon (1989)	$V=-\alpha.k+\beta$	Videographic data on pedestrian traffic in four walkways in Central Bangkok. The linear model represented the best fit.
Weidmann (1993)	$v= v_m \{ 1 - \exp[-\gamma (\frac{1}{u} - \frac{1}{u_M})] \}$ *Where:* v_m: free pedestrian speed γ : fitting a free parameter. u_M : maximum admissible density	
Lam (1995)	$v(k) = v_f - \theta.k$ *where:* v_f: free flow speed	

	k: density, θ: parameter	
Tewarson (2002)	$v(k) = v_f - \theta.k$	
Al-Azzawi (2007)	Ln S = α ln V – β ln D + ε *Where:* S: speed, V: volume or flow D: density, ε : random noise (constant) α, β: constants	Pedestrian movement on sidewalks in the United Kingdom. To develop speed, flow, and density relationships.
Bruno (2008)	Kladek non-linear formula Weidman (1993): $v = v_m \{ 1 - \exp [-\gamma (\frac{1}{u} - \frac{1}{u_M})] \}$	The study estimates the v_m, γ and u_M in Kladek formula taking into account various factors that influence the density-velocity relation such as **age, culture, gender, travel purpose, type of infrastructure, walking direction** represented in parameters α and β
Hongfei (2009)	$V = -\alpha.k + \beta$	Data collected in the Chinese passenger transport terminal—Xizhimen underground station using video recording.
Laxman (2010)	$V = -\alpha.k + \beta$	Data collected at four locations in a medium-sized city of India and a metropolitan city in India.
Chen, Ye, & Jian (2010)	Level passageway: $V = 75.267 \times D \times e^{-\frac{1}{2}\left(\frac{D}{1.534}\right)^2}$ Ascending stairway: $V = -0.917D^3 - 1.234D^2 + 36.166D$ Descending stairway: $V = -0.12D^3 - 7.74D^2 + 46.754D$ Two-way stairway: $V = 0.161D^3 - 9.113D^2 + 46.698D$	Confined level passageways, ascending stairways, descending stairways, and two-way stairways in Shanghai, China, Metro stations with massive passenger volumes were observed.

Rahman (2013)	V=$\alpha - \beta$.k + e Linear formula with the addition of e, a random error term due to stochastic variations	Data collected from three different locations in Dhaka. Pedestrian speed-flow-density relationships are predicted using a weighted regression method.
Rastogi (2013)	v(k) = v_f .exp (-$\frac{k}{\theta}$)	Data collected from five cities in India.
Das (2015)	U = $U_f - (\frac{U_f}{k_j})$ k U = $U_f\ e^{\frac{-k}{k_m}}$ *Where:* U_f: free-flow speed, k_j: jam density k_m: optimum density	From speed-density relation, the Greenshield (1935) and Underwood (1961) models were fitted to determine the parameters U_f, k_j and k_m. The study describes bidirectional flow characteristics on sidewalks and carriageways around transport terminals in India.
Kretz (2016)	v(ρ) = $v_0 - (1 - \lambda)\ \tau\ A \frac{1}{e^{\frac{1}{B\rho}} - 1}$ *where:* v_0: the desired speed of pedestrian (the same for all pedestrians) A>0, B>0, 0≤λ≤1, τ>0 are appropriately chosen values	Derived from the Social Force Model for Steady-States in Single-File Movement.
Nikolić (2016)	$v_e = v_f$. exp (-($\frac{k}{\theta}$) $^{\gamma}$) *where:* v_e: equilibrium speed, v_f : desired velocity, θ, γ : pedestrian specific parameters, k: density	Derived from the microscopic social force model proposed by Helbing and Molnar (1995). Tragenza model (1976) Two datasets: Pedestrian underpass at Lausanne train station and a controlled experiment at the Technical University of Delft.

Description of problems

The top two priorities under emergencies are saving and protecting life, as well as the elimination of damage to properties. Numerous studies have been conducted to replicate previous emergencies to study the deficiencies and errors in emergency responses and develop better emergency response plans. Emergency evacuation planning had become an inevitable process to protect the general public in unforeseen emergency situations (Alexander, 2013). Although researchers have been able to simulate the policy factors, human factors are very difficult to replicate. Some studies use simulation models to simulate pedestrian moving velocity, pedestrian density, required space to move, and step length. However, human factors such as relationship to other evacuees, the purpose of the trip, and other psychological differences among people are difficult to quantify. Some studies have used interviews as an approach (Cocking et al., 2009). Also, in Purser and Raggio's study in 1995 and Purser and Bensilum's study in 1999 (as cited in Purser & Bensilum, 2001) video and questionnaire analyses were used to investigate occupancy types, human behavior and psychological changes during emergency events, especially during evacuations. In the present day, researchers are still seeking accurate methods to understand human behavior during emergency events.

Current studies of emergencies generally lack human behavior investigation, especially in emergency planning modeling. Therefore, the goal of this study was to evaluate various factors that affect the efficiency of evacuation during an emergency. Case study 1 investigated the effect of the number of exits and the number of passengers on the efficiency of evacuation at emergencies. Case study 2 investigated the effect of the number of passengers and the evacuation policies on the efficiency of evacuation. Case study 3 investigated the effect of group travel and instructions on evacuation at emergencies. Finally, Case study 4 used a multiscale model for the optimal design of pedestrian queues to mitigate infections disease spread.

Case study 1

Research Question and Hypothesis

This study investigated the effect of the number of exits and the number of passengers on the efficiency of evacuation. In this study, the first null hypothesis (H_0) was to validate the model by comparing the average of the total evacuation time, which would not be significantly different from the actual evacuation time. The second hypothesis (H_1) for the experiment was that an increased number of passengers would not significantly affect a total evacuation time. The last hypothesis (H_2) was that the number of exits would not have a significant effect on the total evacuation time.

Methodology

This study used AnyLogic Simulation Software to simulate an airport emergency evacuation that occurred when passengers began to de-board from the aircraft and predicted a total evacuation time for the passengers to evacuate from the airport. Hence, the simulation clock started when the first passenger began to disembark at the airport's second floor. The simulation clock ended as soon as the last passenger successfully escaped from one of the available airport's exits. Figure 4 illustrates the flowchart of the evacuation scenario. In the next sections, the data sources and format were described for the development of the baseline model.

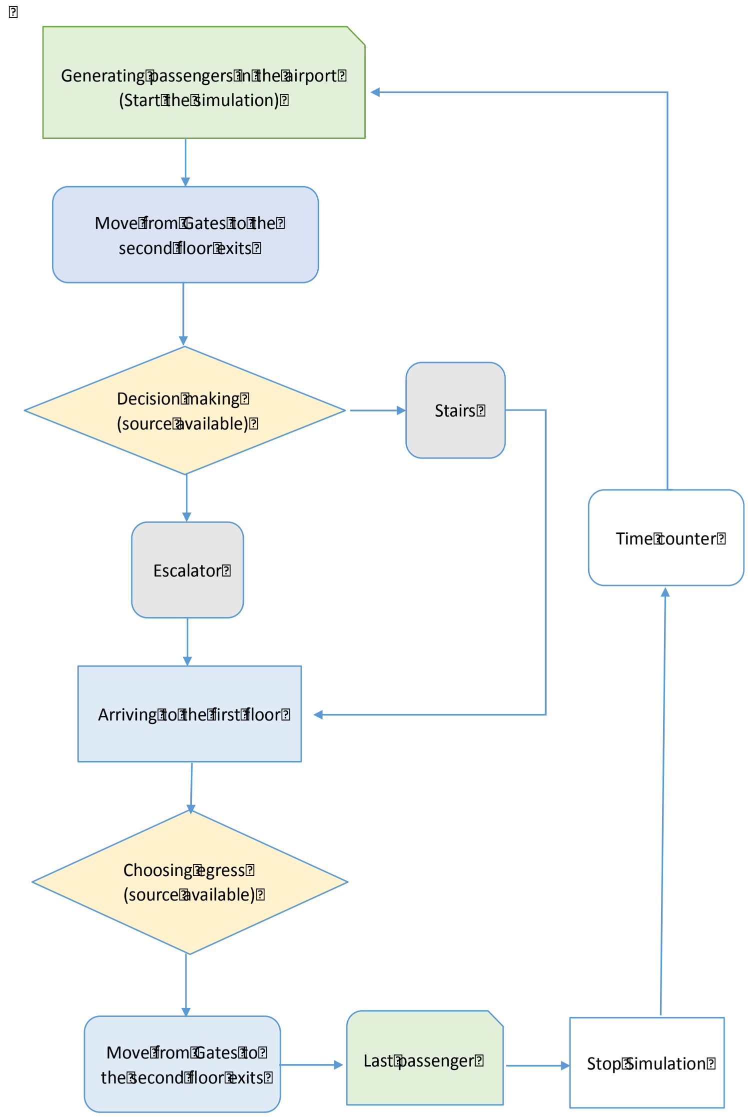


Figure 4. Airport evacuation events flowchart.

Parameter settings. The parameter settings in the model consisted of two data sources. The first part of the data source came from the author, who collected the data by observing at the airport. The second part of the source came from the review of the corresponding parameter settings from the previous studies.

Airport layout. This study uses a local airport as a testbed. The airport terminal used in the study consists of two floors. The first floor was the public area with six exit doors, as shown in figure 5. Passengers who arrived at the terminal gate on the second floor had to go to the first floor and choose one of the exit doors to evacuate from the airport terminal.

The second floor had the security checkpoint and six gates for boarding and de-boarding, as shown in figure 6 and figure 7. Noticeably, the layout, as shown in figure 5 and figure 6 showed that there was just a one-way route to reach the first floor. The evacuation event was designed to simulate an evacuation scenario that happened at the concourse area on the second floor, and the passengers were assigned equally to the exit doors on the first floor under the guidance of emergency leaders. Until the condition became safe for the passengers, they would remain outside of the airport terminal.

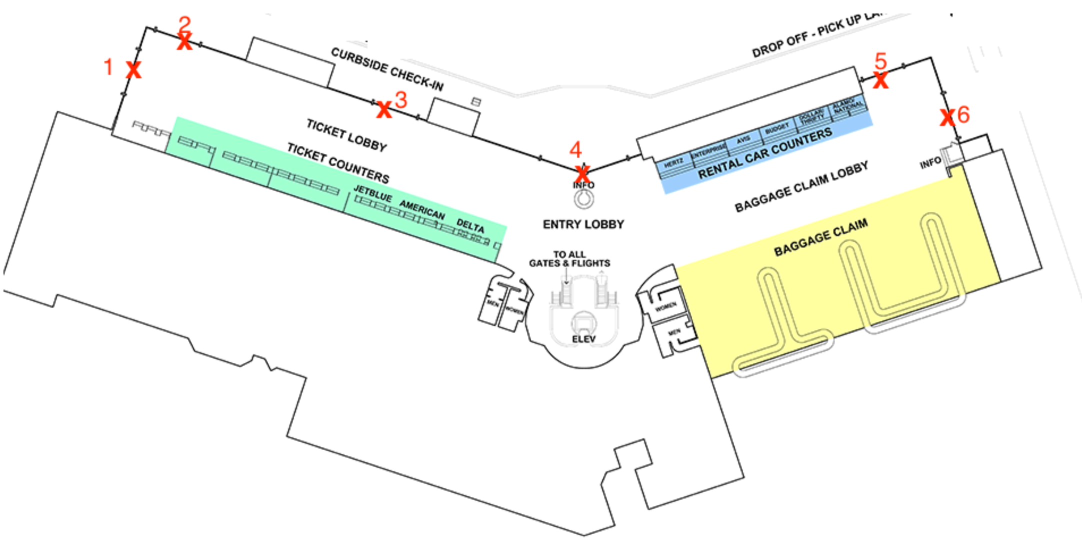


Figure 5. The first floor of the airport. Adapted from Daytona Beach International Airport. Retrieved February 28, 2017, from *http://www.flydaytonafirst.com/airport-information/terminal-layout.stml*

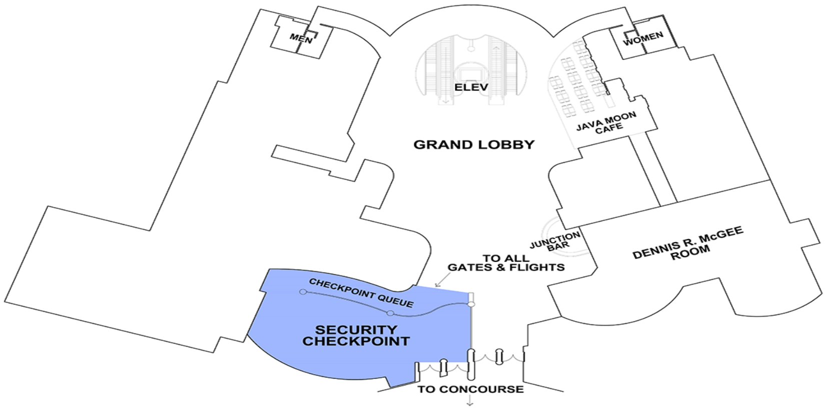


Figure 6. The second floor of the airport. Adapted from Daytona Beach International Airport. Retrieved February 28, 2017, from *http://www.flydaytonafirst.com/airport-information/terminal-layout.stml*

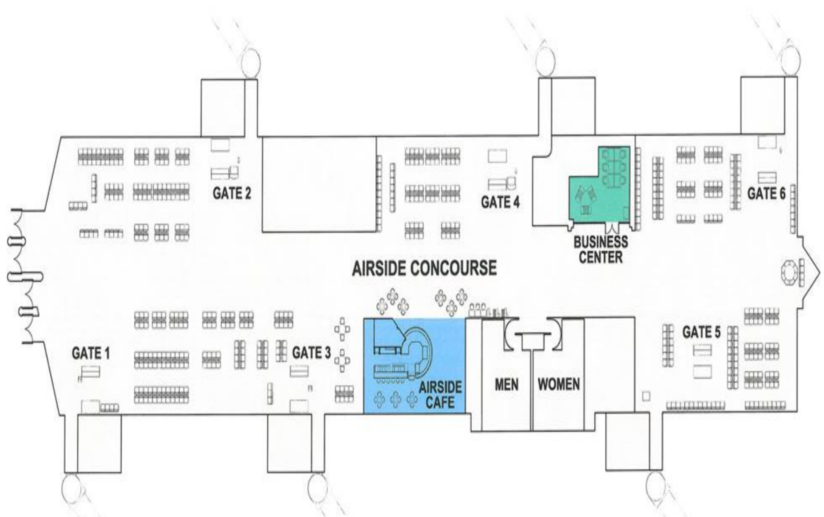


Figure 7. Airport concourse layout on the second floor. Adapted from Daytona Beach International Airport. Retrieved February 28, 2017, from http://www.flydaytonafirst.com/airport-information/terminal-layout.stml

To simulate the model as close as an actual situation at the airport, the author observed the airport and collected data such as the passenger arrival rate, passenger traffic volume, and leaving time from the airport. For the actual arrival rate of passengers, the author observed seven flights with a total of 44 samples at the airport, as shown in Appendix A. The actual average appear rate for passengers de-boarding was calculated as 2.98 sec/person by using a statistical analysis method. Meanwhile, the author observed additional 32 arriving flights at the airport, as shown in Appendix B. This observational data indicated the passenger volume per flight and the duration of the passengers leaving the airport.

Facilities and passenger settings. In addition to the data collected from the airport, the study also referred to other sources to assist and calibrate the parameter settings in the simulation model. In the simulation model, the elevator was ignored due to the following reasons. The first reason for neglecting the elevator was that passengers had rarely used it during the author's observation in the airport. The second reason was that it is prohibited to use the elevator at an emergency. The third reason was that the passengers who used the elevator normally have disabilities, and disabled passengers were excluded in this study. Therefore, in the simulation model, it was assumed that passengers could only use the escalators and the stairs.

From the observations in the airport, most of the passengers remained stationary when they used the escalator. Therefore, the pedestrian speed can be assumed to be equal to the escalator's speed at that moment. In the previous studies, the constant average speed of an escalator was set to 0.5 m/s in their baseline models (Uimonen et al., 2016; Carrillo, Díaz-Dorado, Cidrás, & Silva-Ucha, 2013; Li et al., 2015). Therefore, the escalator speed of 0.5 m/s was used in the baseline model as a pedestrian moving speed when they used the escalator in normal conditions.

Under the emergency conditions, Li et al. (2015) and Kinsey, Galea, and Lawrence (2014) found that people would walk on the stairs of an escalator to accelerate their escape speed. Through recording and observing 810 escalator walkers, the average speed in the downward direction was calculated to be 0.82 m/s (Kinsey et al., 2014). Thus, the 0.82 m/s was the parameter to simulate the speed when pedestrians using the escalators in an emergency condition.

Fujiyama and Tyler (2010) studied pedestrians' walking speed at the stairs. They randomly selected 33 participants and divided them into two groups based on their age. They observed the participants on four types of stairs and recorded the descending speed, as shown in Table 2. After statistically analyzing the collected data, the normal distribution of the average descending rate was 0.67 ± 0.16 m/s. This rate is the average walking speed in the baseline when pedestrians walk downstairs in normal conditions. Whereas to simulate the emergency conditions, the normal distribution of the fastest descending speed, 0.90 ± 0.20 m/s was used.

Table 2

Participants Walking Speed on the Stairs

	Stairs			
Patterns of speeds	Stair No	Degree	Elderly (Age: 60-81)	Young (Age: 25-60)
Normal descending	Stair 1	38.8	0.47 ± 0.12	0.59 ± 0.14
	Stair 2	35	0.58 ± 0.16	0.65 ± 0.14
	Stair 3	30.5	0.64 ± 0.15	0.74 ± 0.17
	Stair 4	24.6	0.80 ± 0.23	0.87 ± 0.19
Fastest descending	Stair 1	38.8	0.62 ± 0.17	0.87 ± 0.20

Stair 2	35	0.70 ± 0.18	0.92 ± 0.19
Stair 3	30.5	0.84 ± 0.18	1.08 ± 0.23
Stair 4	24.6	1.01 ± 0.26	1.18 ± 0.20

Note. The unit was m/s. Adapted from "An Explicit Study on walking speed of pedestrians on stairs" by Fujiyama, and Tyler, 2010, *Transportation Planning and Technology,* Copyright by Fujiyama, and Tyler.

Passengers in the model were categorized into people who disembarked from the aircraft and those who were waiting in the concourse area for the departure flights. Based on the flight schedule, the passengers deplaned from the arriving flights and entered the concourse area on the second floor of the airport.

Chandra and Bharti (2013) collected and analyzed the normal distribution of pedestrian walking speeds on the wide sidewalk, which was 1.36 ± 0.19 m/s. In this study, the walking speed in the baseline was adjusted to 1.36 ± 0.19 m/s, as shown in Table 3. In the emergency conditions, human physiology factors would lead to changes in speed. In the emergency evacuation simulation, the passenger's walking speed was uniformed distributed between 1.2 and 1.8 m/s (Fang et al., 2004).

In 1994, the Boeing Company had used the 757-200 aircraft as a baseline for simulating the de-boarding and deplaning time for the 757-300 aircraft. The results of the deplaning speed were approximately ten minutes for 757-200 aircraft with 201 passengers, and nearly 12.5 minutes for 757-300 aircraft with 240 passengers (Boeing, n.d.). Combined the deplaning results from the Boeing company and the observing results from the author, the arrival rate was conclusively set up to 3 sec/person in the baseline model. Table 3 listed the parameter settings that were applied in the baseline model and the experimental models.

Table 3

Model Parameter Setting

	Baseline (m/s)	Experimental design (m/s)
Pedestrians' walking speed	1.36 ± 0.19 (normal distribution)	1.2 ~ 1.8 (uniform distribution)
Escalator	0.5 (constant)	0.82 (constant)
Stairs	0.67 ± 0.16 (normal distribution)	0.90 ± 0.20 (normal distribution)

In the models, the passengers who had the fast walking speed could pass slow-walking passengers. To maintain safety, the constant speed was applied when passengers using the escalator. It implied that passengers would not be able to exceed each other.

Baseline Model. The baseline was developed based on the observed normal disembarking process. The scenario of the model was designed that passengers disembark from the airplanes on the second floor to the exits on the first floor with the considerations of the actual airport configuration. The baseline model consisted of three sections. It began with generating passengers from the concourse area at the second floor, then created routes that passengers walked from the concourse area to the first floor, and finally made selections of different egress at the first floor. Figure 8 illustrates the first two sections of the model. The arrived passengers first would walk from the concourse area to the escalator or stairs area on the second floor. At that point, they would either take the escalator or walk down the stairs to the first floor, according to an observed probability by the author. As soon as they arrived on the first floor, they would be equally assigned to the access paths to the exit doors, which is shown in figure 9.

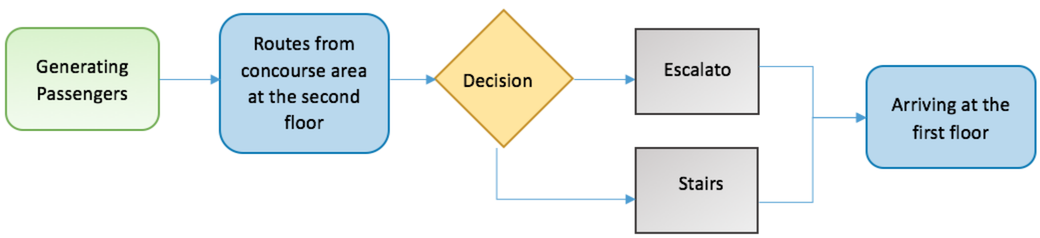


Figure 8. Passengers from the concourse area on the second floor

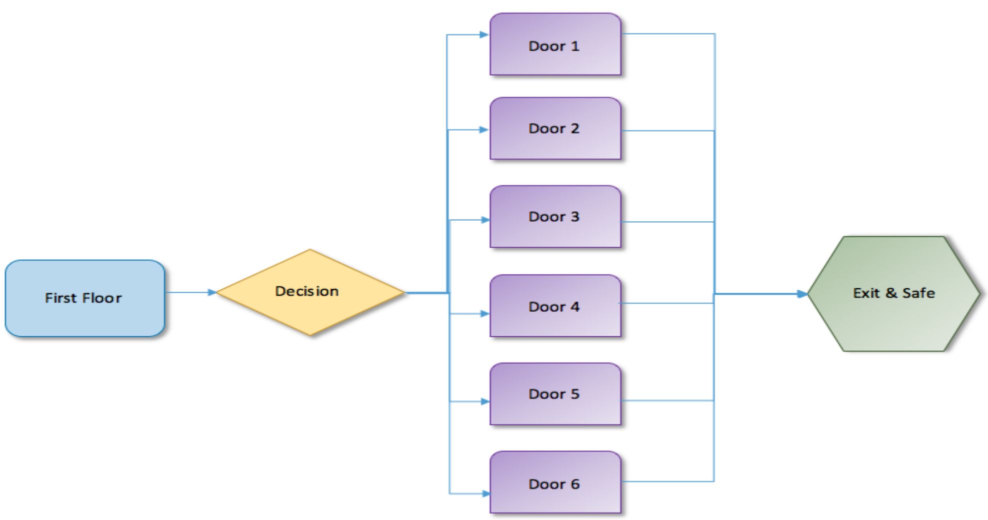


Figure 9. Passengers select different available egresses to exit at the first floor

Validation of the Baseline Model. The data collected from the author's observation was used to calibrate the parameters in the baseline model. A statistical t-test method was used to validate the baseline model. The t-test compared the average duration of the evacuation of the simulation model and observed evacuation time and was tested whether there was a significant difference between them. An alpha level of .05 was used as the significance threshold for the t-test.

Experimental Model. Once the baseline model was validated, an experimental simulation model was developed. The author adjusted the parameters from the baseline model to the experimental model. The experiment assumed that under the emergency, people were equally guided to the available egress, and their paths were not allowed to change.

The experiment was primarily designed to test the two independent variables, namely, number of passengers and number of exits. When investigated the number of passengers, the passenger volume was set up at three levels, which represented as the minimum, the maximum, and the future passenger traffic volume of flights that simultaneously arrived at the airport. So, when only one flight arrived, the passenger volume was at the minimum level. When all six airport gates were being used at the same time, the passenger volume reached the maximum level. The future passenger volume was assumed to be 1000 people based on the forecast.

When investigating the number of exit doors at the airport, the variables were also set at three levels, which was shown in table 4. Generally speaking, they represented a minimum, medium, and a maximum number of available exit doors when the passengers evacuated from the airport.

Table 4

Three Levels of Exit Doors

	Number of Exit Doors		
Available	1	3	5
Unavailable	5	3	1
Total	6	6	6

A two-way between-subjects ANOVA test was conducted to test the effect of the two independent variables on the total evacuation time, and an alpha level of 0.05 was used as the significance threshold for the test.

The experimental results were to verify whether the dependent variable, total evacuation time, would be significantly affected by the two independent factors. Also, the statistical results could approximately provide a theoretical evacuation time with a different number of passengers and a different number of exit doors.

Results

This section detailed the results from the baseline and the experimental models. A *t*-test and a two-way between-subjects ANOVA test were used to analyze the results. The significance level used to determine the validity of the assumptions was set at 0.05. The Sidak post hoc tests were used to determine the significant differences of the two-way between-subjects ANOVA test.

Baseline model validation results. Through the observation at the airport, the author collected the total evacuation time of the passengers from different airlines and flight schedules between March 1 and April 13, 2017, shown in Appendix B. Table 5 showed the results of the average exit time that passengers walked from the concourse area to the exits. Figure 10 illustrates the screenshots of the baseline model in the AnyLogic software.

Table 5

Observations of Exit Time at the Airport

		Passengers	Exit Time (second)
N	Valid	31	31
	Missing	0	0
Mean		111	620.81
Std. Deviation		50	212.06

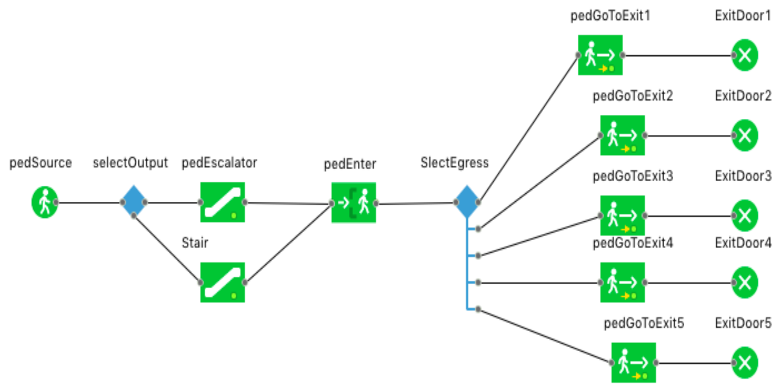


Figure 10. Simulation Baseline from the AnyLogic

Based on the statistical analysis, the average passenger volume was 111 people on each flight. Therefore, the arrivals of 111 passengers were generated in the baseline model and ran a sample of 13 replications for the baseline simulation. The simulated total evacuation time, as shown in figure 11, was used to compare with the actual observed evacuation time in the airport. The *t*-test was based on the null hypothesis that the average of the simulation exit time was not significantly different from the actual time. The result of *t*-test was not significant at the alpha level of .05, $t(13) = .205$, $p = .839$. As a result, the null hypothesis was retained, and the model baseline was statistically validated.

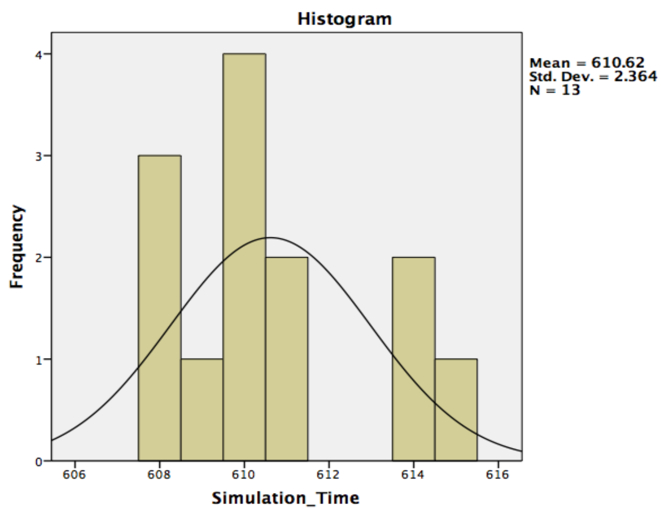


Figure 11. Simulation baseline

Experiment results. Based on the validated baseline model, an experimental model was developed to include the passenger moving speed change under emergent situations. The experimental design was aimed to test whether the total evacuation time would be influenced by the different number of passengers and the number of exits available during an evacuation. As mentioned in the previous paragraph, the statistically analyzed result of average passenger volume was 111 passengers per flight. Therefore, the passenger volume of six flights was 666 passengers.

A two-way between-subjects ANOVA was applied in the experimental design. A 3 (number of passengers: 111, 666, 1000 people) x 3 (number of exit doors: 1, 3, 5) two-way between-subjects ANOVA was conducted on evacuation time. As shown in table 6, the results showed a significant main effect of the number passengers at the alpha level of .05, F (2, 531) = 9548.020, $P < .05$, and a significant main effect of number of exits, F (2, 531) = 49.236, $P < .05$, and a significant effect of interaction between numbers of passengers and number of exits, F (4, 531) = 44.552, $p < .05$.

Table 6

Two-way Between-subjects ANOVA Table

Dependent Variable: Evacuation Time

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	9466962.200[a]	8	1183370.275	2421.590	.000	.973
Intercept	129551120.417	1	129551120.417	265106.955	.000	.998
Passengers	9331756.233	2	4665878.117	9548.020	.000	.973
Exits	48120.700	2	24060.350	49.236	.000	.156
Passengers * Exits	87085.267	4	21771.317	44.552	.000	.251
Error	259486.383	531	488.675			
Total	139277569.000	540				
Corrected Total	9726448.583	539				

a. R Squared = .973 (Adjusted R Squared = .973)

Experimentation results for the number of passengers. The experimental simulation investigated three levels of passenger traffic volume during an evacuation, and the mean of each level was shown in table 7. Base on the alpha level set at .05, the results indicated that the mean evacuation time for 111 passengers (M = 317.200, SD = 18.422) was significant lower than the mean evacuation time for 666 passengers (M = 516.300, SD = 28.146) and 1000 people (M = 635.917, SD = 32.763). Table 8 displayed the results of the Sidak post hoc tests for the main effect of the number of passengers.

Table 7

Evacuation Time Based on Number of Passengers (in seconds)

Number of Passengers	Mean	Std. Deviation	N	95% Confidence Interval	
				Lower Bound	Upper Bound
111	317.200	18.422	180	313.963	320.437
666	516.300	28.146	180	513.063	519.537
1000	635.917	32.763	180	632.680	639.153

Table 8

Pairwise Comparisons in Evacuation Time (in seconds) - Number of Passengers

Number of Passengers	Number of Passengers	Mean Difference	Std. Error	Sig.[b]
111	666	-199.100*	2.330	.000
	1000	-318.717*	2.330	.000
666	1000	-119.617*	2.330	.000

Note. Based on estimated marginal means

*. The mean difference is significant at the 5% level.

Experimentation results for the number of exits. The experimental simulation considered that three different levels, which when one exit door, three exit doors, and five exit doors were available for the evacuation. For each level, all the possibilities of the exit doors were included. By using the combination methods, there were six possible combinations when one exit door ($\binom{6}{1}$) and five exit doors ($\binom{6}{5}$) were available during the evacuation; 20 possible combinations when three exit doors ($\binom{6}{3} = \frac{6!}{3!\,3!}$) were available during the evacuation. The post hoc analysis of the results of all the combinations of available exits doors was shown in Table 9 and 10.

As the alpha level set at .05, the results indicated that the mean for one exit door (M = 503.156, SD = 153.447) was significant higher than the mean for three exit doors (*M* = 483.089, *SD* = 125.164) and five exit doors (*M* = 483.172, *SD* = 121.888). Table 9 displayed the Sidak post hoc tests for the main effect of the different number of exits.

Table 9

Evacuation Time Based on Number of Available Exits

Number of Exits	Mean	Std. Deviation	N	95% Confidence Interval	
				Lower Bound	Upper Bound
1	503.156	153.447	180	499.919	506.392
3	483.089	125.164	180	479.852	486.326
5	483.172	121.888	180	479.935	486.409

Table 10

Post Hoc Analysis Results - Number of Exits Effects on Evacuation Time (in Seconds)

Number of Exits	Number of Exits	Mean Difference	Std. Error	Sig.[b]
1	3	20.067^{*}	2.330	.000
	5	19.983^{*}	2.330	.000
3	5	-.083	2.330	1.000

Note. Based on estimated marginal means

*. The mean difference is significant at the 5% level.

Experimentation results for the effect of passengers and interaction relationships between exits and passengers. Table 11 and Table 12 displayed the means and the standard deviations for each combination of the two independent variables, which were the number of passengers and the number of exits.

Table 13 showed the results of the Sidak post hoc tests of the interaction relationships with certain amount of exits with a quantity of passengers. As the alpha level set at .05, the results had shown that when only one exit door was available during the evacuation, 1000 passengers (M = 667.40, SD = 36.873) significantly needed spending more time than 111 passengers (M = 306.25, SD = 24.283) and 666 passengers (M = 535.82, SD = 39.240) did; once three exit doors were available for the evacuation, 1000 passengers (M = 619.12, SD = 15.931) still spent significantly longer time than 111 passengers (M = 320.37, SD = 13.012) and 666 passengers (M = 507.67, SD = 12.534) did; when five exit doors were available, 1000 passengers (M = 619.12, SD = 11.354) also needed significantly more time than 111 passengers (M = 324.98, SD = 8.765) and 666 passengers (M = 505.42, SD = 11.089) did. Figure 13 clearly presented the relationships of the two independent variables, which was based on the different number of exits with certain number of passengers.

Table 11

Simple Main Effect – Number of Passengers & Exits

Number of Passengers	Number of Exits	Mean	Std. Deviation	N
111	1	306.25	24.283	60
	3	320.37	13.012	60
	5	324.98	8.765	60
	Total	317.20	18.422	180
666	1	535.82	39.240	60
	3	507.67	12.534	60
	5	505.42	11.089	60
	Total	516.30	28.146	180
1000	1	667.40	36.873	60
	3	621.23	15.931	60
	5	619.12	11.354	60
	Total	635.92	32.763	180
Total	1	503.16	153.447	180
	3	483.09	125.164	180
	5	483.17	121.888	180
	Total	489.81	134.333	540

Table 12

Simple Main Effect – Passengers & Exits (in seconds)

				95% Confidence Interval	
Passengers	Exits	Mean	Std. Error	Lower Bound	Upper Bound
111	1	306.250	2.854	300.644	311.856
	3	320.367	2.854	314.760	325.973
	5	324.983	2.854	319.377	330.590
666	1	535.817	2.854	530.210	541.423
	3	507.667	2.854	502.060	513.273
	5	505.417	2.854	499.810	511.023
1000	1	667.400	2.854	661.794	673.006
	3	621.233	2.854	615.627	626.840
	5	619.117	2.854	613.510	624.723

Table 13

Pairwise Comparison – Exits with Different Number of Passengers (in seconds)

Exits	Passengers	Passengers	Mean Difference	Std. Error	Sig.[b]
1	111	666	-229.567*	4.036	.000
		1000	-361.150*	4.036	.000
	666	111	229.567*	4.036	.000
		1000	-131.583*	4.036	.000
	1000	111	361.150*	4.036	.000
		666	131.583*	4.036	.000
3	111	666	-187.300*	4.036	.000
		1000	-300.867*	4.036	.000
	666	111	187.300*	4.036	.000
		1000	-113.567*	4.036	.000
	1000	111	300.867*	4.036	.000
		666	113.567*	4.036	.000
5	111	666	-180.433*	4.036	.000
		1000	-294.133*	4.036	.000
	666	111	180.433*	4.036	.000
		1000	-113.700*	4.036	.000
	1000	111	294.133*	4.036	.000
		666	113.700*	4.036	.000

Note: Based on estimated marginal means

*. The mean difference is significant at the 5% level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

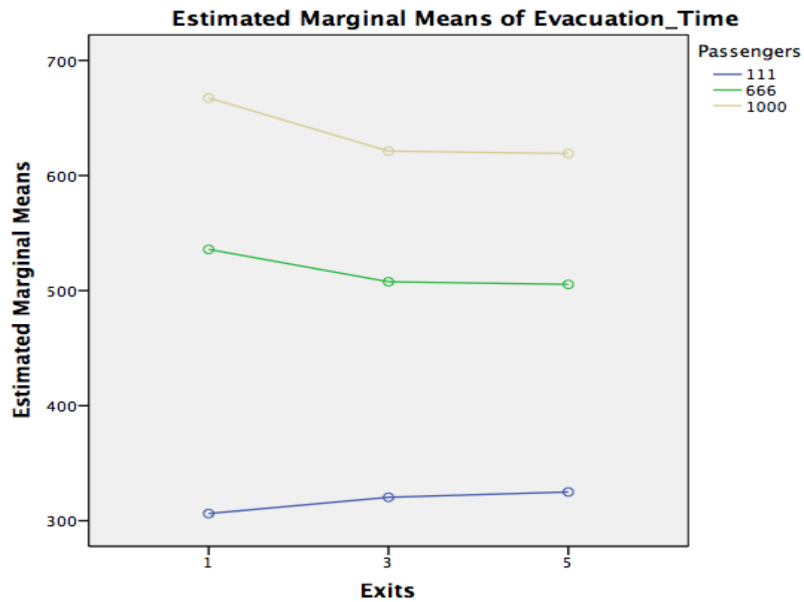


Figure 12. Evacuation time based on passengers

Experimentation results for the effect of exits and interaction relationships between exits and passengers. Table 14 shows the results of the Sidak post hoc tests. It indicated another relationship between the different number of passengers and the number of exit doors were available.

With the alpha level set at .05, the results demonstrated that when there were 111 passengers evacuated from the airport, the evacuation time of one exit door available (*M* = 306.25, *SD* = 24.283) was significantly faster than the evacuation times of three exit doors available (*M* = 324.98, *SD* = 8.765) and five exit doors available (*M* = 320.37, *SD* = 13.012). However, the evacuation time of three exit doors available and the evacuation time of five exit doors available were not significantly different when there were the 111 passengers during the evacuation. When 666 passengers were involved, the evacuation time of one exit door available (*M* = 535.82, *SD* = 39.240) was significant slower than the evacuation times of three exit doors available (M = 507.67, SD = 12.534) and five exit doors available (M = 505.42, SD = 11.089). The evacuation time between three and five exit doors available, similarly, did not have a significant difference. When 1000 passengers were evacuated, the evacuation time of one exit door available (M = 667.40, SD = 36.873) was significantly different from the evacuation time of three exit doors available (M = 621.23, SD = 15.932) and five exit doors available (M = 619.12, SD = 11.354) for the passengers to evacuate from the airport. Again, there was no significant difference between the evacuation time of three and five exit doors available during the evacuation.

Table 14

Pairwise Comparison – Passengers with Different Available Exits (in seconds)

Passengers	Exits	Exits	Mean Difference	Std. Error	Sig.[b]
111	1	3	-14.117*	4.036	.001
		5	-18.733*	4.036	.000
	3	1	14.117*	4.036	.001
		5	-4.617	4.036	.253
	5	1	18.733*	4.036	.000
		3	4.617	4.036	.253
666	1	3	28.150*	4.036	.000
		5	30.400*	4.036	.000
	3	1	-28.150*	4.036	.000
		5	2.250	4.036	.577
	5	1	-30.400*	4.036	.000
		3	-2.250	4.036	.577
1000	1	3	46.167*	4.036	.000
		5	48.283*	4.036	.000
	3	1	-46.167*	4.036	.000
		5	2.117	4.036	.600
	5	1	-48.283*	4.036	.000
		3	-2.117	4.036	.600

Note. Based on estimated marginal means

*. The mean difference is significant at the 5% level.

Discussion

From the results, the number of passengers and the number of exit doors available was the main factors that significantly influenced the duration of the airport evacuation. However, the differences of the evacuation time were not significant between three and five exit doors available during the evacuation. The following section concluded and discussed the results in detail.

Simulation validation. The result of the t-test retained the first null hypothesis (H0), which the average of the model evacuation time was not significantly different from the actual evacuation time. It meant that the simulation baseline was correct, and the difference of the observational data collected by the author was not ominously dissimilar with the baseline model. Furthermore, it revealed the baseline was very close to a daily de-boarding duration at the airport.

Experimental design results. Based on the two-way between-subjects ANOVA test, the experimental design results rejected the second hypothesis (H1) and the third hypothesis (H2). The experimental design showed that an increased number of passengers (H1) and the number of available exit doors (H2) had significant effects on the total evacuation time. Additionally, the second and third hypothesis had interactional relationships affected the total evacuation time.

Number of passengers. The statistical results illustrated that the passenger volume was the main factor that could influence a total evacuation time. Figure 13 indicated that a smaller volume of passenger traffic always had a lesser amount of evacuation time. As shown in figure 12, it could be explained as the congestion occurred when a larger amount of people evacuated from the airport. When the congestion appeared, the limited personal space-restricted individuals from moving as quickly as they could. Therefore, a larger number of passengers would need more time to evacuate from the airport. As a result, an increased number of passengers had a positive interaction relationship with the total evacuation time.

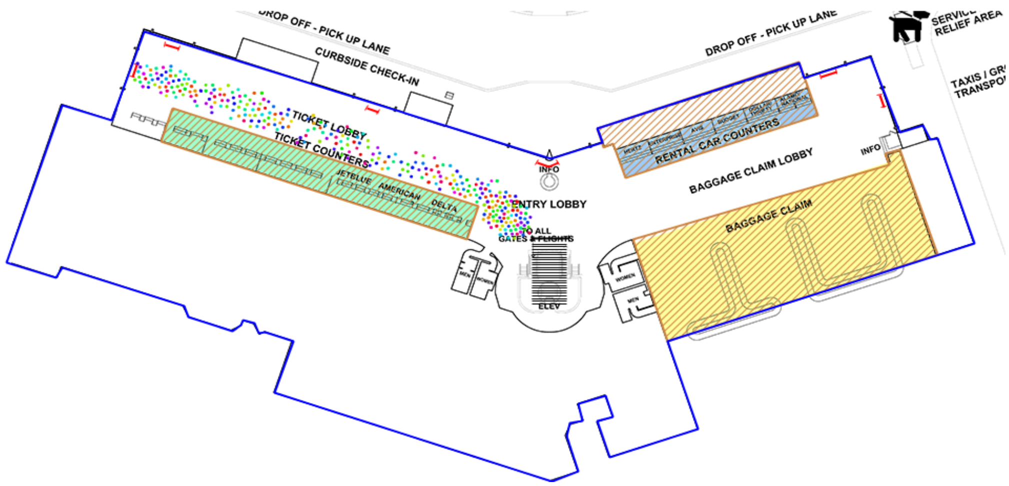


Figure 13. Evacuation simulation for one exit. Adapted from the Screenshot from AnyLogic.

Number of exit doors. The results of the simulation validated that the number of exit doors was another main factor that affected the total evacuation time. When only one exit door was available during the evacuation, passengers spend a significantly longer time to evacuate than when three and five exit doors were available. However, when three or five exit doors were accessible, the differences in evacuation time were not significant. It could be explained as that the congestion and the waiting time for the exit queuing were not substantial when passengers used multiple exits, shown in figure 13 and figure 14. As a result, there was a negative relationship between the number of exit doors and the evacuation time. It indicated that the evacuation time would increase when a smaller number of exit doors were available during the evacuation.

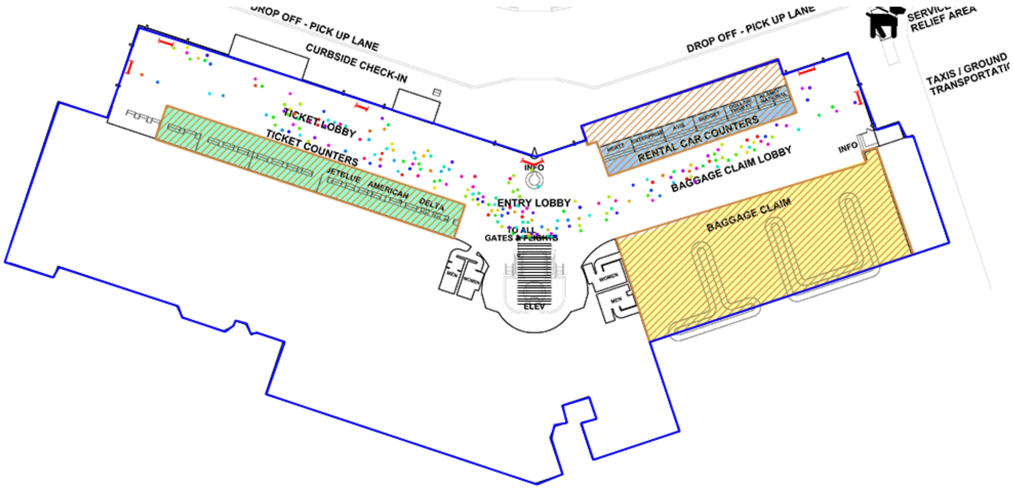


Figure 14. Evacuation simulation for five exits. Adapted from the screenshot from AnyLogic.

Relationship between the number of passengers and the exit doors. Figure 15 indicated an interactional relationship between the number of passengers and the number of available exit doors. It could be explained as that the impacts of the exit-door factor were not the same across all levels of the passenger factor. Especially, the total evacuation time was not significantly different when compared the exit accessibilities between three exit doors available and five exit doors available. On the contrary, when only one exit was available, the duration of the evacuation was significantly longer than when three or five exits were available for the evacuation. It could be interpreted as the fact that the more available exits were better to decrease evacuation duration. However, this advantage would be gradually reduced when the number of passengers and the number of exit doors reached a certain amount.

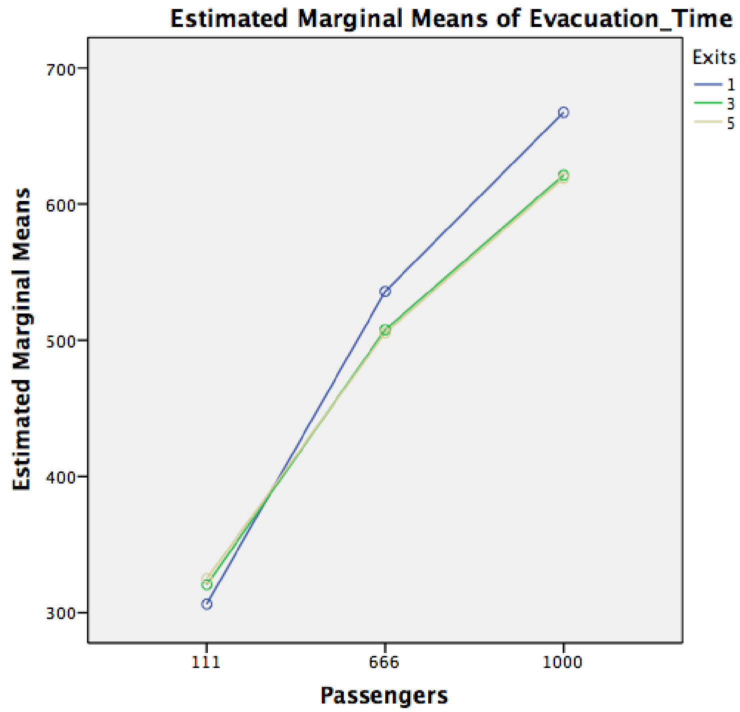


Figure 15. Evacuation simulation for interaction relationships

Case study 2

Research Question and Hypothesis

This study investigated the effect of the number of passengers and the evacuation policies on the efficiency of evacuation. In this study, the first null hypothesis (H_0) was that there would be no significant difference regarding the evacuation time for the number of passengers. The second hypothesis (H_1) for the experiment was that there would be no significant difference regarding the evacuation time between the equal distribution and the shortest queue evacuation policy.

Methodology

The baseline model and alternative models were built with AnyLogic. In this study, the normal evacuation was simulated in the baseline model, where the normal walking speed of pedestrian was used. In the baseline model, the number of passengers was set as 120, whom all evacuated via one exit, this number is based on the actual observation from the airport. Upon the validation of the baseline model, the emergency evacuations were simulated in the alternative models, modified from the baseline model where the running speed of pedestrians was used.

In comparison with the baseline model, the experimental model also supported with more levels on the number of passengers and the evacuation policies. The validation of the baseline model was achieved by comparing the time of normal evacuation generated by AnyLogic to the actual observed leaving time of passengers during daily operation at a local airport (KTAR). For the experimental model, the independent variables in this study were the number of passengers and the different evacuation policies. The dependent variable, the evacuation efficiency, was operationally defined as the total evacuation time for all the passengers. A quantitative approach was used in this study. ANOVA was performed in the data analysis program SPSS, with the significance level of 5%.

Design and procedures. Manipulating agents in different conditions and collecting output regarding their performance, the design of this study was considered as experimental. A baseline model of normal evacuation was created in AnyLogic based on the data collected from KTAR. The collected data included the number of arriving passengers in each flight, and the time used for all the passengers to leave the terminal building.

In the baseline model, passengers were designed to proceed the evacuation under several essential steps: (1) leave the aircraft and enter the terminal through the aerobridge at the second floor; (2) proceed to the escalator and the stairs that connect the second floor with the first floor; (3) choose whether to use escalator or the stairs; (4) reach the first floor via the choice they make; (5) choose one among the available doors to exit; (6) proceed to the selected door and to leave the terminal. Also, passengers in the baseline model were designed to choose the exit doors at an equal distribution. In other words, each door among all six doors has an equal chance (16.67%) to be selected by each passenger to evacuate.

The validation for the baseline model was processed after the configuration of the simulation model was done. The baseline model was built, including the above six steps in the evacuation, and data input, including walking speed, was also collected from the observation and Case study 1. The output for the baseline model regarding the evacuation time was compared to the actual time taken by passengers to complete evacuation in normal situations. A t-test between the average observed evacuation time, and the output from a group of 20 simulations was conducted at the significance level of .05. If there was no significant difference between the observed value and the baseline model, the baseline model is considered validated.

The number of passengers was one of the independent variables in this study. The observation indicated an average number of passengers as 120, and it was used in the baseline model. As for the setting of the experimental model, the number of passengers was set as three levels. According to KTAR's website, there were six daily flights, two Sunday to Friday flights, and one flight that operated four days a week. Airlines serving this airport utilized Airbus 320 with 150 seats, Canadian Regional Jet 900 with 76 seats, and McDonnell Douglas MD-88 with 149 seats to carry passengers. The number of passengers was estimated as 600 when six flights are arriving at the same time, utilizing all the six gates on the second floor. Considering the future growth of this local airport, the highest-level of 1000 passengers was also taken into the design. Thus, the three levels for passenger setting were 120 passengers, 600 passengers, and 1000 passengers.

According to the terminal layout shown below in Figure 5 of KTAR, there are six doors to exit the terminal building on the first floor. Each door has two possibilities to either be used or not to be used. During an evacuation, it can range from zero door is used to all six doors are used. Therefore, there are 2^6= 64 combinations of possibility. The combinations are representing the situations that no exits are available to the situations that all exits are available respectfully. For this study, only that situation with three available doors would be considered, with the other three doors were blocked. The three most typical scenarios were chosen to analyze the effect of the IVs.

The three scenarios were designed in three possible conditions. In the first condition, an emergency occurred at the baggage claim area, which is on the right-hand side of Figure 5, on the first floor of the terminal building. In this case, Door 5 and Door 6 were not available because it was dangerous to walk next to the emergency hazard. For the rest of the exits, Door 4 was the closest exit from the escalator and the stairs, Door 3 was the second closest, and Door 1 and Door 2 were at the similar distance in the same direction. Because the experiment was set with three exits, Door 1 was omitted. Thus, Door 2, Door 3, and Door 4 were designed to be available for the first scenario. The second choice designed for the situation when an emergency happened at the Ticket Lobby, which is on the left-hand side of Figure 5. In this case, Door 1, 2, & 3 on the left-hand side were taking out of consideration, because it would be very dangerous for passengers to walk next to the emergency. Therefore, Door 4, 5, & 6 were chosen in this second scenario. The last scenario was designed when an emergency happened in some places other than the first floor. As for this situation, all six exits would be available. Within this situation, it would be easier to choose the closer exits for passengers to evacuate. Comparing the six exits, Door 4 and Door 3 were the first and second closest exit from the escalator and the stairs, while Door 5 and Door 6 were further, and Door 1 and Door 2 were at the highest distance. To meet the setting of the three doors, Door 4 and 3 were chosen as the optimal decision; Door 1 and Door 2 were taken out of consideration under the comparison with Door 5 and Door 6; Door 5 was omitted between by Door 6. As a result, Door 3, Door 4, and Door 6 were chosen within this situation.

When the emergency happened at the Entry Lobby, which is located right in front of the escalator and the stairs, passengers would not be able to use any of the exits shown in Figure 5 on the first floor. Because the emergency hazard could block their way from the escalator and the stairs to all the doors, in this situation, the airport operation would instruct passengers to evacuate using special emergency exits, which would not be covered in this study. In conclusion, to effectively compare three groups of choices, the scenarios were set in the order of numbers from lower to higher for the gate choices. The scenario sequence was Door 2, Door 3, and Door 4; Door 3, Door 4, and Door 6; Door 4, Door 5, and Door 6.

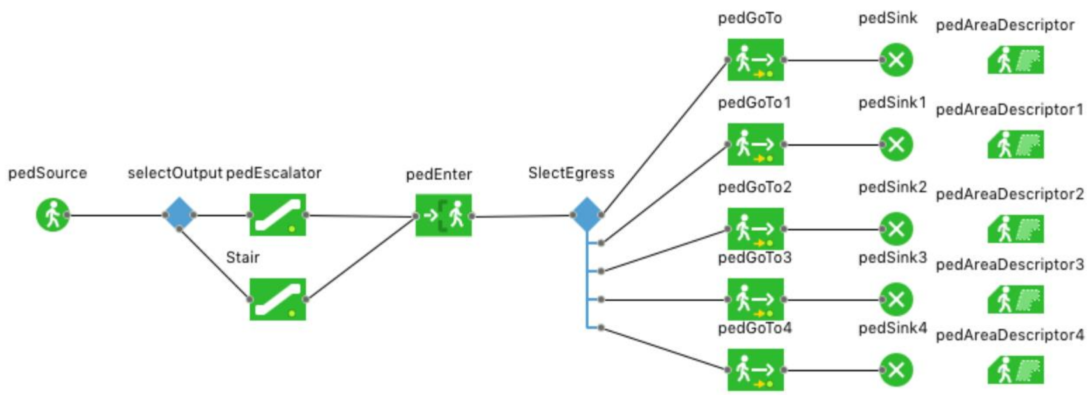


Figure 16. Agents' evacuation process

The process of this simulation was built based on the flow chart shown above in Figure 16. As briefly introduced earlier, passenger first de-boarded at specific gates and then walked from each gate to the escalator and the stairs, which is the connection between the first and second floor of the terminal building. At the connection, passengers were supposed to make a decision either to choose the stairs or the escalator to reach the first floor. The probability of passengers choosing stairs and choosing escalators was based on the researcher's observation at the airport, where 90% percent of the passengers would choose the escalator, and the rest of the passengers would choose the stairs. Once passengers arrived at the first floor, they were supposed to enter the selection stage of deciding which gate on the first floor to evacuate through. Passengers were manipulated in two policies selecting exits, which were the same distribution policy and the shortest queue policy. At the end of this system, passengers walked to the gates they had chosen and exited the system.

Alternative models were created based on the baseline model. Settings of the alternative models were manipulated by the researcher according to the three scenarios mentioned above. Within this study, two alternative models were designed. The function of "Select OutPut5" in AnyLogic was utilized to mimic the passengers' choices. Within AnyLogic, the function of "Select OutPut5" was the only available choice to simulate a selection with three choices. The selection has three modes to be proceeded: by probabilities, by conditions, or by exit numbers. The modes of probabilities and conditions were utilized in this study. Under the option of probabilities, five probabilities for five exits would be defined with the sum as 1. As for the option for conditions, there are four conditions (0 to 3) to be manipulated. The AnyLogic would evaluate the four conditions sequentially, one by one, when an agent arrives. If condition 0 is true, the agent selects the first option linked to condition 0. Otherwise, condition 1 is evaluated, etc. If all four conditions are false, the agent exits via the last exit automatically.

The first alternative model was designed for the evacuation policy of equal distribution, namely, in which situation passengers would choose each of the three doors at an equal probability. In other words, the probability of each gate chosen by each passenger, known as one agent in the simulation, was designed to be equal. For the five probabilities in this mode, three selections representing the three available doors were set as 1.0 / 3 identically, and the rest two probabilities were set as zero. The function of randomization in AnyLogic would allow the system with variance in assigning passengers, which means even under equal probability, each door might not have the equal number of passengers choosing it.

The second alternative model was designed to manipulate the agents' decision when choosing exits, following the rules of "first arrive, first serve." As queues could appear at exit doors during evacuations, the researcher was intended to produce a policy with expected higher efficiency, instructing each passenger to choose the exit with the shortest queue when he or she makes the decision. The mode of conditions was applied to realize this policy, manipulating passengers' choices. The scenario of choosing doors among Door 2, 3, and 4 could be explained as an example. The system would evaluate the conditions for each of the passengers who just arrived on the first floor. For the four conditions, the first two, condition0 and condition1, were both sets as "false," so that the system would evaluate the third and fourth conditions. The condition2 would be coded as below:

```
pedGoTo2.size() <= pedGoTo3.size() && pedGoTo2.size() <= pedGoTo4.size()
```

"pedGoTo2.size()" indicated the number of passengers who had already chosen Door 2 to evacuate at the time when the next passenger arrived on the first floor. This number would include both the passengers that are queuing at Door 2 and the passengers that are on their way to Door 2. Passengers that had already successfully evacuated via Door 2 were not counted in this calculation. Similarly, the pedGoTo3.size() and pedGoTo4.size() indicated the number of passengers that had already chosen Door 3 and Door 4 to evacuate respectfully. The condition2 formed of two formulas represented the order to let the system compare the number of passengers chosen to Door 2 with that of Door 3 and Door 4. Condition2 would only be considered as true if the passengers chose Door 2 was the least among the three doors, indicating the shortest queue. In that case, this specific passenger would choose Door 2 to evacuate. Otherwise, the system would consider the condition2 as false and continue evaluating condition3, which was set as below:

pedGoTo3.size() <= pedGoTo2.size() && pedGoTo3.size() <= pedGoTo4.size()

The condition3 worked similarly with condition2, making the system to determine if the queue for Door 3 was the shortest. If the result turns out to be false, the system will proceed with the last selection as default as all four conditions were calculated as false.

The conditions discussed above apply to the scenario in which Door 2, Door 3, and Door 4 were available. In other scenarios that different doors were available, the conditions were edited accordingly. All the output for the three scenarios were collected to proceed with data analysis.

While agents were simulated to choose gates, the "pedAreaDescriptor" function was deployed at each of the exiting areas. For each exit, an area was drawn in front of the exit in the shape of green dotted polygons shown below in Figure 17. Within these areas, agents were designed with walking speed and throughput rate to simulate the congestion of exits. The walking speed was limited below the running speed because of the observed congestion within the areas. The throughout rate was limited as two people per second to define only up to two people to evacuate at the same second. The reason for the setting was the limited width of each door.

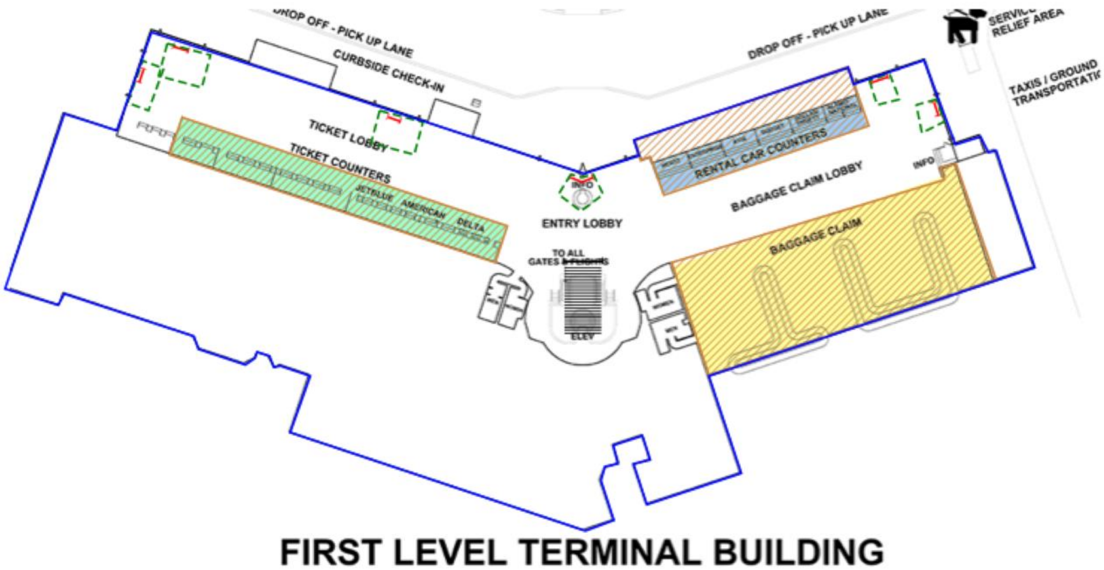


Figure 17. The layout of the first floor with Area Descriptors. Adapted from Daytona Beach International Airport. Retrieved February 28, 2017, from *http://www.flydaytonafirst.com/airport-information/terminal-layout.stml*

This study was manipulated as a 3 (number of passengers: 120, 600, 1000) * 2 (evacuation policy: equal distribution, shortest queue) experimental design with six different levels of setting in terms of the number of passengers and the evacuation policies. Besides the six levels of setting, the simulation was multiplied 40 times for each of the scenarios based on different choices of gates. In general, 720 runs were simulated by the researcher.

Sources of data. The data inputted in this study was collected from three sources. Real observation collected an average number of arriving passengers for each observed flight, as well as the time, is taken by passengers to leave the airport terminal building. The website of airport KTAR supported the constructional design of the terminal and the weekly flight schedules. The terminal map showed six gates in the terminal. Additionally, the information on the airport's website also helped the researcher to make a forecast for future passenger growth. The researcher was able to design passenger settings into three levels by combining the two sources of data.

In addition to the observation and the airport's website, the previous studies also supported the researcher with operational data, including walking speed, running speed, and the average speed on escalators and stairs. With the data mentioned, the researcher was able to adjust the evacuations into normal and emergency settings. The output as evacuation time was measured in seconds by AnyLogic.

The validation of models was important, because the simulation was supposed to perform in a way that was close enough to reality. A baseline model for validation was built to simulate the passengers' normal evacuation process. The data used for validation were referred from observation on airport evacuation from Case study 1. Case study 1 observed passengers' evacuation for non-emergency. Based on the data, Case study 2 compared the time taken by the passengers in reality and the time taken in the simulation of the baseline model.

Treatment of data. In this study, the researcher made numbers of manipulations regarding the choices of exit doors and the policies or evacuation. The manipulation for the evacuation policies and the number of passengers were treated as two independent variables, and the total evacuation time measuring from the first arriving passenger appear at the gate on the second floor after debarking to the last passenger leaving the terminal was recorded as the dependent variable. Each scenario was simulated multiple times to collect the output.

After the data output from each run of the simulation was recorded, the researcher exports the data into an Excel file. The Excel file was split into three groups based on the three scenarios, which were the availability of (1) Door 2, Door 3, & Door 4; (2) Door 3, Door 4, & Door 6; and (3) Door 4, Door 5, & Door 6 for passengers to evacuate the terminal building. To conduct the statistical analysis, the researcher imported the Excel file into the SPSS, and statistical analysis was applied to compare the means and variances among all groups.

For the validation of the baseline model, a t-test was utilized to examine the null hypothesis, which was that there was no significant difference between the mean of observed evacuation time and the evacuation time of the baseline model. As the study was conducted in the number of passengers of three levels and two kinds of evacuation policies, a 3 (number of passengers: 120, 600, 1000) x 2 (evacuation policies: equal distribution, shortest queue) two-way between-subject ANOVA test was performed to examine if there was significant difference of the evacuation times among respect experimental settings. The two null hypothesizes for this study were: 1) there was no significant difference among the evacuation times in three levels of amounts of passengers; 2) there was no significant difference among the evacuations times between the two evacuation policies. An alpha level of 0.05 was used to examine if the difference was significant or not.

In addition to the two independent variables, the choices of doors were also taken into consideration to compare the evacuation plans better. The researcher generated three sets of choices of exit doors and compared the evacuation times within these three scenarios. The data collected under the three scenarios using different exit doors were then analyzed with a one-way ANOVA in SPSS. This factor of choices of doors was not a concentration of this study, but the researcher would be able to compare different situations that could happen in an emergency with the help of data comparison.

Results

After the implementation of the methods discussed in Chapter III, the researcher was able to collect the records of the dependent variables by running multiple simulations. Taken the data into SPSS, the results are presented in this chapter.

Results of validation. Based on the data from Case study 1, the mean of the evacuation time from the observation was 621 seconds. Taken the behavioral data into the designation, the researcher ran 20 simulations and received the statistical data shown in Table 15. Within the t-test between the observed value and the sample means, there were approved without a significant difference between the baseline value and the experimental model, t (19) = .766, p = .453, the p-value is larger than 0.5, the null hypothesis cannot be rejected. Thus, the baseline model was validated.

Table 15

Results of Validation

	Test Value = 621					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Simulation time	.766	19	.453	.65000	-1.1258	2.4258

Descriptive statistics. The dependent variable for this study was the evacuation time for all the passengers. Table 16 showed the descriptive statistics among three levels of passenger numbers and two kinds of evacuation policies from the experimental model.

Table 16

Descriptive Statistics for the Number of Passengers and the Evacuation Policies

Number_Passengers	Evacuation_Policy	Mean	Std. Deviation	N
120	Equal Distribution	291.1671	10.94224	120
	Shortest Queue	282.9029	9.16033	120
	Total	287.0350	10.88768	240
600	Equal Distribution	390.8942	21.05556	120
	Shortest Queue	374.6092	9.40645	120
	Total	382.7517	18.20369	240
1000	Equal Distribution	499.9400	15.82835	120
	Shortest Queue	486.2433	12.19808	120
	Total	493.0917	15.68201	240
Total	Equal Distribution	394.0004	86.94319	360
	Shortest Queue	381.2518	83.89878	360
	Total	387.6261	85.61308	720

Hypothesis testing. The two independent variables as the number of passenger and the evacuation policies were checked independently of each other. The null hypothesis was that there were no significant differences among the evacuation times in different levels of the number of passengers for each of the evacuation policies.

A 3 (Number of Passengers: 120, 600, 1000) * 2 (Evacuation Policy: Equal Distribution, Shortest Queue) two-way between-subject ANOVA was conducted on evacuation times. The results as in Table 17 showed the effect of number of passengers was significant, F (2, 714) = 13492.361, $p < .05$; the effect of evacuation policy was significant, F (1, 714) = 154.680, $p < .05$; and the effect of number of passenger * evacuation policy was significant as well, F (4, 714) = 5.316, $p < .05$. Therefore, the null hypothesis was rejected.

Table 17

Tests of Between-subjects Effects in the Two-way Between-subject ANOVA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	5134941.442[a]	5	1026988.288	5430.007	.000	.974
Intercept	108182881.451	1	108182881.451	571996.584	.000	.999
Number_Passengers	5103675.660	2	2551837.830	13492.361	.000	.974
Evacuation_Policy	29254.875	1	29254.875	154.680	.000	.178
Number_Passengers * Evacuation_Policy	2010.906	2	1005.453	5.316	.005	.015
Error	135040.277	714	189.132			
Total	113452863.170	720				
Corrected Total	5269981.719	719				

a. R Squared = .974 (Adjusted R Squared = .974)

Number of passengers. The null hypothesis stated that there was no significant difference in evacuation time among the three levels of passenger numbers. The results shown in Table 18 indicated that the mean evacuation time at the passenger number of 120 (M = 287.035, SD = 10.888) was significantly lower than the mean evacuation time at the passenger number of 600 (M = 382.752, SD = 18.204) and passenger number of 1000 (M = 493.092, SD = 15.682), with p-value of $p < 0.05$. Therefore, the null hypothesis was rejected.

Table 18

Pairwise Comparison Between Number of Passengers

(I) Number_ Passengers	(J) Number_ Passengers	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
120	600	-95.717*	1.255	.000	-98.721	-92.712
	1000	-206.057*	1.255	.000	-209.061	-203.052

600	120	95.717*	1.255	.000	92.712	98.721
	1000	-110.340*	1.255	.000	-113.345	-107.335
1000	120	206.057*	1.255	.000	203.052	209.061
	600	110.340*	1.255	.000	107.335	113.345

Based on estimated marginal means

*. The mean difference is significant at the 5% level.

b. Adjustment for multiple comparisons: Sidak.

Evacuation policies. The null hypothesis was that there is no significant difference in evacuation time between the equal distribution policy and the shortest queue policy. The results shown in Table 19 indicated that the mean evacuation time for the equal distribution policy (M=394.000, SD = 86.943) was significantly higher than the evacuation time of the shortest queue policy (M=381.252, SD = 83.898), with a p-value of $p < 0.05$. As a result, the null hypothesis was rejected.

Table 19

Comparison Between Evacuation Policies

(I) Evacuation_Policy	(J) Evacuation_Policy	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
Equal Distribution	Shortest Queue	12.749*	1.025	.000	10.736	14.761
Shortest Queue	Equal Distribution	-12.749*	1.025	.000	-14.761	-10.736

Based on estimated marginal means

*. The mean difference is significant at the 5% level.

b. Adjustment for multiple comparisons: Sidak.

Relationship between the number of passengers and the evacuation policies. Table 20 showed the pairwise comparisons for the interaction of the two independent variables. The SPSS output showed that at the passenger number of 120, the mean evacuation time (in minutes) for the equal distribution policy (M = 291.167, SD = 10.942) was significantly longer than the mean evacuation time for the shortest queue policy (M = 282.903, SD = 9.160); at the passenger number of 600, the mean evacuation time for the equal distribution policy (M = 390.894, SD = 21.056) was significantly longer than the mean evacuation time for the shortest queue policy (M = 374.609, SD = 9.406); at the passenger number of 1000, the mean evacuation time for the equal distribution policy (M = 499.940, SD = 15.828) was significantly longer than the mean evacuation time for the shortest queue policy (M = 486.243, SD = 12.198). Figure 18 indicated the reflections of the two independent variables on the evacuation times that the growing number of passengers increased the evacuation time, and it also showed that the equal distribution policy cost longer evacuation time on each level of the passenger numbers.

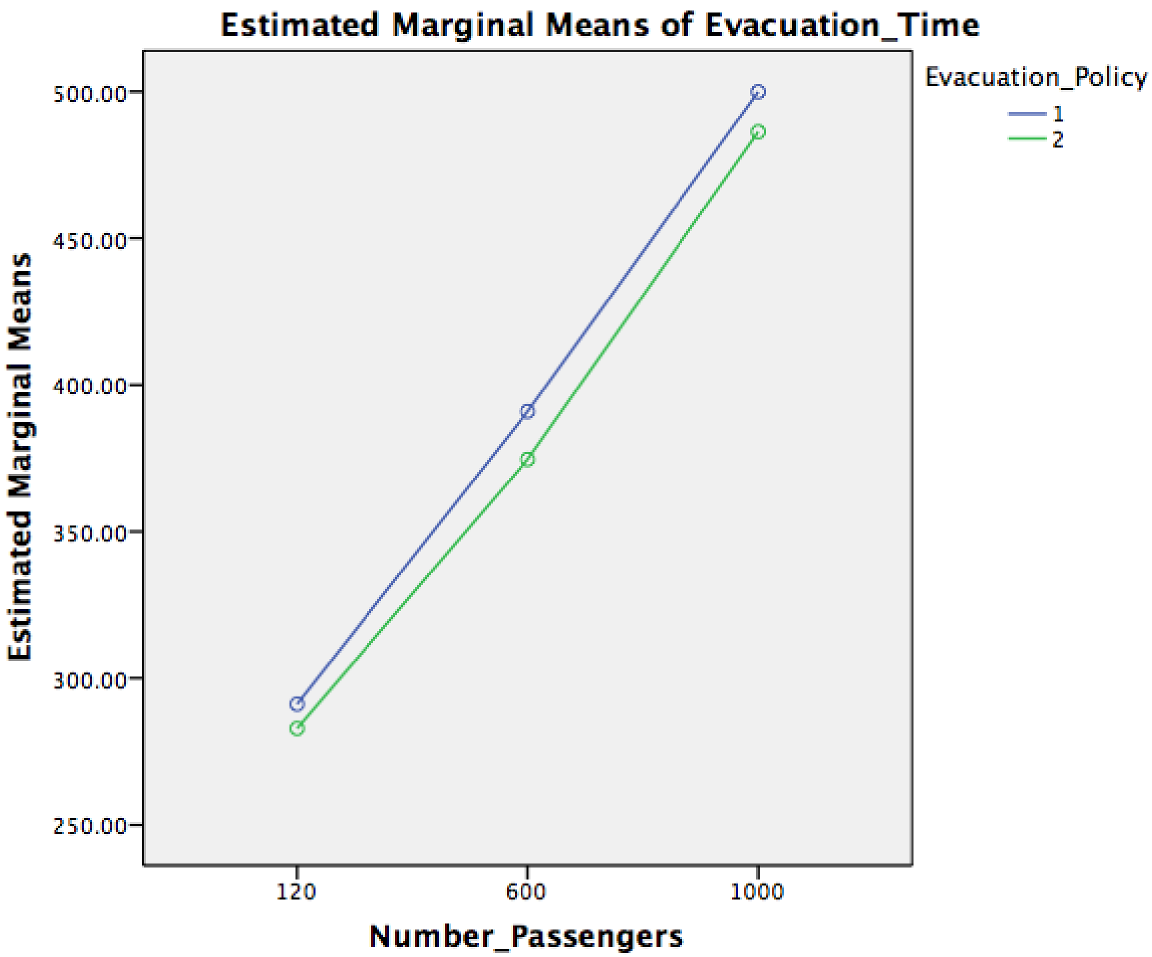


Figure 18. Evacuation time based on number of passengers

Table 20

Pairwise Comparison Between the Number of Passengers and the Evacuation Policies

Dependent Variable: Evacuation_Time

Number_Passengers	(I) Evacuation_Policy	(J) Evacuation_Policy	Mean Difference (I-J)	Std. Error	Sig.[b]	97.5% Confidence Interval for Difference[b] Lower Bound	Upper Bound
120	Equal Distribution	Shortest Queue	8.264*	1.775	.000	4.276	12.252
	Shortest Queue	Equal Distribution	-8.264*	1.775	.000	-12.252	-4.276

600	Equal Distribution	Shortest Queue	16.285*	1.775	.000	12.297	20.273
	Shortest Queue	Equal Distribution	-16.285*	1.775	.000	-20.273	-12.297
1000	Equal Distribution	Shortest Queue	13.697*	1.775	.000	9.709	17.685
	Shortest Queue	Equal Distribution	-13.697*	1.775	.000	-17.685	-9.709

Based on estimated marginal means

*. The mean difference is significant at the 5% level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Choices of gates. To make the simulation fitted in more realistic scenarios, the researcher conducted three methods in choosing gates: Door 2, 3, & 4; Door 3, 4, & 6; and Door 4, 5, & 6. To compare the three scenarios in the simulation, a one-way between-subject ANOVA was conducted to compare the performance in different choices of gates.

The null hypothesis was that there was no significant difference between the different choices of gates. With the alpha-level set at .05, the one-way between-subject ANOVA was significant, $F\ (2, 717) = 188.225$, $p < .05$, $\eta^2 = .01$. The equal variance post hoc test, Sidak, shown in Table 21, indicated that the mean evacuation time for the door choice of Door 3, 4, & 6 ($M = 375.470$, $SD = 81.591$) was significantly lower than the mean evacuation time for the door choice of Door 4, 5, & 6 ($M = 394.385$, $SD = 91.636$), and significantly lower than the mean evacuation time for the door choice of Door 2, 3, & 4 ($M = 393.023$, $SD = 82.293$).

Table 21

Multiple Comparisons Between Choices of Gates

Dependent Variable: Evacuation_Time

Sidak

(I) Door_Choices	(J) Door_Choices	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
234	346	17.55208	7.78650	.072	-1.0836	36.1877
	456	-1.36292	7.78650	.997	-19.9986	17.2727
346	234	-17.55208	7.78650	.072	-36.1877	1.0836
	456	-18.91500*	7.78650	.045	-37.5507	-.2793
456	234	1.36292	7.78650	.997	-17.2727	19.9986
	346	18.91500*	7.78650	.045	.2793	37.5507

*. The mean difference is significant at the 0.05 level.

Discussion

Number of passengers. The number of passengers was considered as a factor affecting the evacuation time. As three levels were designed for this factor, the result in evacuation times reflected that the higher level of the number of passengers led to significantly longer time to complete the evacuation. The result came without surprise, not only because the increase in passenger numbers led to longer process, but also the higher number of passengers was more likely to cause congestions while evacuating.

More passengers would certainly increase the total evacuation time, as the number of units who need to proceed at the exits increased. Through the researcher’s observation during the simulation, when there were 120 passengers in the system, there were not obvious congestions; while the simulation for 1000 passengers tended to cause much more congestions than that of 600 passengers, this can be easily observed from the simulation model through AnyLogic. The congestion reduced the evacuation efficiency; it is a significant factor considered in the simulation because it made the simulation more applicable to the real scenarios.

Evacuation policies. The evacuation performance was evaluated under two policies: the equal distribution among exits policy and the shortest queue assignment policy. Under the equal distribution policy, passengers choose each gate with an equal probability, representing the scenario that evacuee choose the exit in a random manner; and for the second policy, passengers were assigned to the exit that had the shortest queue when they arrive at the first floor, representing the scenario that there is someone there guiding the evacuation process, in order to balance the queue length among the different exits. The evacuation time for the equal distribution was found to be significantly longer than the shortest queue policy, showing the latter policy had higher efficiency in evacuations, demonstrating the effects of having guidance for the exit assignment during the evacuation process. Furthermore, comparing the shortest queue policy to the equal distribution one, it was found that more passengers were assigned to the closer gates, as the queue length reduced faster in the closer gate, making advantages of the shorter distance for the evacuation. The result echoes with the researcher’s expectation that the shortest queue policy guided by authority presents a more efficient way to evacuate during emergencies.

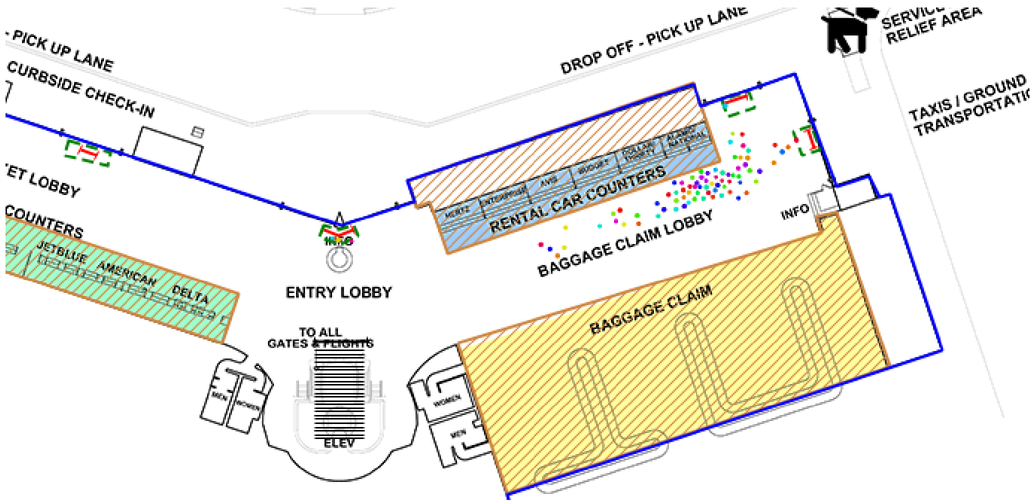


Figure 19. End of shortest queue evacuation. Adapted from the Screenshot from AnyLogic.

Figure 19 shown above, was captured at the end of a simulation run with 1000 passengers using the shortest queue policy, and the gate chosen for this scenario was Door 4, 5 & 6. It can be seen that the passengers at Door 4 were about to finish evacuating when there were still several passengers that were on their way to Door 5 and Door 6. This situation was caused by the time when passengers made a choice and the different distances from the escalator to each gate. Passengers were designed to decide once they arrived on the first floor, choosing the door that had the least people queue at that moment. Moreover, as each of the gates was at different distances from the escalator, the time taken for the passengers to walk from the escalator was different. The two reasons mentioned could explain the situation shown above. Because the time takes to Door 4 was shorter than the time taken to Door 5 and Door 6, passengers who had chosen Door 5 and Door 6 would be still halfway to their destination when the passengers chose Door 4 had already successfully evacuated. Since passengers were not allowed to change their assigned exits during the evacuation, the queue length changed quickly as the evacuation process occurs. For a situation like this, especially involved more people, a more flexible policy should be considered to accommodate the dynamic changes in the situation.

Relationship between the number of passengers and the evacuation policies. The interaction between the number of passengers and the evacuation policies can be seen from Figure 20. Increased number of passengers led to the increase of evacuation time, and the shortest queue policy acted more efficiently than the equal distribution.

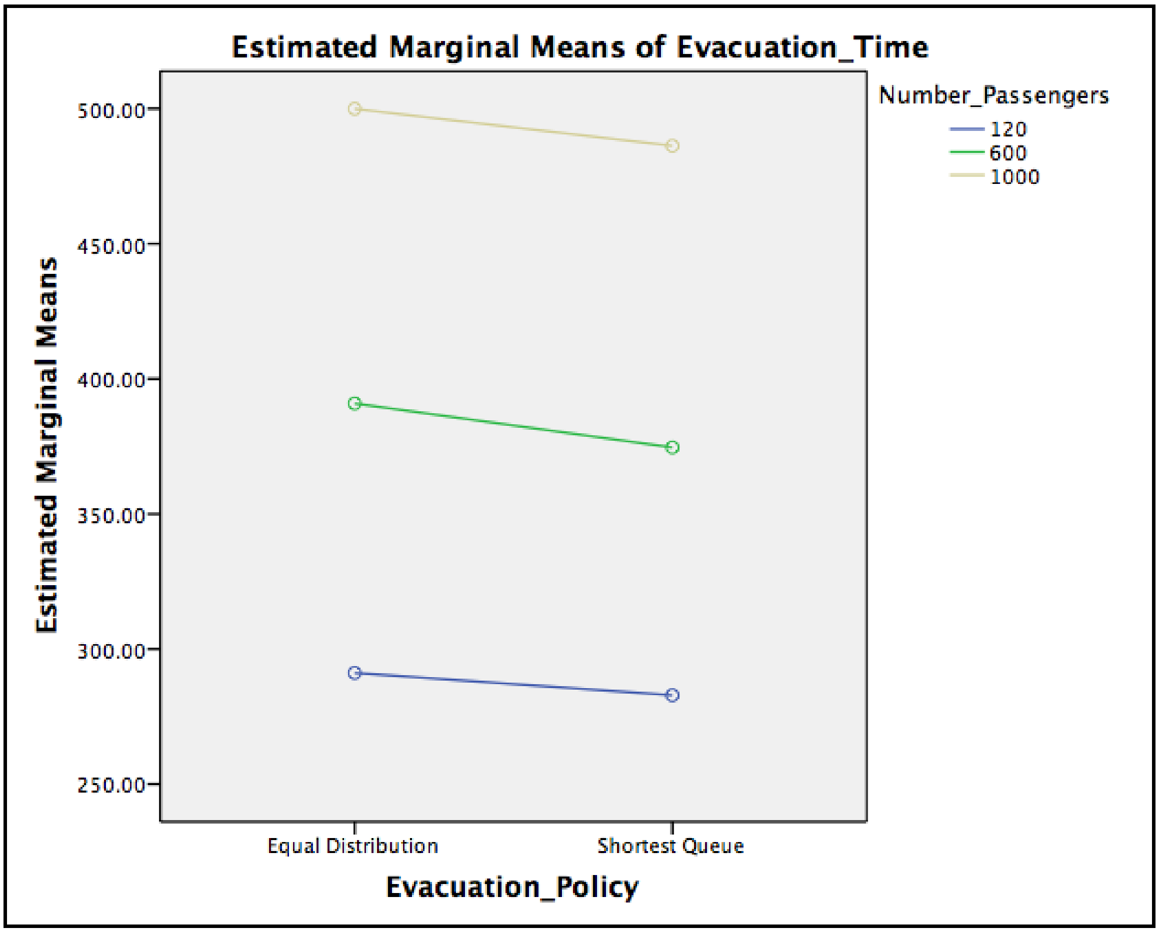


Figure 20. Evacuation times based on the evacuation policies.

Choices of gates. In this study, three plans for choosing the gates were conducted and compared. Results indicated that among the three plans (Door 2, 3, & 4; Door 3, 4, &6; Door 4, 5, & 6), the plan of choosing Door 3, 4, & 6 performed better than both Door 2, 3, & 4 and Door 4, 5, & 6. Comparing the plans choosing Door 3, 4, & 6 and Door 2, 3, &4, the distance to Door 6 was shorter than Door 2, causing less evacuation time. Also, the fact that Door 2 and Door 3 were both on the left side of the terminal could cause congestion that makes the process even longer. The reasons why choosing Door 4, 5, & 6 costs longer time for evacuation were supposing the same as mentioned: all doors have different distance to the starting point, Door 5 was farther than Door 3, and all passengers evacuating to the right side of the terminal could cause congestion on the way to exits. Thus, the plan of choosing Door 3, 4, & 6 was recommended with the best performance among other plans in this study. The difference of the exit distances added more complexity to the situation, which makes a single static policy not suitable for the optimization of the evacuation time. A more effective policy might be more proper to account for the travel distance of the exits.

Case study 3

Research Question and Hypothesis

The purpose of this study was to investigate the effect of group travel and instructions on the overall evacuation efficiency. This would help people understand how these two factors influence the efficiency of an evacuation, which, in turn, lead to better policy and decision-making process for this situation. By understanding these effects, the authorities would have a clearer picture of the whole evacuation program, making appropriate proactive evacuation plans.

Instructions to the closest exits from authorities might help people to find the most efficient way to evacuate from the emergencies. The study focused on two factors of evacuation efficiency. One is group travel, and the other is instructions. When an emergency occurred, people might fail to find the fastest and the closest route to evacuate. At that time, instructions of closest exits from authorities might help people to find the most efficient way to evacuate the dangerous situations. This study addressed the questions of whether group travel influences the efficiency of evacuation and whether instructions are affecting the efficiency of evacuation. Therefore, the first hypothesis (H_{01}) of the study was that group travel actions would not significantly affect the evacuation time. The second hypothesis (H_1) was that instructions would not significantly influence the evacuation time. A two-way ANOVA analysis was applied to test the above three hypotheses, with a significant level set at 5%.

Methodology

Research approach. This study was conducted to analyze the airport evacuation process under emergent situation at a small local airport using a simulation model. Agent-based simulation, Anylogic was used to develop the baseline model and the experimental model. SPSS was used to conduct statistical analysis.

In this study, the baseline model was built to simulate the normal evacuation process for the current situation for validation purposes. In the normal evacuation process, pedestrians were assumed to evacuate the airport building individually. Under normal conditions, there are no connections between pedestrians. The average rate of moving speed of pedestrians was set as a constant. The walking speed of pedestrians used in the baseline model was from 1.08 to 1.27 m/s (Galea et al., 2006), following a normal distribution, which was based on the previous studies. In the experimental model, this average moving speed of pedestrians was not changed; however, group travel behaviors and instructions were added to the validated baseline model as the independent variables. The dependent variable both the baseline model and the experimental models was the time of the evacuation process (in seconds). Case study 1 validated the baseline model by comparing the total time of normal evacuation generated by Anylogic to the actual leaving time of passengers observed in the small local airport. The experimental model was developed based on the validated baseline model, and two-way analysis of variance (ANOVA) was utilized to investigate the effect of group behaviors and instruction on the evacuation time. Significant level was set at 5%.

This study applied a 2×3 experimental design. The procedures of this study were designed based on the activities taken by pedestrians in a small local airport when an emergency occurs.

The procedures of this study included 7 steps, which covered the process from when passengers evacuated the aircraft and went to the gates, to the point where every pedestrian got out the small local airport. These steps included; a) generate group and travel in different group size, b) get off the aircraft and enter the terminal through aerobridges on the second floor, c) go to the escalator or stairs connecting the first floor and the second floor, d) choose to use escalator or stairs to get down to the first floor, e) get down to the first floor by the choice they made, f) choose exit from all available doors, g) leave the building through the door they chose. Figure 21 and Figure 22 illustrate the floor configurations for the airport.

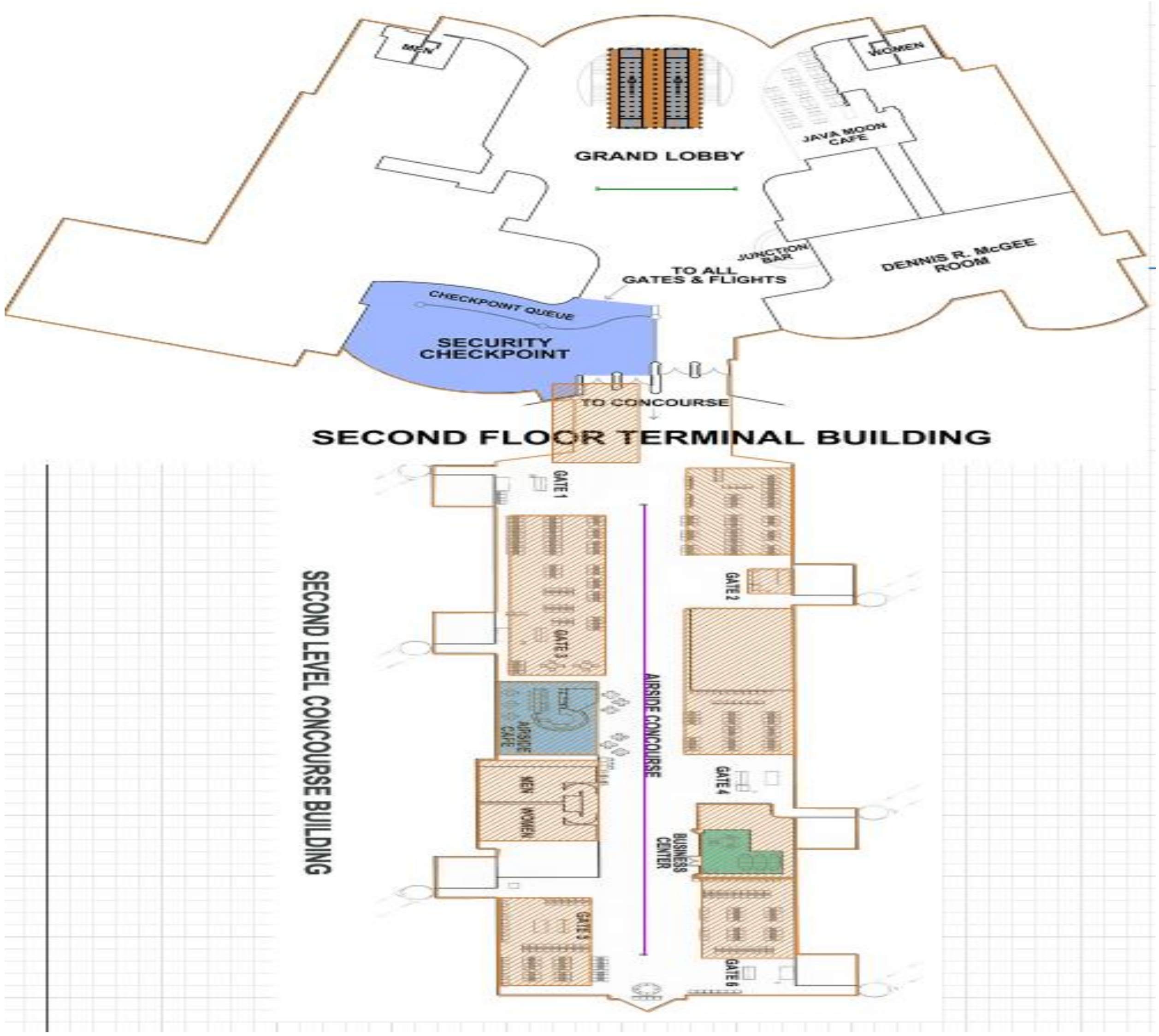


Figure 21. The second floor of the terminal. Retrieved February 28, 2017, from

http://www.flydaytonafirst.com/airport-information/terminal-layout.stml

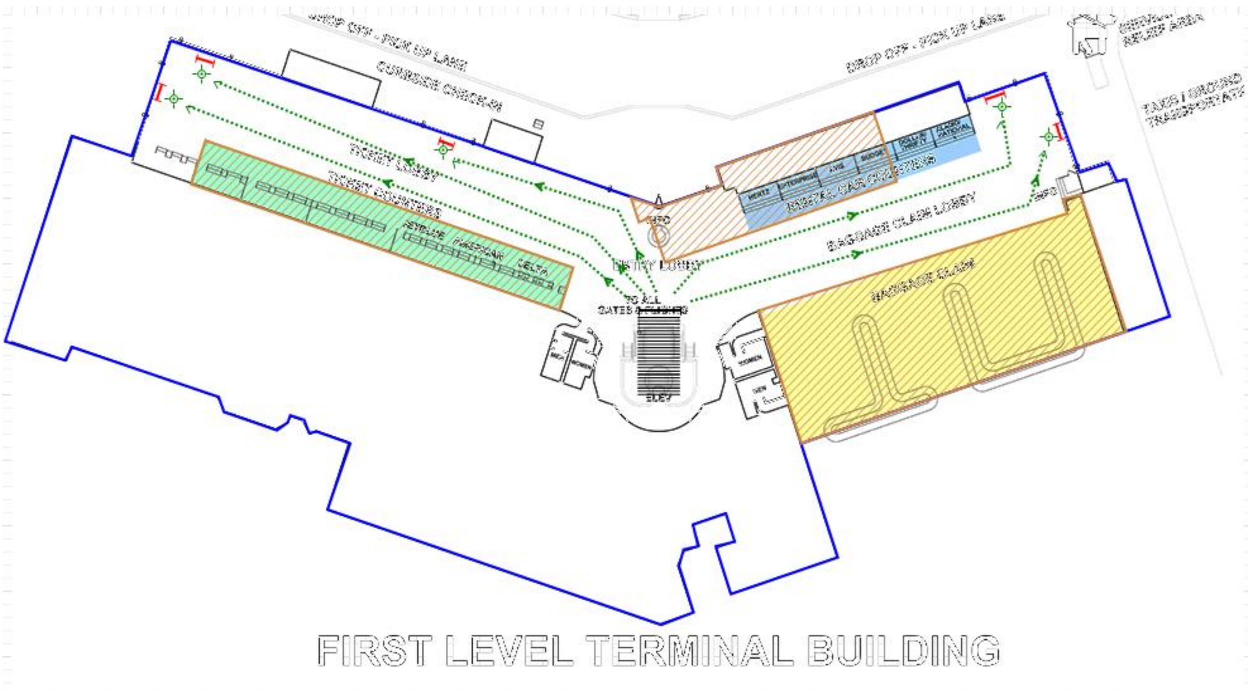


Figure 22. The first floor of the terminal. Retrieved February 28, 2017, from http://www.flydaytonafirst.com/airport-information/terminal-layout.stml

The validation of the baseline model was done Case study 1. The maximum level of the number of passengers of this small local airport would be 1000 at the same time from six gates located on the second floor. According to Figure 23, six gates were located on the second floor of the terminal; pedestrians would run out of the six gates when an emergency occurs. On the first floor of the terminal, six exit doors were in different positions of the building. As shown in Figure 23, the sort red lines were referring to exit doors that can be used by pedestrians to evacuate from the emergency. However, in this study, the researcher was assuming that there was a fire at the point of the closest door to the downstairs exit of the escalator. According to Figure 23, the door in the middle could not be used. Pedestrians could only use the other 5 doors to evacuate the airport.

The independent variable group travel behaviors had three levels. These levels included group traveling size of 1, 3, and 6. Group size of traveling pedestrians was set up at the beginning of the simulation. It was set at the Ped Source palette in the Pedestrian library of Anylogic software. The simulation without group travel behaviors (group size of 1) simulated the no group scenario, which is, every pedestrian was evacuating individually. For the group travel behaviors simulations, pedestrians moved with each other in different group sizes. The group sizes were set at 1 (as the control group), 3, and 6. For a group size of 1, when an emergency occurs, pedestrians do not need to wait for anyone and can evacuate as soon as possible.

Another independent variable was instructions. Two levels of the independent variable were set in this study, with and without instructions in the evacuation process. Under the without instruction condition, when an emergency occurs, pedestrians will randomly choose the exit because they may be in a panic situation and lose their situational awareness. For the with instruction scenario, an authority was set at the bottom of the escalator in the first floor the authority would give pedestrian instructions which way was the most efficient way to exit, which is based on the smallest number of people on that exit. This implies that a pedestrian might not go the shortest distance.

When there were no instructions, the pedestrians would choose the exit doors by themselves. The probability of choosing each door was set equal to mimic a random selection of exits. On Figure 23, the five dotted lines were the evacuate routes on the first floor of the terminal of the small local airport. To realize the goal of the equal chance of every exit, pedSelectOutput palette was used in the pedestrian library of Anylogic software. There were five exports of a pedSelectOutput palette. The setting of probabilities for each exit was 0.2. The flow chart of the baseline model was shown in Figure 23.

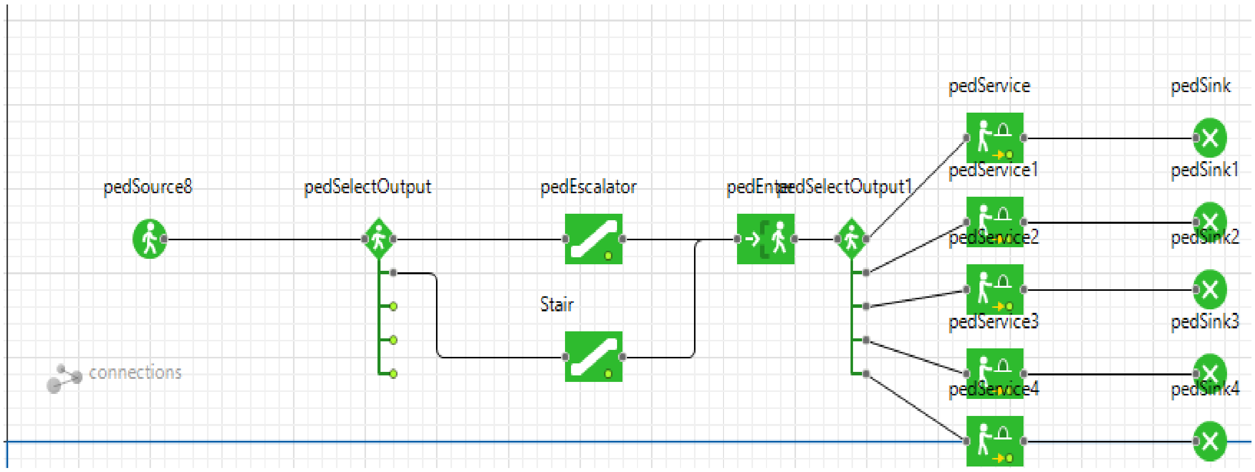


Figure 23. Flow chart of the models without instructions

For the experimental models with group travel behaviors (group size of 1, 3, and 6) and without instructions, the same flow chart was used. Compared to individual evacuation (group size of 1), the only setting changed was that pedestrians showed up in groups as opposed to traveling individually. Also, when they faced several routes to choose, they would make a decision together and evacuate together, they would not be separated during the evacuation process.

Another experimental model was without group travel behaviors (group size of 1) and with instructions. In this model, pedestrians would choose to the exit randomly (with equal probability) to evacuate to the exit doors. With this method, pedestrians would choose the shortest way to evacuate from the emergency.

In models with instructions, because of the setting of the shortest queue available, the pedService palette was used to control the pedestrians follow the shortest way to evacuate to, as shown in Figure 24. However, even though there was a setting of the closest queue in the pedService palette, it could not be used to realize without instructions because the pedestrians would choose only one route to evacuate. Thus, the researcher made five services to realize the equal probabilities of choosing evacuate routes.

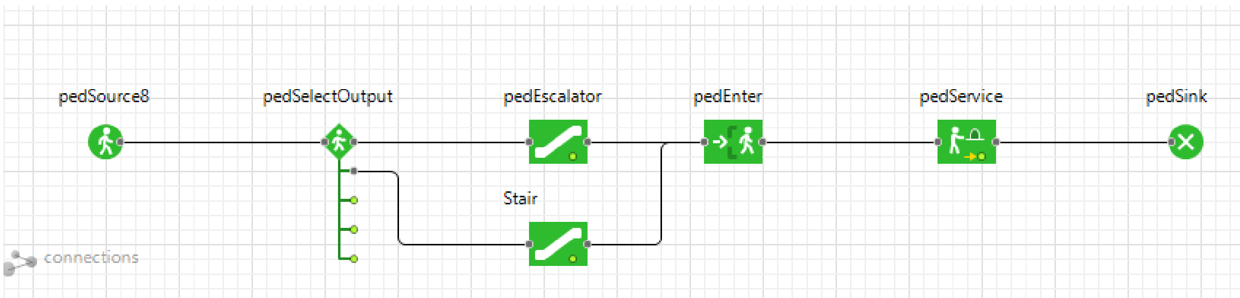


Figure 24. Flow chart of the models with instructions

Finally, the last two experimental models were with group travel behaviors (group size of 3 and 6) and with instructions. The same flow chart of the model without group travel behaviors and with instructions was applied.

Sources of data. The data used in this study was from previous research. First, the walking speed of the pedestrians in this study was set between 1.2 and 1.8 m/s because according to Fang et al. (2004), in the emergency evacuation simulation, the passenger's walking speed was uniformed distribute between 1.2 and 1.8 m/s. Next, the number of arriving passengers was 1000, and the arriving rate of passengers based on the observation from Case study 1. The layout of the airport terminal was based on the picture published local airport website.

In addition to the sources of data mentioned above, the average speed of pedestrians on escalator and stairs were also provided by previous studies. For the data collection device, this study was collecting the total evacuation time from when the first passenger emerged on the second floor to when the last passenger left the terminal. The time data could be collected by Anylogic software using clock palette.

Instrument reliability and validity. This study was aiming to simulate the conditions of real life. Therefore, the validation of the models was essential. The data used in this study were referred from Case study 1 to test the effect of group travel behaviors and instructions on the efficiency of evacuation from emergencies.

Treatment of data. Group travel behaviors and instructions were two independent variables in this study. With or without group travel behaviors and with or without instructions were manipulated by the researcher. The dependent variable was the time of the whole evacuation process. The evacuation process started from when the first passenger appeared at the gates, which were located on the second floor of the terminal and ended when the last passenger left the terminal. There were six models to be simulated totally, and each model was simulated several times to collect the output. The six models were the model without group travel behaviors (group size of 1) and with instructions; the model without group travel behaviors (group size of 1) and without instructions; the model with group travel behaviors (group size of 3) and with instructions; the model with group travel behaviors (group size of 3) and without instructions; the model with group travel behaviors (group size of 6) and with instructions; the model with group travel behaviors (group size of 6) and without instructions; After the simulation of each model, the output data was recorded by the researcher and exported to SPSS. Statistical analysis was conducted using the SPSS software.

Results

In total, there were six models developed for different conditions, and each model was simulated 50 times. The data of the simulations was exported to excel files and converted into SPSS. The analysis was done in the SPSS software. Two-way ANOVA was used to test the null hypotheses of this study.

Situation models. At the beginning of the simulation, pedestrians would be assembled on the second floor of the terminal because they were getting out of the gates. Figure 25 shows the beginning status of the second floor of the terminal building. It was noticed that it was crowded at the origin point when the evacuation started, and pedestrians started running to the escalator or the stairs. As shown in Figure 26, pedestrians were rushing to the escalator and stairs to evacuate from emergencies as soon as possible. When on the escalator, the group still stick together to evacuate. For example, if one pedestrian in one group chose to evacuate by stairs, the other pedestrians in that group would use stairs to evacuate as well. After arriving at the first floor of the terminal, pedestrians started to head towards the exits according to the instruction or not. The simulation screenshot was shown in Figure 27. Pedestrians were rushing out from the exits of escalator and stairs. When they reached the first floor, they would evacuate through doors of the terminal and complete the evacuation.

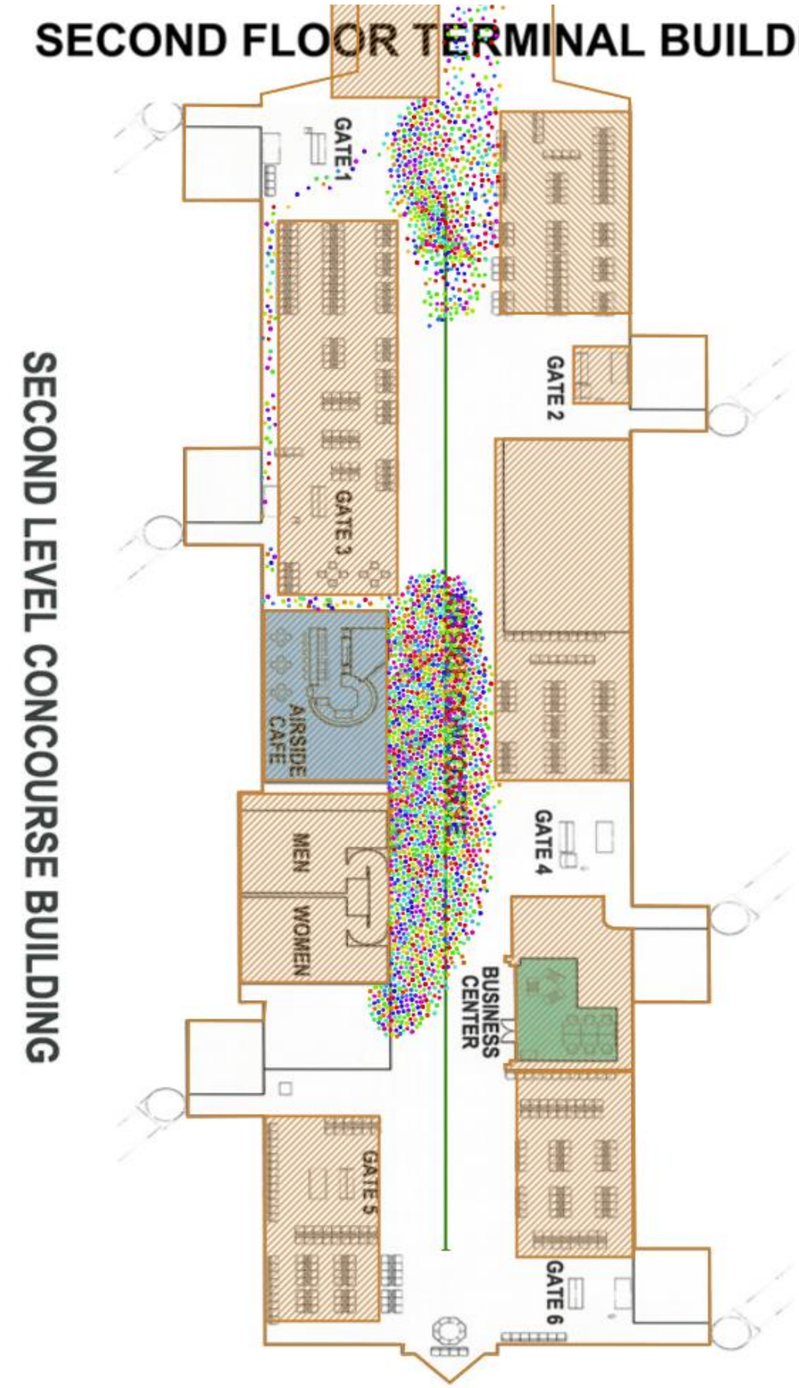


Figure 25. The second floor of simulation. Adapted from the screenshot from AnyLogic.

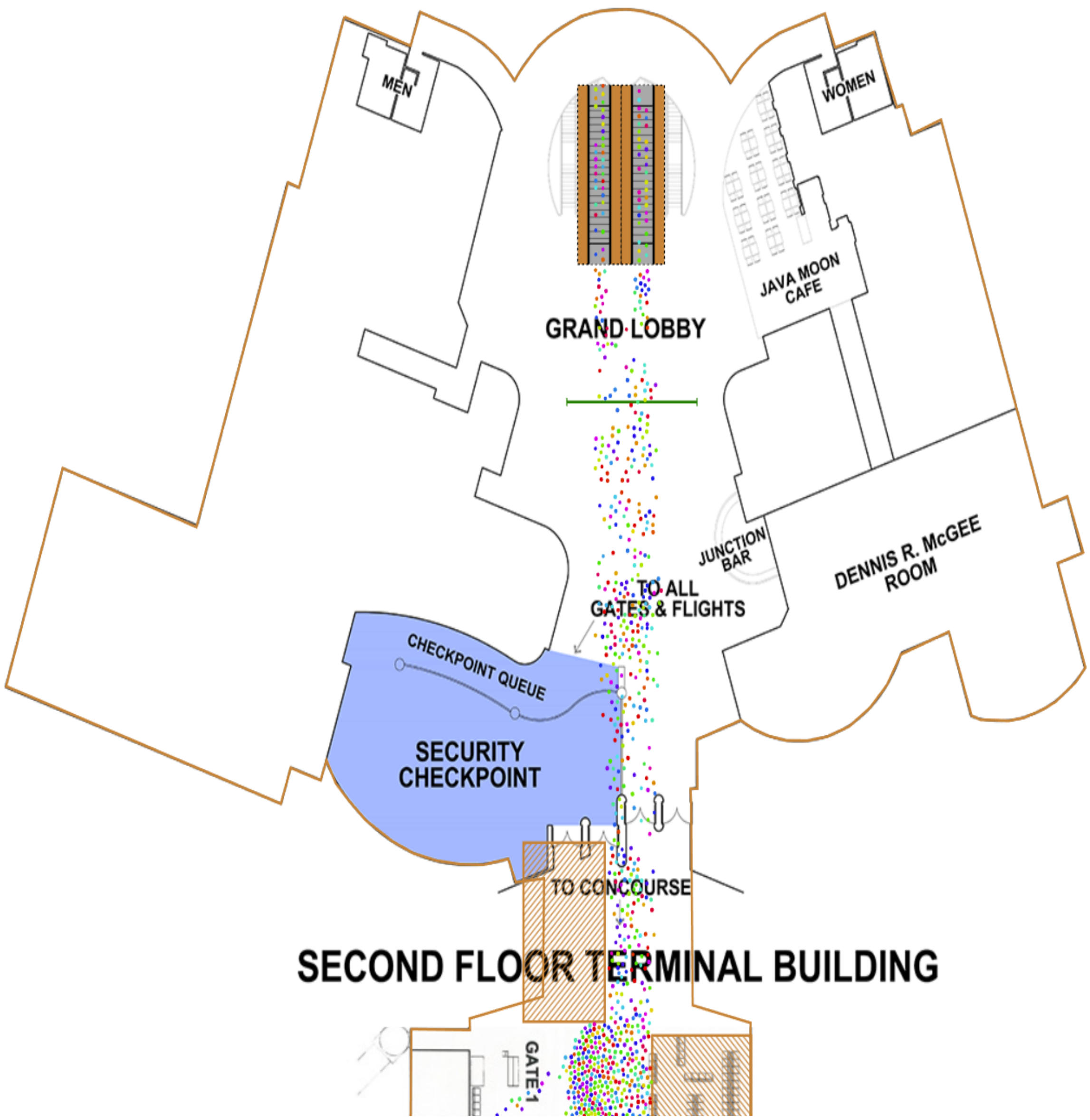


Figure 26. Escalator of the simulation. Adapted from the screenshot from AnyLogic.

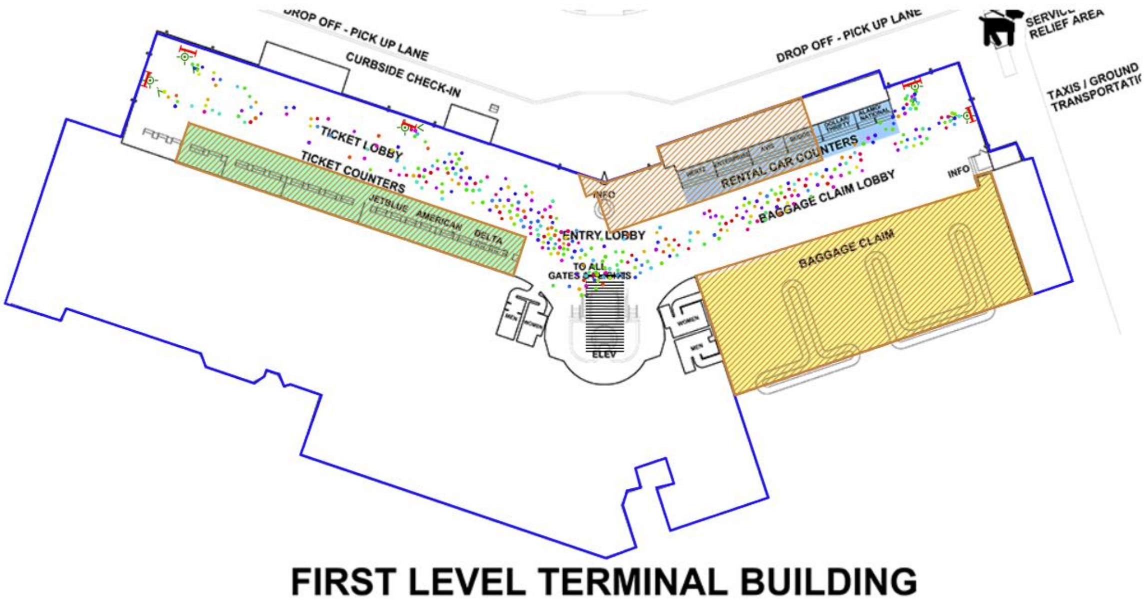


Figure 27. The first floor of the simulation. Adapted from the screenshot from AnyLogic.

Descriptive statistics. The dependent variable of this study was the total time of the whole evacuation process. Six models were simulated by the researcher, and the data was analyzed in the SPSS software. Table 22 showed the descriptive statistics of the evacuation time of six models. In this study, the researcher coded instructions with 1, and 0. 1 represent the model with instructions, and 0 represented for the model without instructions.

Table 22

Descriptive Statistics of Total Evacuation time based on Group Size and Instructions

Dependent Variable: Total time

Groupsize	Instruction	Mean	Std. Deviation	N
1	0	2115.528	47.1961	50
	1	2060.360	34.7588	50
	Total	2087.944	49.6894	100
3	0	2555.320	29.4845	50
	1	2489.396	17.4281	50
	Total	2522.358	40.9644	100
6	0	2702.674	16.2312	50
	1	2515.472	21.2998	50
	Total	2609.073	95.9405	100
Total	0	2457.841	252.4488	150
	1	2355.076	210.9045	150
	Total	2406.458	237.8520	300

As shown in Table 22, the mean evacuation time of the model of without group and without instructions was 2115.5 seconds, which equals to 35 minutes and 15 seconds. As seen in Table 22, when the researchers considered group travel behavior, the average evacuation time had increased from 2115 seconds to 2555 seconds, and for the model of a group size of 6, the average evacuation time had reached 2700 seconds and more.

Hypothesis testing. The two independent variables of this study were group travel behaviors and instructions. There were three levels of group size, and two levels of instructions were tested. The three null hypotheses of this research were that H01: there was no significant difference in evacuation time among group size of 1, 3, and 6, H02: there was no significant difference in evacuation time between with and without instructions, and H03: there was no interaction between group travel behaviors and instructions. A two-way ANOVA test was conducted. The result of the test was shown in Table 23. As shown in Table 23, with the alpha level set at .05, the effect of group travel behaviors was found significant with F (2, 294) =

8783.771, and p < .01; the effect of instructions was also found significant with F (1, 294) = 892.301, and p < .01; and the effect of group travel behaviors * instructions was found significant, with F (4, 294) = 151.417 and p < .01. Thus, all three null hypotheses were rejected.

Table 23

Test Results of Between-Subjects Effects

Dependent Variable: Total time

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	16654533.412[a]	5	3330906.682	3752.535	.000	.985
Intercept	1737312513.021	1	1737312513.021	1957222.903	.000	1.000
Groupsize	15593681.642	2	7796840.821	8783.771	.000	.984
Instruction	792043.254	1	792043.254	892.301	.000	.752
Groupsize * Instruction	268808.516	2	134404.258	151.417	.000	.507
Error	260966.637	294	887.642			
Total	1754228013.070	300				
Corrected Total	16915500.049	299				

Group travel behaviors. The null hypothesis of the effect of group travel behaviors was that there was no significant difference in evacuation time among a group size of 1, 3, and 6. results in Table 22, Table 24, and Table 25 showed that the mean evacuation time of the model of group size of 1 (M = 2087.944, SD = 49.6894) was significantly lower than the mean evacuation time of the model of group size of 3 (M = 2522.358, SD = 40.9644) and group size of 6 (M = 2609.073, SD = 95.9405), and the mean evacuation time of the model of group size of 6 was significantly larger than the mean evacuation time of the model of group size of 1 and group size of 3, p <.01. Thus, the null hypothesis was rejected. There was a significant difference in evacuation time among all group sizes of 1, 3, and 6.

Table 24

Estimates among Group Size

Dependent Variable: Total time

Groupsize	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
1	2087.944	2.979	2082.080	2093.808
3	2522.358	2.979	2516.494	2528.222
6	2609.073	2.979	2603.209	2614.937

Table 25

Pairwise Comparisons among Group Size

Dependent Variable: Total time

(I) Groupsize	(J) Groupsize	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
1	3	-434.414*	4.213	.000	-444.559	-424.269
	6	-521.129*	4.213	.000	-531.274	-510.984
3	1	434.414*	4.213	.000	424.269	444.559
	6	-86.715*	4.213	.000	-96.860	-76.570
6	1	521.129*	4.213	.000	510.984	531.274
	3	86.715*	4.213	.000	76.570	96.860

Instructions. The null hypothesis of the instructions was that there was no significant difference in evacuation time between with and without instructions. The results in Table 22 and Table 26 indicated that the mean evacuation time of model with instructions (M = 2355.076, SD = 210.9045) was significantly lower than the mean evacuation time of model without instructions (M = 2457.841, SD = 252.4488), $p < .01$. As a result, the null hypothesis of instructions was rejected. There was a significant difference in evacuation time between with and without instructions.

Table 26

Estimates between Instructions

Dependent Variable: Total time

Instruction	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
0	2457.841	2.433	2453.053	2462.628
1	2355.076	2.433	2350.288	2359.864

Relationship between group travel behaviors and instructions. The null hypothesis stated that there was no relationship between group travel behaviors and instructions. The results in Table 22 and Table 27 indicated that for group size of 1, the mean evacuation time of the model with instructions (M = 2060.360, SD = 34.7588) was significantly lower than the model without instructions (M = 2115.528, SD = 47.1961). For the group size of 3, the mean evacuation time with instructions (M = 2489.396, SD = 17.4281) was significantly lower than the mean evacuation time without instructions (M = 2555.320, SD = 29.4845). For the group size of 6, the mean evacuation time with instructions (M = 2515.472, SD = 21.2998) was significantly lower than the mean evacuation time without instructions (M = 2702.674, SD = 16.2312), $p < .01$. Therefore, the null hypothesis was rejected. The larger the group size was, the longer the evacuation time would be taken by pedestrians to evacuate from emergencies. Instructions could reduce the evacuation time for pedestrians. There was an interaction between group travel behaviors and instructions. Instruction works the best for the largest group size, resulting in a significant reduction of the evacuation time. As shown in Figure 28, the plot indicated that there was a positive interaction between two independent variables, especially obvious when the group size increased to 6.

Table 27

Pairwise Comparisons Based on Estimated Marginal Means

Dependent Variable: Total time

				95% Confidence Interval	
Group size	Instruction	Mean	Std. Error	Lower Bound	Upper Bound
1	0	2115.528	4.213	2107.236	2123.820
	1	2060.360	4.213	2052.068	2068.652
3	0	2555.320	4.213	2547.028	2563.612
	1	2489.396	4.213	2481.104	2497.688
6	0	2702.674	4.213	2694.382	2710.966
	1	2515.472	4.213	2507.180	2523.764

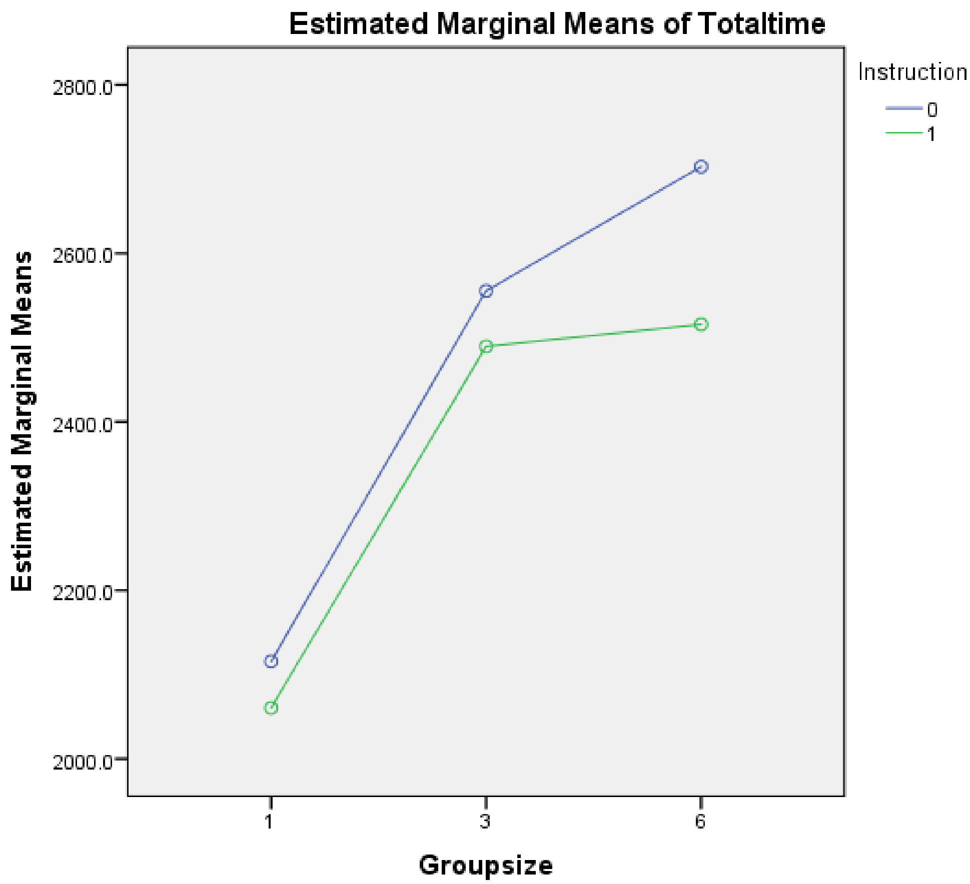


Figure 28. Plot chart of independent variables and marginal means

Further analysis of results. According to Table 28, the result of levene's test of equality of error variances was significant, which means the homogeneity assumption was violated. Therefore, even though the two-way ANOVA was so robust that the results of the statistical analysis could be accepted, a separate one-way ANOVA was conducted to confirm the ANOVA results and to make the results of the study more persuasive. For this reason, t Welch and Brown-Forsythe test for both independent variables were conducted.

Table 28

Levene's Test of Equality of Error Variances

Dependent Variable: Total time

F	df1	df2	Sig.
31.570	5	294	.000

As shown in Table 29 and Table 30, the result of the one-way ANOVA test of group size showed there was a significant difference in total time among different group sizes. The results of welch and Brown- Forsythe showed a similar result. This result is further illustrated in Figure 29.

Table 29

ANOVA Test of Group Travel Behaviors

Dependent variable: Total time

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	792043.254	1	792043.254	14.639	.000
Within Groups	16123456.800	298	54105.560		
Total	16915500.050	299			

Table 30

Robust Tests of Equality of Means

Dependent Variable: Total time

	Statistic[a]	df1	df2	Sig.
Welch	14.639	1	288.859	.000
Brown-Forsythe	14.639	1	288.859	.000

a. Asymptotically F distributed.

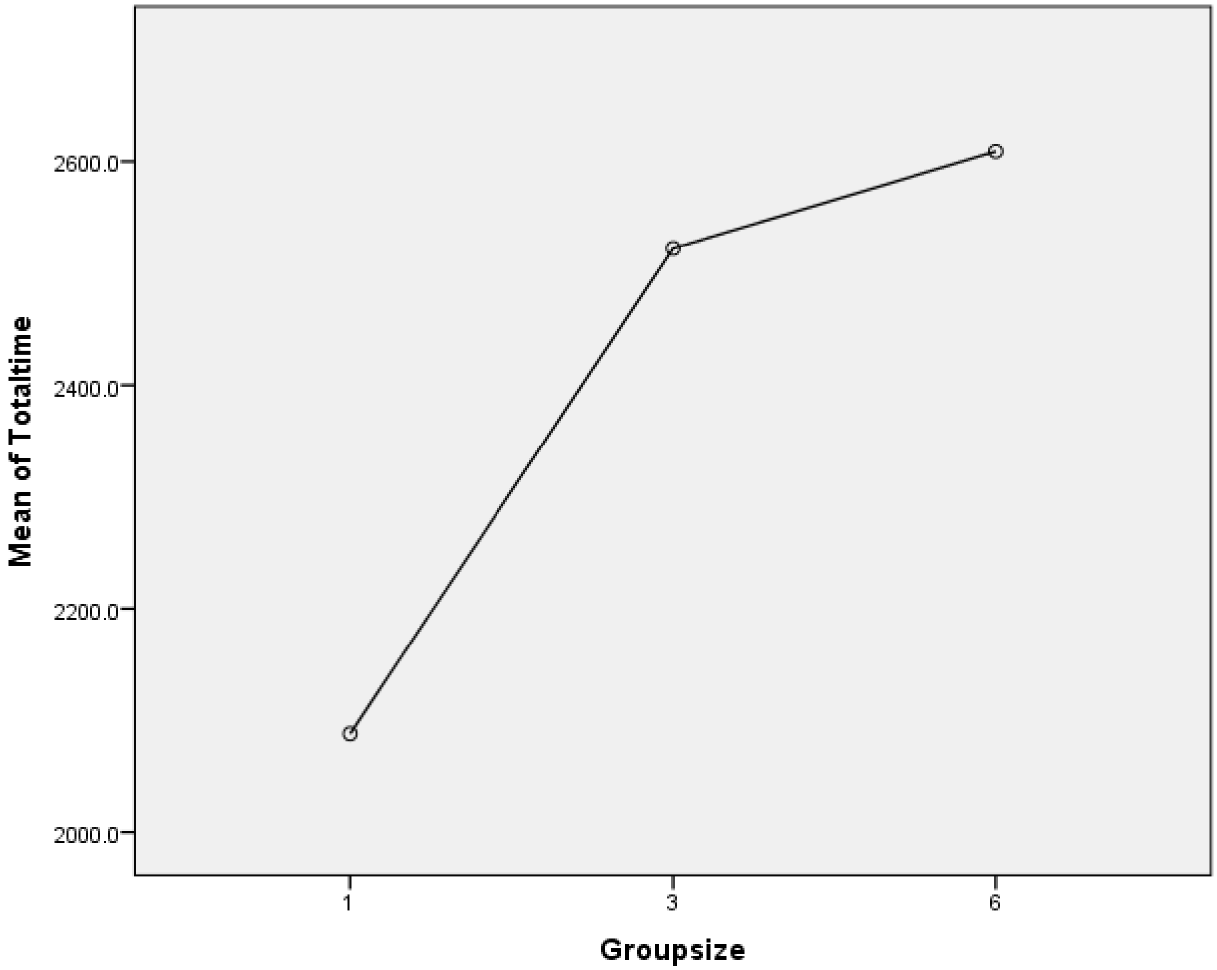


Figure 29. Mean plot of group size

Table 31 and Table 32 shows further tests for the effect of instructions on the efficiency of evacuation. The one-way ANOVA test showed the significant result of instructions. Also, the Welch and Brown-Forsythe showed significant results, which is illustrated in Figure 30.

After testing both two independent variables of this study separately, it was confirmed the results from the previous ANOVA. The results of this study indicated that the group travel behaviors could decrease the efficiency of evacuation during emergencies, and the larger the group size, the slower the evacuation was. Instructions were also affecting the efficiency of evacuation during emergencies, and instructions could increase the efficiency of the evacuation.

There was an interaction between group travel behaviors and instructions on evacuation efficiency during emergencies; instruction helps to reduce the evacuation time more at the bigger group size level.

Table 31

ANOVA Test of Instructions

Dependent Variable: Total time

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	792043.254	1	792043.254	14.639	.000
Within Groups	16123456.800	298	54105.560		
Total	16915500.050	299			

Table 32

Robust Tests of Equality of Means

Dependent Variable: Total time

	Statistic[a]	df1	df2	Sig.
Welch	14.639	1	288.859	.000
Brown-Forsythe	14.639	1	288.859	.000

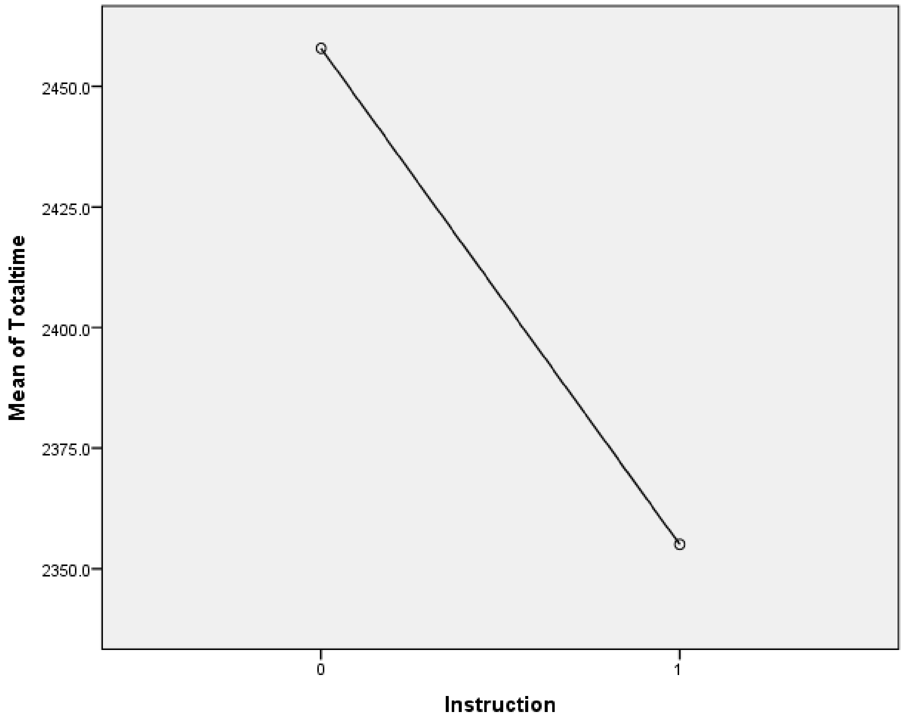


Figure 30. Mean plot of instruction

Post hoc tests. Post hoc tests were conducted to test effect for different pairs of the group sizes. Results of Post hoc analysis was presented in Table 33; it was found that the difference in evacuation time between all three pairs of a group size of 1 and 3 were significant.

Table 33

Post Hoc Tests

Dependent Variable: Total time

Games-Howell

(I) Groupsize	(J) Groupsize	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	3	-434.4140*	6.4398	.000	-449.626	-419.202
	6	-521.1290*	10.8045	.000	-546.708	-495.550
3	1	434.4140*	6.4398	.000	419.202	449.626
	6	-86.7150*	10.4320	.000	-111.439	-61.991
6	1	521.1290*	10.8045	.000	495.550	546.708
	3	86.7150*	10.4320	.000	61.991	111.439

Discussion

Group travel behaviors. Group travel behaviors were considered as one of the essential factors that influencing the efficiency of evacuation during emergencies. Three levels of group travel behaviors were investigated in this study. The results indicated that the higher the number of the group size, the less efficient of the evacuation, as measured by the evacuation time. There was a significant difference in evacuation time among different group sizes. The larger the group size was, the more likely to have congestion during the evacuation process.

Additionally, if the group size was large, people needed to wait for their groupmates to evacuate together. Compared to evacuate individually, evacuating in the group increased the total time of each person in the group because of the waiting process. Therefore, the total evacuation time of large group sizes was significantly longer than the small group size.

The effect of group size can also be observed visually from the simulation animation. Through the observation of simulations, during the running of the simulation of a group size of 1, it was observed that there were only small congestion groups at the exit doors. However, when the group size increases to 6, much more large congestion groups appeared at each exit door after pedestrians rushed to the doors. The congestions significantly increased the evacuation time. This also explains that group travel behavior was a significant factor that influencing the efficiency of evacuation during emergencies and could be applied to real life.

Instructions. Two levels of instructions were investigated in this study. The results showed that instructions have a significant influence on the overall efficiency of evacuation during emergencies. Instructions increase the efficiency of evacuation. The reason was that no matter how large the group size, the instructions still could make a difference in the efficiency of evacuation during emergencies.

Additionally, although the results demonstrated that there was a significant difference in evacuation time between with and without instructions, some exception could occur in the simulations. As shown in Figure 31, pedestrians were congested at the doors on the right side. However, the doors at the left side were empty. The reason for this unbalanced queue was that the pedestrians were choosing evacuation door at the point of the exit of the escalator or stairs. After deciding which way to go, it was assumed that pedestrians could not change anymore, which cause congestion at the doors sometimes, especially for larger group sizes. Another reason for this phenomenon was that the distance of each evacuation route was different. When the pedestrians decided which route to evacuate, they had taken different time to get to the doors they chose. Even though the queue the pedestrians chose was the shortest at that time, the distance they had to go through might not be the best one.

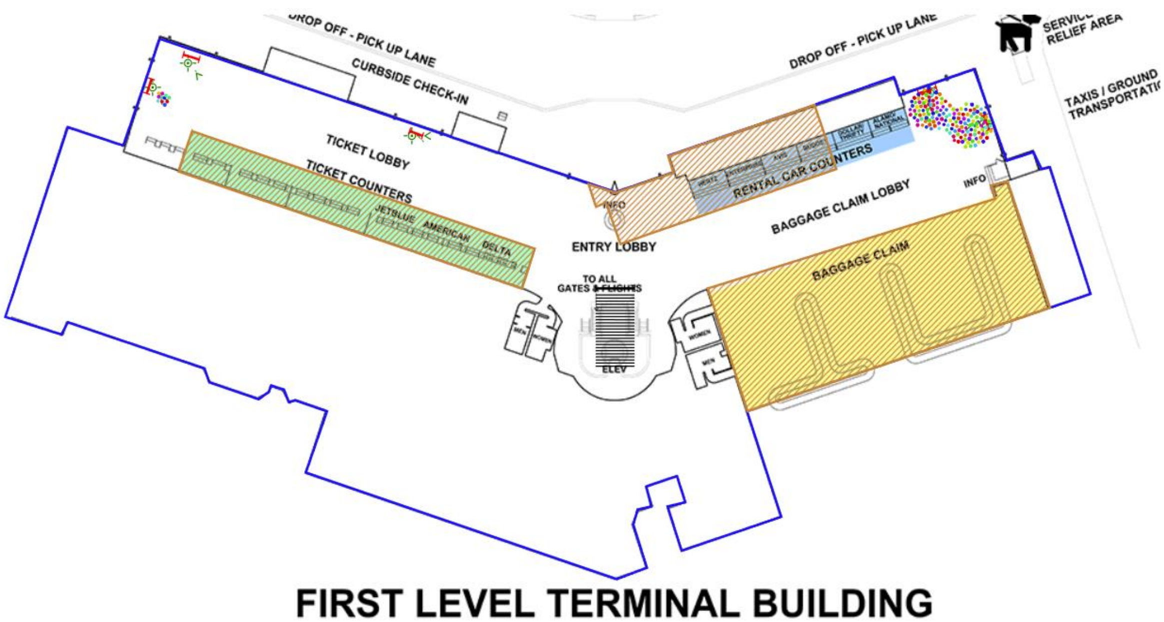


Figure 31. Congestion at the doors. Adapted from the screenshot from AnyLogic.

Relationship between group travel behaviors and instructions. When the group size grew, the total evacuation time increased at the same time. However, instructions could increase the efficiency of evacuation. The reason was that no matter how large the group size, the instructions still could make a difference in the efficiency of evacuation during emergencies. When pedestrians arrived at the exits of the escalator and stairs, the authorities would give pedestrians the instructions about the shortest queue at that time, and the same group would evacuate through the same route, which was the shortest queue at that time. Therefore, even though the group size was large, they would go to the same exit door when evacuating from the terminal. The effect of instruction is more evident for larger group sizes (6), as in this group size, it is more likely to cause imbalanced exit queue length. Having an instruction will help to reduce this imbalance among exits and facilitate the evacuation process.

Case study 4

Research Question

Pedestrian crowds are commonly observed in all public locations offering entertainment, transportation, social or religious activities. The mass gathering of people congregated in limited space often elevates the risk of infectious disease spread due to the increased contacts between susceptible and infectious individuals. Further, individuals with different levels of vulnerability and receptivity due to variations in genetic background and intervention usage often congregate in tourist attractions (Wilson, 1995). There is direct evidence for the occurrence of multiple epidemic outbreaks in high pedestrian density locations such as transportation hubs, entertainment venues, (e.g., theme parks, stadiums) and mass gatherings. Gautret and Steffen (2016) report that 68 cited instances of outbreaks among crowds occurred between 1980 and 2016. Numerous reports deal with the spread of diseases like influenza, SARS, and measles during air travel (Centers for Disease Control and Prevention, 1983; Mangili & Gendreau, 2005; Olsen et al., 2003). Examples of epidemics in entertainment venues include the influenza outbreak in 2002 during the winter Olympiad and measles outbreak in Disney World in 2016, resulting in 125 cases (Gundlapalli et al., 2006; McCarthy, 2015). Several outbreaks of directly transmitted gastrointestinal and respiratory diseases have been reported in religious and social outdoor mass gatherings (Pfaff et al., 2010; Verhoef et al., 2008; Zieliński, 2009), international meetings (Botelho-Nevers et al., 2010; Foo et al., 2009), and concert halls (Evans et al., 2002).

Disease spread in high pedestrian density locations is inherently a multidisciplinary and multiscale problem involving epidemiology and crowd dynamics. Deterministic and stochastic epidemiological models, including Susceptible-Infected-Recovered (SIR) models, are practical tools for understanding epidemic spread (Anderson & Britton, 2012; Brauer & Castillo-Chavez, 1995). However, such models do not account for discrete human interactions in pedestrian crowds. Computationally intensive agent-based models, *e.g.* EpiSimdemics, and stochastic models include human interactions through behavioral rules but are targeted at modeling simple interactions over large populations and geographical areas, rather than evaluating the impact of fine-scale interactions (Barrett, Bisset, Eubank, Feng, & Marathe, 2008; Germann, Kadau, Longini, & Macken, 2006). Instances mentioned above involve a high density of pedestrians over relatively small areas. Modeling non-uniform mixing in such instances and designing strategies for mitigation can only be achieved through multiscale modeling involving the combination of epidemic modeling with pedestrian crowd dynamics.

Understanding pedestrian dynamics and efficient crowd management practices are essential to enable efficient flow of the pedestrians, and for meeting safety standards in high pedestrian, density environments noted above. Pedestrian crowd management often involves the combination of crowd psychology and engineering methods for assessing the capacities of corridors, ramps, stairs, and other bottlenecks (National Research Council, 1983; Fruin, 2002). While several approaches including cellular automata, fluid flow models have been used for modeling pedestrian dynamics, social force models have the advantage of evaluating the complete individual trajectories necessary for contact estimation in epidemic studies (Burstedde et al., 2001; Helbing et al., 2000; Helbing & Molnar, 1995; Henderson, 1971). Since its conception, there have been several advances in social force models involving force field estimations, algorithmic developments and applications in situations like panic, traffic dynamics and evacuation (Lämmel, & Plaue, 2014; Li & Jiang, 2014; Mehran et al., 2009; Treiber et al., 1999; Wei-Guo et al., 2006; Zanlungo et al., 2011). Namilae et al. (2017a; 2017b) have used pedestrian dynamics described by the social force model in a multiscale model to study the spread of epidemics during air travel.

Despite separate developments in pedestrian dynamics and epidemiology, there is a paucity of epidemiological models that utilize detailed information from pedestrian dynamics for contact estimation. There is a strong correlation between contact and infection rates in several disease epidemics, such as SARS and Ebola (Lipsitch et al., 2003; Rivers et al., 2014). Given the preponderance of epidemic outbreaks in high pedestrian density locations, a model that accounts for pedestrian dynamics in contact estimation can be a design tool for developing mitigation strategies. In this paper, the researchers develop such a multiscale model and utilize it to study disease spread in pedestrian queues. Winding queue formation is a ubiquitous crowd control procedure.

Consequently, individuals in crowded gatherings often spend a significant amount of time in waiting for queue lines. In the multiscale model, pedestrian dynamics is used to generate trajectories of pedestrian motion and estimate the rate of contacts between infected and susceptible individuals. The researchers incorporate this information into a stochastic infection dynamics model with infection transmission probability and contact radius as primary inputs. This generic model is applicable for several directly transmitted diseases like Ebola, SARS, and H1N1 influenza by varying the input parameters related to infection probabilities and transmission mechanisms. The researchers utilize this multiscale model to analyze disease spread in various pedestrian queue configurations, suggest preferred layouts, and design strategies that would reduce contacts and consequently mitigate the overall disease spread.

Methodology

Pedestrian dynamics. To first estimate the number of contacts between susceptible and infectious individuals, the researchers model each mobile pedestrian as a particle and immobile objects like walls as groups of stationary particles. The evolution of pedestrian particles and their interaction with other pedestrians and stationary particles are described by molecular dynamics like the social force model (Helbing et al., 2000). The net force $\bar{f}_i$ acting on i^{th} pedestrian (or particle) can be defined as:

$$\bar{f}_i = \frac{m_i}{\tau}\left(\bar{v}_0^i(t) - \bar{v}^i(t)\right) + \sum_{j \neq i} \bar{f}_{ij}(t) = m_i \frac{dv_i}{dt} \tag{1}$$

with the pedestrian position at a given time obtained by integration as $\bar{r}^i(t) = \int \bar{v}^i(t)dt$. $\bar{v}_o^i(t)$ refers to the desired velocity of pedestrian, and $\bar{v}^i(t)$ that of the actual velocity. m_i is the particle's mass and τ is the evolution time constant. The momentum generated by a pedestrian's intention, denoted by $\frac{m_i}{\tau}\left(\bar{v}_0^i(t) - \bar{v}^i(t)\right)$, results in a self-propulsion force that is balanced by a repulsion force $\overline{f}_{ij}(t)$ to obstacles in the direction of motion. In this study, the researchers use the Lennard –Jones type repulsion term used earlier by Namilae et al. (2017a; 2017b).

While equation (1) describes the general motion of pedestrians, the researchers need to introduce modifications to this equation to account for slow-moving pedestrian queues. Pedestrians in a queue move at the speed of the nearest person ahead in the line. To model this scenario, the researchers introduce location dependence to the desired velocity in the self-propulsion term as:

$$v_0^i(t)\,\hat{e}_1 = \begin{cases} (v_A + \gamma_i v_B)\left(1 - \frac{\delta}{\min\{r_{ij|front}\,;\, i\neq j\}}\right)\hat{e}_1;\ \delta = \begin{cases} \delta_1\ ; if\ i\ \&\ j\ of\ same\ group \\ \delta_2\ ; if\ i\ \&\ j\ of\ different\ groups \end{cases} \\ 0\ ; if\ r_{ij|front} < \delta \end{cases} \tag{2}$$

where $\hat{e}_1$ is the desired direction of motion. v_A and $\gamma_i v_B$ are the deterministic and stochastic components of the desired velocity respectively. The values of walking speed terms (v_A and $\gamma_i v_B$) can be varied to obtain a given distribution of age groups and gender of travelers (Zeleba, Ciepka, & RezA, 2012). δ is the cut-off distance constant between the i^{th} and j^{th} pedestrians at which the desired velocity of the i^{th} pedestrian reduces to zero velocity (stationary condition).

To mimic the real-life scenarios, the researchers also account for the formation of groups of pedestrians. The groups' formation is controlled by adjusting the distance (δ) in equation (2). Our empirical observations on a theme park queue (see section 2.3) and comparisons with the literature (Moussaïd, Perozo, Garnier, Helbing, & Theraulaz, 2010) indicate that δ separation values are different between pedestrians belonging to a group (e.g., family or friends in the queue) and other pedestrians. Based on this, an average distance of δ_1 =0.46 m is chosen for pedestrian particles within the same group, while this distance between independent pedestrians is given a value of δ_2 =0.64 m.

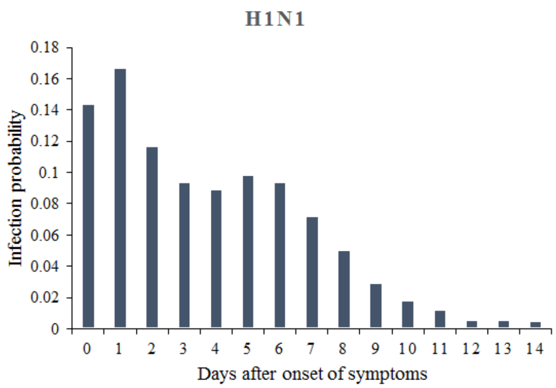
Contact estimation and infection model. Consider a population of size N consisting of I(t) infected and S(t) susceptibles at time t. Pedestrian position of particle i ($r_i(t)$) evolves through pedestrian dynamics and is a function of age, sex, and infection status. A susceptible can become infected when coming into direct contact with an infected. Given the trajectory of pedestrians over time, the number of contacts m_i can be evaluated by counting the instances when the distance between *i* and *j* pedestrians (r_{ij}) is less than a virus-specific contact radius (x). This transmission distance (x) used to define the contacts is dependent on the type of pathogen and mechanisms for its spread. For diseases like Ebola, studies indicate that the primary mode of transmission is through contact droplets (Osterholm et al., 2015; Judson, Prescott, & Munster, 2015).

Consequently, a distance that enables direct touch needs to be used for estimating contacts for such diseases. Other infectious diseases like SARS and influenza are known to be transmitted by both shorter- and longer-range airborne mechanisms (Clark & de Calcina-Goff, 2009; Yuen & Wong, 2005). Studies show that micrometer-sized aerosol clouds generated during cough traveling over 2 m (Bourouiba, Dehandschoewercker, & Bush, 2014; Gupta, Lin, & Chen, 2009). The researchers vary the contact radius between these distances to account for the various infection spread mechanisms.

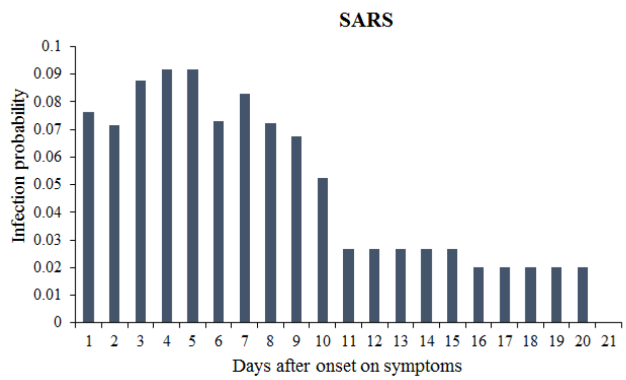
Next, the researchers consider the probability (P_{inf}) that a contact between a susceptible and an infective results in a successful infection transmission The researchers divide this input parameter into two components: a viral shedding probability distribution (P_c) which is a function of time since acquiring infection for the specific virus in question, and a pathogen spread mechanism component (P_m). This includes contributions of several independent mechanisms comprising (a) aerosol exposure and inhalation probability (P_a) common in infections such as SARS and influenza, (b) Coarse pathogen droplet inoculation (P_d) common in infectious diseases like Ebola (Clark & de Calcina-Goff, 2009; Osterholm et al., 2015; Yuen & Wong, 2005). Other mechanisms, including fomite mechanism, which involves contaminated surface-to-hand transfer would contribute to the infection spread, but such mechanisms do not involve human-human contacts in this context and are not considered here. The infection probability would then be defined as:

$$P_{\text{inf}} = P_c . P_m = P_c \left(P_a + P_d \right) \quad (3)$$

First, consider the viral shedding probability distribution (P_c). Studies indicate that the amount of viral shedding is typically dependent on the length of the incubation period and the number of days since the appearance of symptoms. In a previous study, Namilae et al. (2017b) used CDC data on the amount of RNA (ribonucleic acid) virus copies in the blood serum since the illness contraction to generate this probability distribution for Ebola (Towner et al., 2004). A similar approach can be used for other diseases, for example, for SARS pathogen, the viral gene expression of the nucleocapsid (N) protein, detected at different rates along with the evolution of the virus from post-onset of the symptoms till convalescence is indicative of viral shedding (Zhao, 2007). For influenza, nasal, oral, or ocular shedding of the H1N1 virus has been detected by determining the relative equivalent unit from viral RNA level (Paquette et al., 2015). Such data can be used to generate the P_c distribution. Figure 32 shows the viral shedding distributions the researchers generated based on Zhao (2007) for SARS and H1N1 influenza, respectively.



(a)



(b)

Figure 32. Viral shedding probability distributions (P_c) for (a) H1N1 influenza and (b) SARS

There are many formulations in the literature to compute the mechanism-specific probability of transmission. Table 34 lists the details of the popular mechanisms for aerosol and coarse droplet mechanisms. The functional form of the aerosol inhalation probability is described in the data-driven modeling framework in Teunis et al. (2008), which, in turn, is based on Riley's Dose-response model (Riley & O'Grady, 1961). The probability for coarse droplet inoculation mechanism considers the droplet cone emitted during expiratory events like coughing and exposure surface of the susceptible (Teunis, Brienen, & Kretzschmar, 2010).

The probability that an infectious individual "i" in the crowd comes into contact with other individuals is m_i/N, where m_i is the number of contacts. Using Bayes' theorem for conditional probability P (contact and infection) = P (infection |contact). P (contact) = $P_{inf} \cdot \frac{m_i}{N}$. To account for the demographic stochasticity of the susceptible individuals, the number of newly infected by this infective "i" is estimated by a binomial distribution $I_i(t) \sim B(n_i, p_i)$ with parameters $n_i = S_i(t-1)$, the number of susceptibles exposed to the contagion at time t, and $p_i = P_{inf} . \frac{m_i}{N}$. Equation (3) is used for estimating P_{inf} .

For each infective individual, all the possible permutations are run, and the binomial distribution is obtained at each run. Repeating the same process for all the infectives with different days of infection c, further binomial distributions are obtained over a range of newly infected pedestrians in the queue. Denote by the variable λ the possible number of newly infected pedestrians ranging from zero to the maximum obtained number N_{inf} ($\lambda = 0, \ldots, \lambda_i, \ldots, N_{inf}$). To obtain the mean binomial distribution of the number of people infected at time t by all the possible permutations, denoted "Comb" of the infectives with varying age of infection "c". Also, let w_i be the frequency of obtaining λ_i in the runs. The researchers combine the probability plots and average them as given by:

$$I(t) \sim \sum_{c=1}^{d} \sum_{i=1}^{i_c^0} \{Binomial\ [S_i(t-1), P_m . P_c\ \frac{\mathrm{m_i(t-1)}}{N}]\}^* \ w_i\ (\lambda_i)\ /\ \mathrm{Comb} \tag{4}$$

Note that the contacts are defined when pedestrians are within a specific transmission distance, which is dependent on the transmission mechanism. Instead of using fixed parameters for defining contact, the researchers will treat contact distance and transmission probability as parameters in assessing epidemic spread. The researchers will vary these parameters over a broad range to model the different diseases and transmission mechanisms for several pedestrian queue configurations. Based on the above discussion, the researchers vary the contact distance between 2.1 m and 0.9 m. Similarly, the infection probability (P_{inf}) is varied from 0 to 0.2 to represent various levels of infectivity.

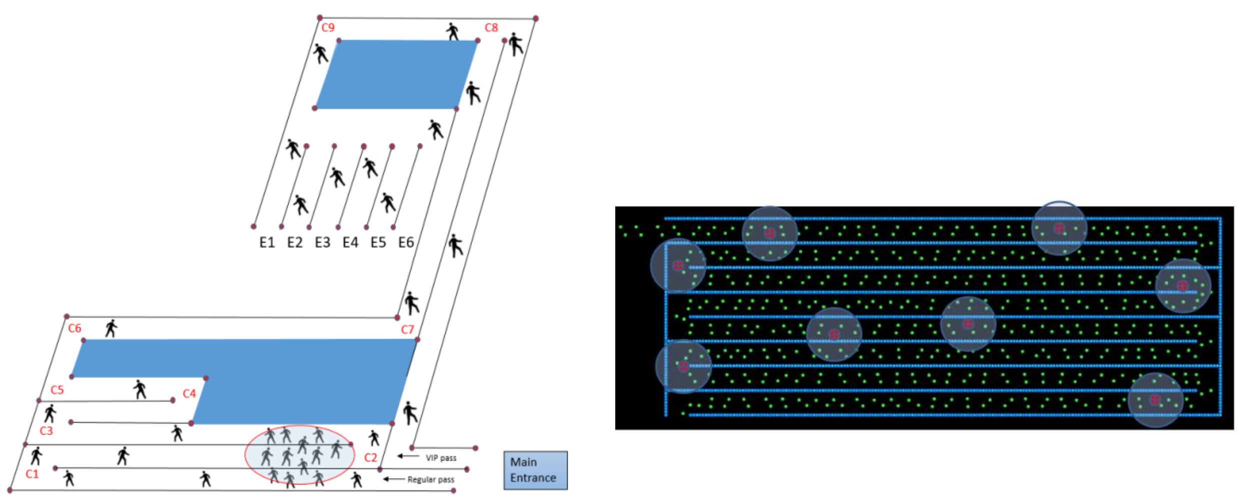
Table 34

Formulations for generating mechanism-specific probability distributions.

Mechanism	Equations	Notes	References
Aerosols mechanism	$P_a = \left(1 - e^{-\frac{QC_a\tau}{V_o}}\right)$	***Data-driven model framework based on dose-response model*** C_a - the maximum initial concentration of contagion in aerosol suspension τ - exposure time Q - respiration rate of susceptibles V_o - volume of infection envelope	Riley & Grady (1961); Teunis, Brienen, & Kretzschmar (2010)
Coarse droplet inoculation	$P_d = \frac{S_A}{S_C} \cdot \frac{V_C}{V_o}$	***Model based on expiratory droplet cone*** V_C - volume of cone in which droplet can fall V_o - room or exposure volume S_A - exposed mucosa surfaces S_C - circular area base of the cone	Teunis et al. (2008)

Model application to pedestrian queue configurations. Pedestrian serpentine queues are an essential component of crowd management. These queues are often unidirectional and have different widths and configurations to fit with the available area and the floor plan. The queues are often separated by rope stanchions for their ease of use; however, temporary walls could also be used for this purpose. Examples of such queues include airport security, waiting areas like at theme parks, and other crowded places. Within the same line and among adjacent lines, many susceptibles are often within contact radius, and viral infection may propagate if an infectious pedestrian is present.

The researchers evaluate the role of motion pattern and contact creation between neighboring pedestrians for different queue configurations. The aisles' geometry and orientation and number of inlets and exits are altered between the different configurations. To model queue configurations that are used in practice, the researchers evaluated a real-life queue at a theme park attraction as shown in Figure 33 and use those dimensions as a basis for the different configurations modeled in the study. In addition to dimensions, empirical data on contacts and groups was collected to guide the simulations. While progressing through the queue, two of our team members recorded, the number of nearby individuals within a 1m radius, at 25 seconds time interval. The data was collected by two observers independently at two different times of the day. The approximate distance between pedestrians, while differentiating between individuals of the same group and various groups was also recorded. Table 35 compares the empirical contact data and the corresponding simulation data in the corners inner and outer aisles.



(a) (b)

Figure 33. Two dimensional (a) actual, (b) simulated floor map of a specific theme exhibition waiting line

Table 35

Evaluation of the number of contacts within 1m radius from empirical and simulation data of a side-by-side (double) pedestrian queue in a theme park exhibition waiting line

	Empirical data		Data from simulation	
Contact	Range	Mean	Range	Mean
At corners	[4-14]	9	[8-12]	10
In outer aisles	[3-7]	5	[5-9]	7
In inner aisles	[5-13]	9	[10-12]	11

The researchers utilize this queue layout as the basis for evaluating the effect of the layout and shape of the queue configurations. The aisles' length and orientation are altered between the configurations of the same area and aisle width. The researchers investigated four different rectangular configurations with the same shape and area, as shown in Figure 34. The four configurations are split vertically (configurations in Figure 34 (b) and (c)) or horizontally (Figure 34 (a) and (d)). Configurations in Figure 34 (a) and (b) have one inlet and one exit whereas configurations in (c) and (d) have two inlets and two exits due to the existence of separated zones. The width of the pedestrian lanes remains 1 m, which allows some pedestrians belonging to the same group to form a double line. The four configurations are termed Config. 1, 2, 3, and 4, respectively.

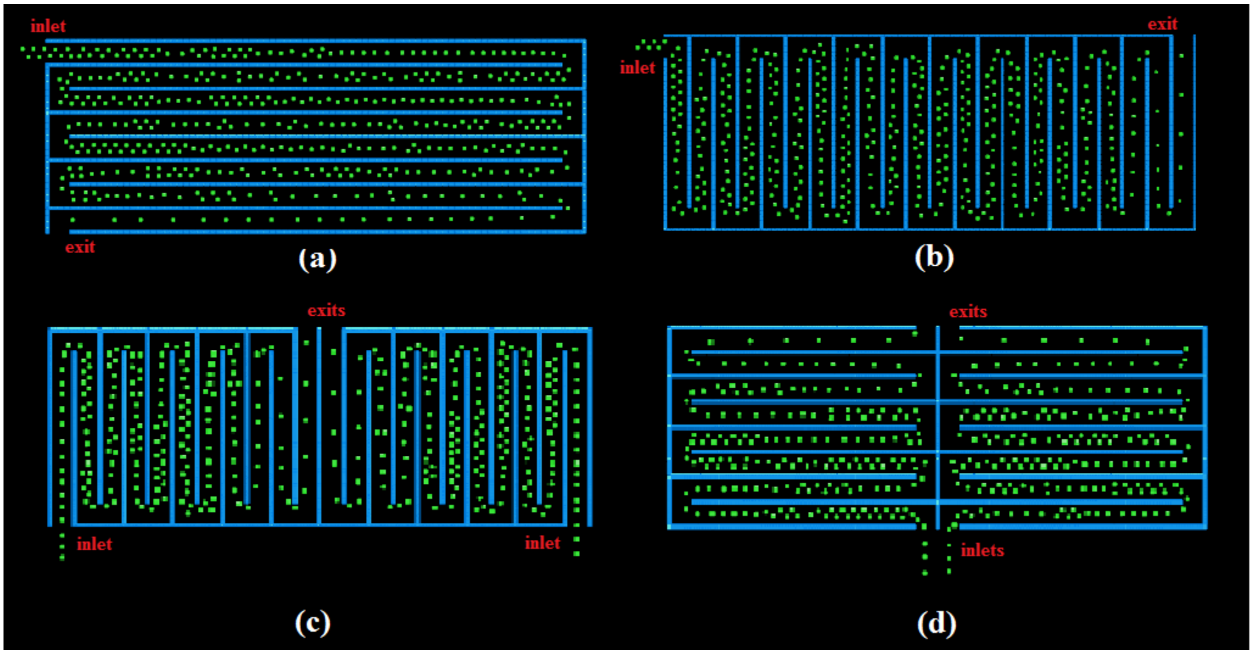


Figure 34. Evolution of pedestrians (t=125s) from simulation of double queue rectangular layouts: (a) Config.1, (b) Config.2, (c) Config.3, (d) Config.4

The researchers also investigate the relationship between the layout shape and the contact evolution, by modeling four square floor plans of the same area as above configurations. In all the simulations, a total of 600 pedestrians are distributed within the waiting area. The researchers consider the possibility of pedestrian groups walking side-by-side, and the formation of a single file separately. For all the configurations, the number of contacts between pedestrians is calculated where rope separators or temporary walls are placed between the aisles. For rope separators, contact extends to pedestrians in the neighboring aisles, whereas for temporary walls, transmission due to contact is limited only between the pedestrians within the same aisle. The data of pedestrian contact is then combined with the infection model to estimate infectious disease spread.

The researchers consider the situation of a single infective in the queue. The infectious individual is unidentifiable; his/her rank in the queue is not known apriori. Therefore, all permutations of the infectious individual's position are simulated to determine the average number of contacts for a given queue configuration. Also, the infectivity of pathogens is characterized by the transmittance mechanism and probability. Airborne viral nuclei vary in size. Expelled fine aerosols travel farther and remain suspended for a longer period than coarse droplets. The researchers account for coarse droplets and aerosols transmission mechanisms by varying the contact radius parameter between 0.9 and 2.1 meters (36-84 inches). The researchers vary the transmittance probability between 0.025 and 0.2 to account for the variation in infectivity of different diseases.

The mean number of newly infected pedestrians is then obtained by combining the number of contacts within a given infection radius, with the infection transmission probability described earlier. The mean number of newly infected is binomially distributed to account for the demographic stochasticity in the immunity and receptivity of the susceptible population. For instance, Figure 35 represents the distribution of newly infected individuals for the four configurations at an infection probability of 0.025 and proximate transmission radius of 1.2 meters for aisles separated by ropes. Under these different infection scenarios, the mean number of newly infected exposed individuals is obtained. In the following, only the peak dispersion of the disease (the mean of the binomial distribution) among the susceptible population is plotted over the parameters space of variation.

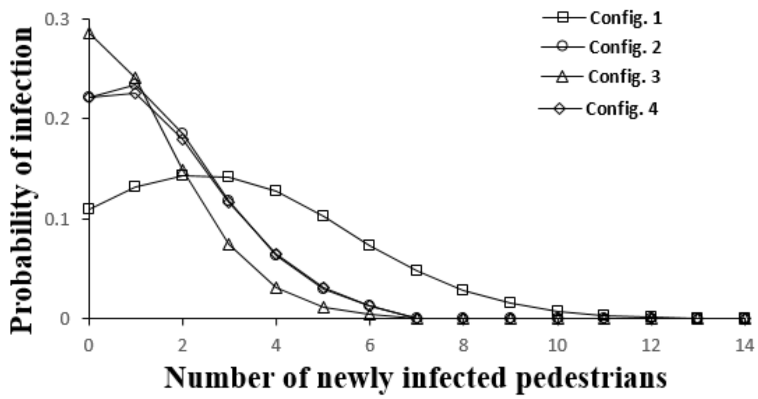
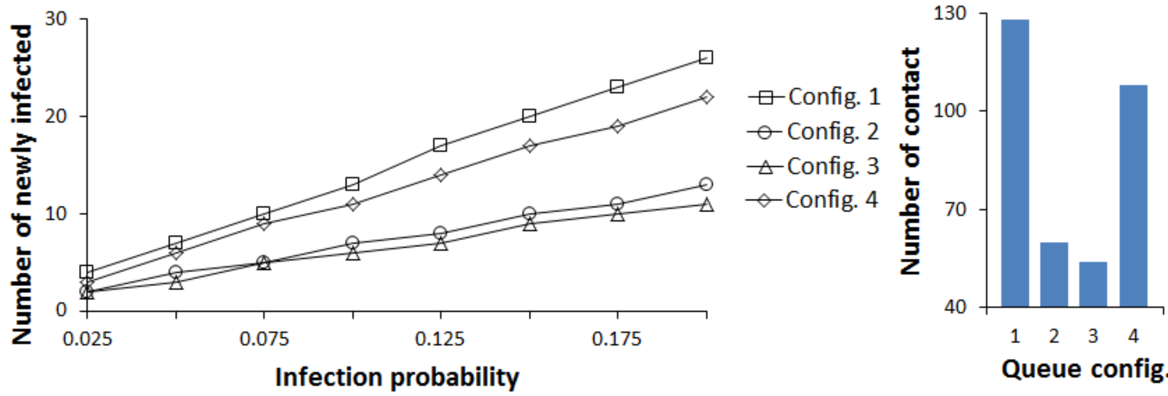


Figure 35. Infection distribution profile for the different configurations at P_{inf}=0.025 and R=1.2m with rope separation

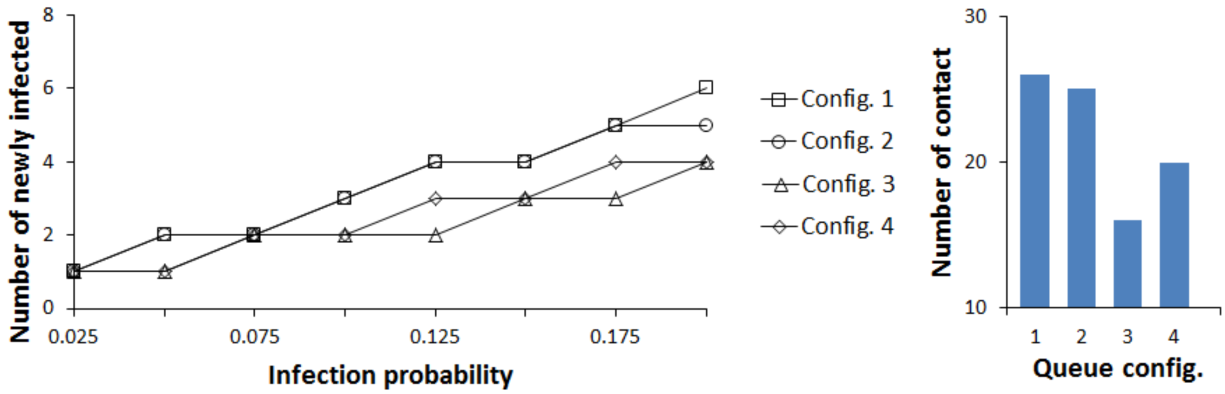
Results

Rectangular floor plan. The researchers first consider the case when two pedestrians belonging to the same group can move abreast or side-by-side in the four rectangular configurations in Figure 34. As initial conditions, the pedestrians are distributed side-by-side inside the aisle and in front of the inlet. The spacing between the pedestrian particles is varied to differentiate between individuals of the same groups and others from different groups, as mentioned earlier in section 2.2. As time evolves, the abreast queues turn into single files in the exit aisles, where the pedestrian speed increases (See Figure 34). The researchers do not consider a waiting time at the exit to decrease the computational effort.

With the commonly used rope separators and an infection radius less than 1.2m, which corresponds to coarse droplet mechanisms, the infective influences the directly adjacent aisles on both sides. The bar chart of Figure 36a estimates the total number of contacts of the infective with the susceptible population. However, a given contact will lead to infection based on the transmission probability. Combining the contact data of the bar chart with the infection model leads to the mean distribution of infection over the probability range, like in Figure 35. In Figure 36, the researchers plot the corresponding mean of the binomial distribution for different configurations and transmission probabilities. Configuration 3 is the best layout for all transmission probabilities, followed by configuration 2 (Figure 36a). In configuration 2, the vertical aisles are short with fewer pedestrians. Configuration 3 has the same aisle geometry as of configuration 2; however, the pedestrian will exit the queue earlier (halfway) compared to that of configuration 2 which results in lower exposure time and consequently fewer contacts. Configurations 1 and 4 results in a higher mean number of infections. These configurations have long open aisles compared to configurations 2 and 3 with the lower aisle length. Therefore, more pedestrians are involved, and interaction occurs more frequently with pedestrians from neighboring aisles in these two configurations. Configuration 1 is the least favorable layout because diverse pedestrians from both sides come into proximity more frequently than in configuration 4 with comparatively shorter aisles. Configuration 4 is worse than configuration 2 because, at the common corners between the left and right zones, the infective comes into contact with additional pedestrians from the neighboring zones.



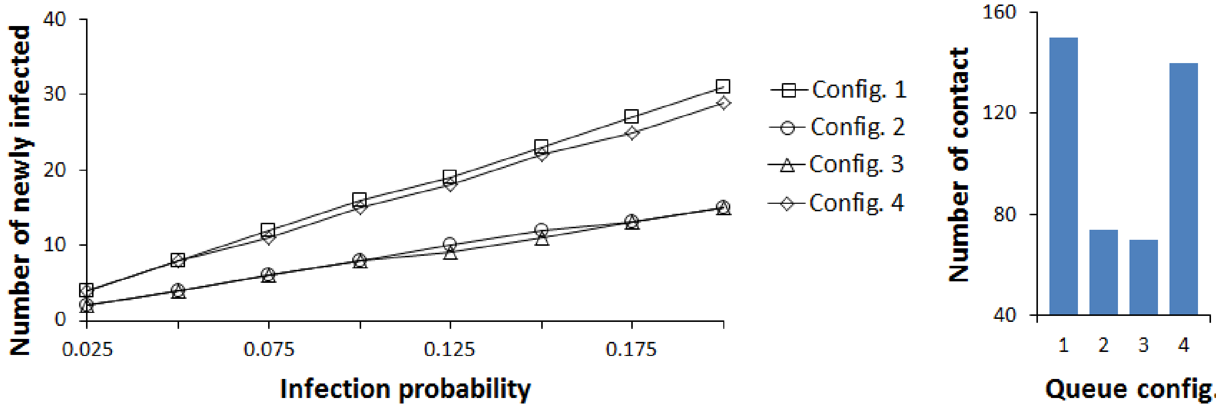
(a)



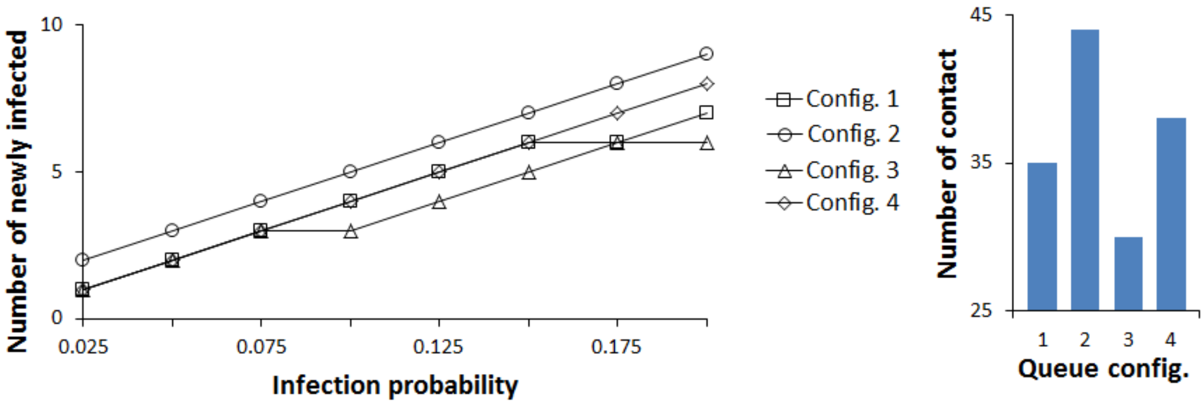
(b)

Figure 36. Infection distribution profile for different double queue configurations at a contact radius of 1.2m. (a) The rope is used for separation between the rows, (b) The temporary shading walls are used for separation between the rows

Use of temporary (or permanent) walls in the place of ropes limits mixing to pedestrians within the same zone and reduces the impact of common corners between zones. In this case, the contagion cannot cross over to the adjacent aisles due to the solid wall barrier, therefore results in a lower number of contacts. Figure 36b shows the mean number of infections when walls are used for crowd control. Overall, the mean number of new infections is significantly lower than when using rope separator. It can be inferred from Figure 36b that configuration 3 still results in the lowest number of infections at all probabilities and configuration 1 with long lines results in the highest number of infections in this case also. The primary difference between using rope separators and walls is in relation to configurations 2 and 4. Configuration 2 resulted in a lower number of infections compared to 4 when using rope separators while this is reversed with walls. In configurations 3 and 4 the exit time is again shorter than that of configurations 1 and 2, resulting in lower overall contacts. Also, at a 1.2m radius of infection, the configurations with long aisles and high pedestrian density corners, result in higher contacts when using wall separators. This is explained by the fact that the same group of pedestrians remains in contact for a prolonged time.



(a)



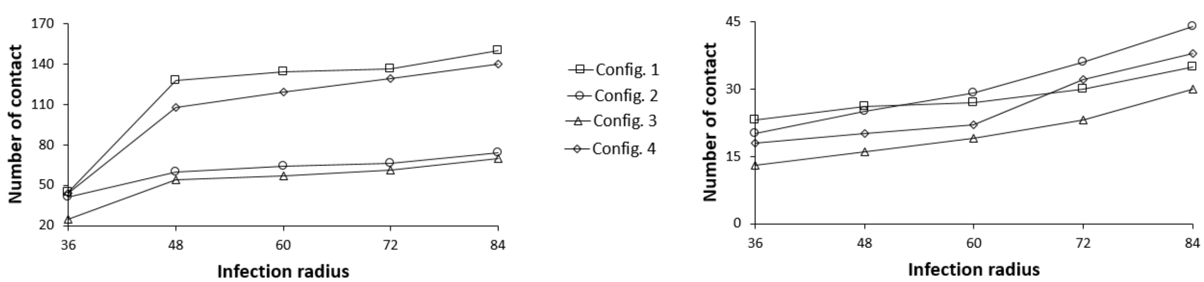
(b)

Figure 37. Infection distribution profile for different double queue configurations at a contact radius of 2.1 m. (a) The rope is used for separation between the rows, (b) The temporary shading walls are used for separation between the rows

Figure 37 shows the results of repeating the transmission probability variation over the same range, but assuming the aerosol transmission mechanism with a longer contact radius of 2.1 m. Configuration 3 still results in the lowest number of contacts for both rope and wall separators. For rope separator, the researchers observe the same pattern of results as with the coarse droplets transmission mechanism, but with increased infection spread (Figure 37a). The similarity between the configurations increases, especially at low transmission probabilities. Therefore, the results of configurations 2 and 3, as well as configurations 1 and 4 overlap. At 2.1 m radius, the dispersion of the fine viral particles crosses the aisle boundaries to two adjacent aisles on each side. Here, the findings of configurations 2 and 3 are nearly identical since the aisles are distributed in the same manner except that configuration 3 has two separated zones. When the transmission radius expands to many neighboring aisles, pedestrians of one zone in configuration 3 come into contact not only with other pedestrians within the same zone but to those in the adjacent zone. Accordingly, configurations 2 and 3 have the same behavior. Here, the separation of these two groups has no effective role in reducing contact. The same principle applies to configurations 1 and 4; the offset between the data of configurations 1 and 4 is reduced compared to that of the coarse droplet transmission mechanism for the same reason. Configuration 1 remains the worst layout, especially at higher probabilities, due to the elongated, abundant contact between pedestrians from adjacent aisles.

Previously, when the coarse droplet transmission with wall separator was evaluated (Figure 36b), the maximum number of contacts for configurations 1 and 2 were highest, followed by configuration 4. With aerosol transmission mechanism (R=2.1 m) as in FIG.6.b, configuration 2 remains the greatest in terms of contacts generated, followed by configuration 4, and the resultant number of contacts of configuration 1 drops. At low contact radius (R=1.2m), pedestrian density within the circle of infection is greater in aisles than at corners. Therefore, long aisles allow greater contact time. However, an infection circle with a 2.1m radius of contact will include more pedestrians at the corners rather than the aisles. Configuration 2 has the shortest aisles, with the greatest number of corners (21 corners), which leads to a higher number of contacts.

The researchers now explore the contacts generated between pedestrians in the four configurations assuming different infection mechanisms represented by the radius variation. Configurations 2 and 3 results in a lower number of infections for rope separators, across the range of infection radii from 0.9 to 2.1 m, as shown in Figure 38a. As explained earlier, for aisles separated with ropes, shorter aisles lead to lower exposure of an infective resulting in this behavior. For walls, the combination of the radius of infection, as well as the interaction time within the aisles and at the corners alter the results as shown in Figure 38b. Each combination of infection radius and queue layout generates a different number of mean newly infected individuals. At low infection, radii short-aisle and low exit time configurations are favorable. At higher radii, configuration with less turning corners is better.



(a) (b)

Figure 38. Contact distribution for different double queue configurations. The contact radius is varied. (a) The rope is used for separation between the rows, (b) The temporary shading walls are used for separation between the rows

Square floor plan. The researchers now consider square layouts with the same area as the rectangular layouts discussed previously. Since the aspect ratio of square configuration changes from that of a rectangular, the aisles number and dimensions vary, as shown in Figure

39. Note that configurations 1 and 2 in Figure 39 (a) and (b), are the same except for rotation. Therefore, the researchers do not discuss them separately. The results shown in Figures 41-43 for these configurations are aggregate of those observed for configurations 1 and 2.

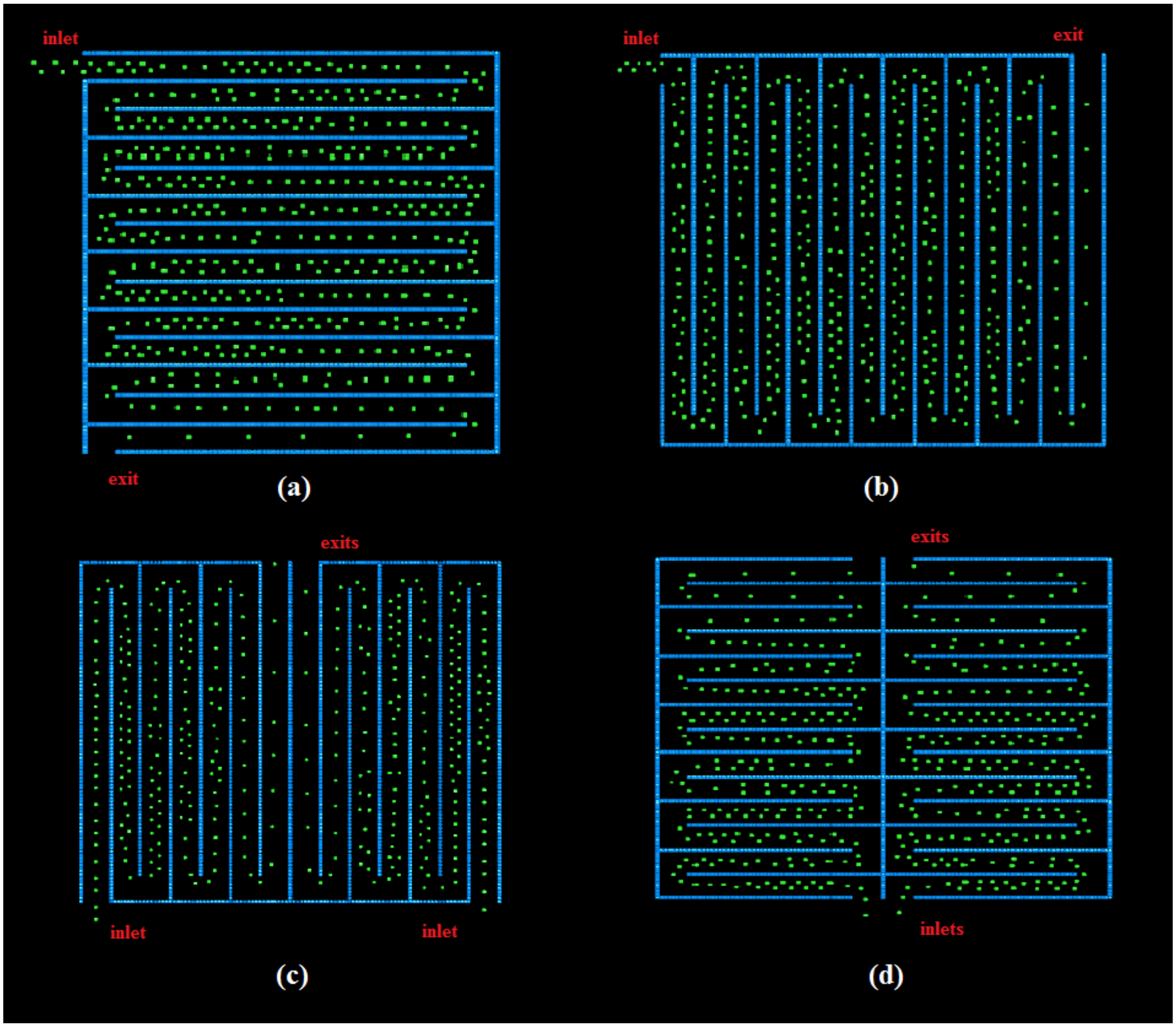
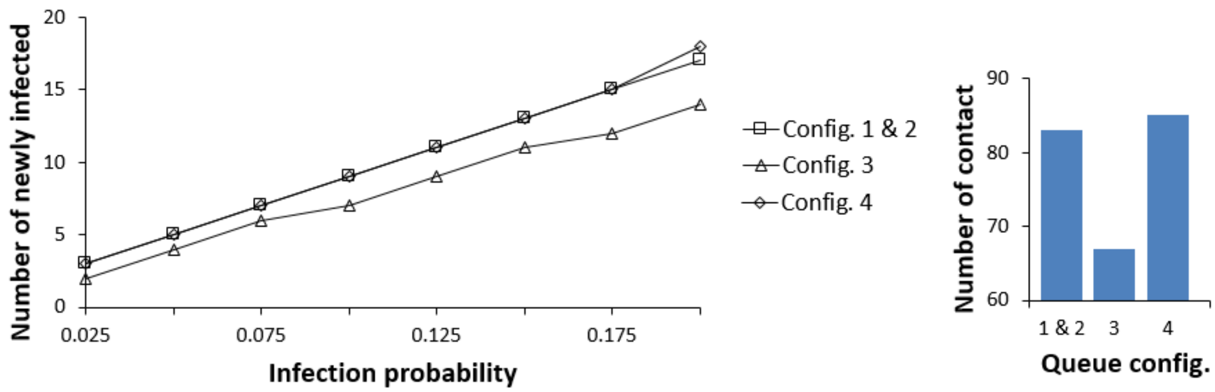
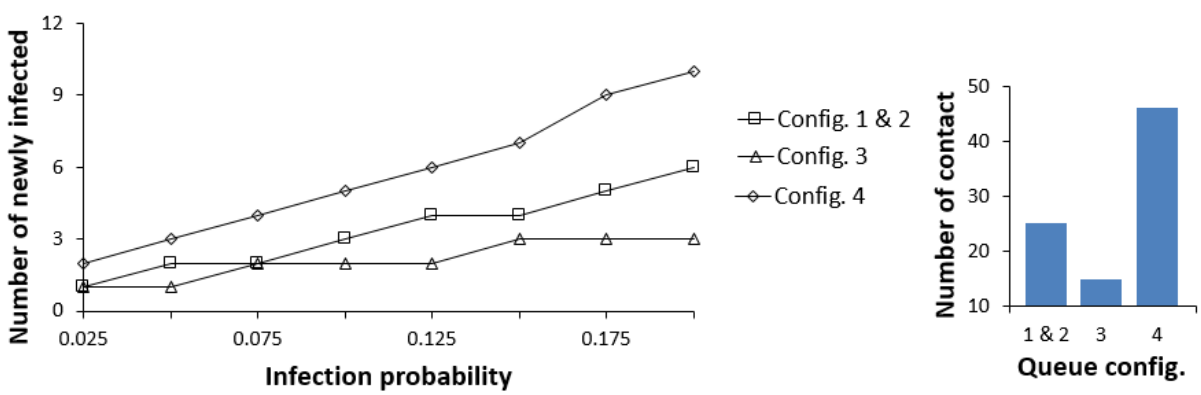


Figure 39. Evolution of pedestrians (t=125s) from a simulation of double queue square layouts: (a) Config.1, (b) Config.2, (c) Config.3, (d) Config.4

Here, the best configuration is again investigated by monitoring the variation of the number of newly infected individuals in terms of infection probability and radius sweep. Looking at the four configurations, by varying the infection probability range, configuration 3 is again the most favorable, whereas, the other three configurations result in the similar number of infections when using rope separators (Figure 40a). Configuration 3 only differs from configurations 1 and 2 by the two left and right zones, enabling faster flow at the inlets and exits. In contrast to configurations 1 and 2 where pedestrians remain in the queue for a longer duration, pedestrians in configuration 3 are exiting halfway with less elapsed time in the waiting line, thus, resulting in less interaction during the shorter wait. Although configuration 4 also possesses two inlets and exits (short exit time), the number of common corners where pedestrians from both zones are at proximate contact is more than that of a rectangular layout. Also, the square configuration 4 here retains the shortest aisle length among all the configurations of the same square layout and even the rectangular ones. Although short aisles with rope separators allow less interaction as mentioned previously, shorter aisles lead to congestions at the corners where pedestrians reduce their walking speed while changing the direction of motion. Therefore, even with a shorter waiting time than the other configurations, Configuration 4 allowed more frequent interactions between pedestrians of both zones resulting in a similar number of newly infected members as configurations 1 and 2, for lower contact radius (Figure 40a). Thus, the long-elapsed time in the queue (aisle and corner) and the abundancy of turning corners have the same effect in increasing infection for rope separators in a rectangular floor layout. For the same configuration geometries, if the floor layout is increased, i.e., wider and longer aisles, configuration 4 will have a better performance as the interaction at the corners and in the aisles as well as the time elapsed in the queue are lower than those of configurations 1 and 2.



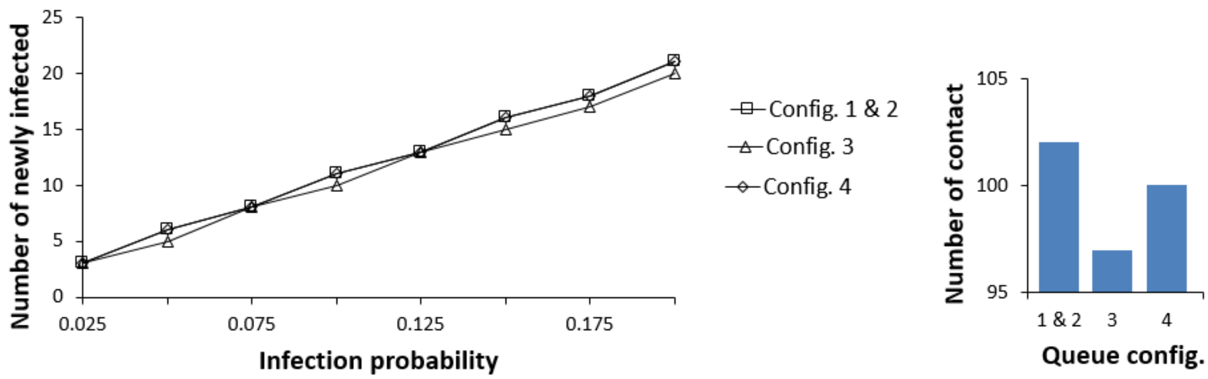
(a)



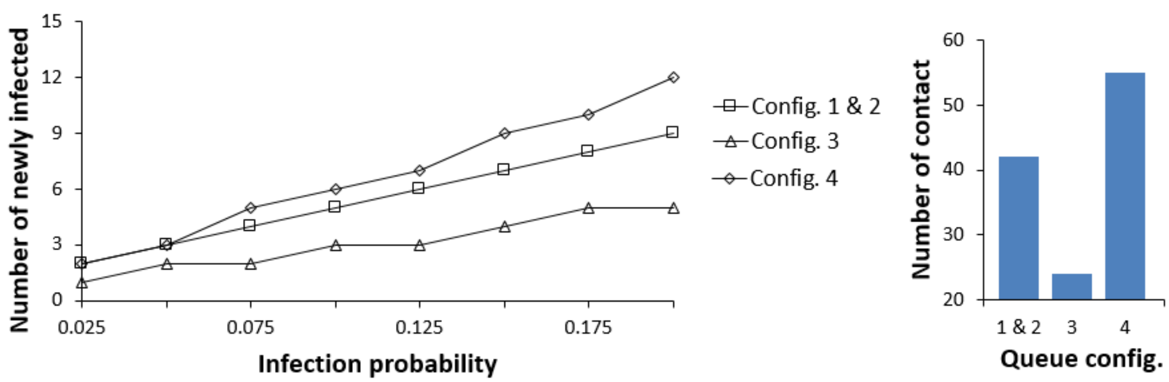
(b)

Figure 40. Infection distribution profile for different double queue configurations at a contact radius of 1.2 m. (a) The rope is used for separation between the rows, (b) The temporary shading walls are used for separation between the rows

With temporary walls used as aisle separators, the order of the configurations alters as shown in Figure 40b. In this case, only the waiting time within the same line and congestion at the corners plays an important role. Referring to Figure 39, it can be noticed that pedestrians' density along the aisles is almost the same between all the configurations. However, at the corners of configuration 4, pedestrians are congregated at higher density than the other layouts leading to an increase in the number of infections for Configuration 4 (Figure 40b). This is explained by the shorter aisles and the necessity to keep changing velocity direction, thus the reduction in the magnitude of the velocity components. This phenomenon also applies to the rope separator scenario. However, with ropes, the maximum interaction with pedestrians in neighboring aisles and corners is of greater importance and frequency than that within the same line. Configuration 3 remains the most favorable as it comprises a combination of moderate aisle length and less waiting time at corners.



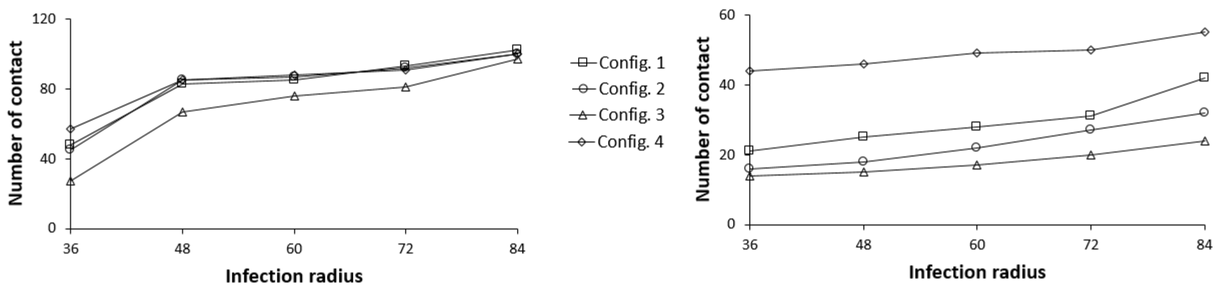
(a)



(b)

Figure 41. Infection distribution profile for different double queue configurations at a contact radius of 2.1 m. (a) The rope is used for separation between the rows, (b) The temporary shading walls are used for separation between the rows

Expanding the contact radius to 2.1 m assuming aerosol transmission mechanism, all configurations behave in the same manner for rope separator, as shown in Figure 41a. With the infective's effect crossing multiple surrounding aisles, separation zones, and the number of corners and aisles have no effect. For walls, the pedestrians' distribution at the corners alters the results with minor differences (Figure 41b). Configuration 4 has the most congested corners and highest number of contacts. Figure 42 summarizes these results. At low infection radius, for a rope separator, configuration 3 is always the best, whereas, with higher contact radii, all configurations almost behave similarly. For walls, pedestrians' density at the corners leads to higher contacts for configuration 4. The short waiting time of configuration 3 makes it competitive in all conditions.



(a) (b)

Figure 42. Contact distribution profile for different double queue configurations. The contact radius is varied. (a) The rope is used for separation between the rows, (b) The temporary shading walls are used for separation between the rows

Single-file pedestrian queue. The researchers now consider single-file pedestrian queues, which are found in many locations, such as ticketing at entertainment locations, airport booking, and security checks, etc. Pedestrian movement is simulated for the four rectangular configurations discussed earlier. Here, the pedestrians are initially distributed in a single file. Since no waiting time is assumed at the exit, the single lanes are preserved as time evolves. However, the distance between these pedestrian increases in the last aisle before exit as no obstructions delay their motion. Also, pedestrian distributions in aisles and at corners vary between the configurations, which causes some differences in the infection results. This variation results from the difference in aisle length, and corners, zones, inlets and exits distributions.

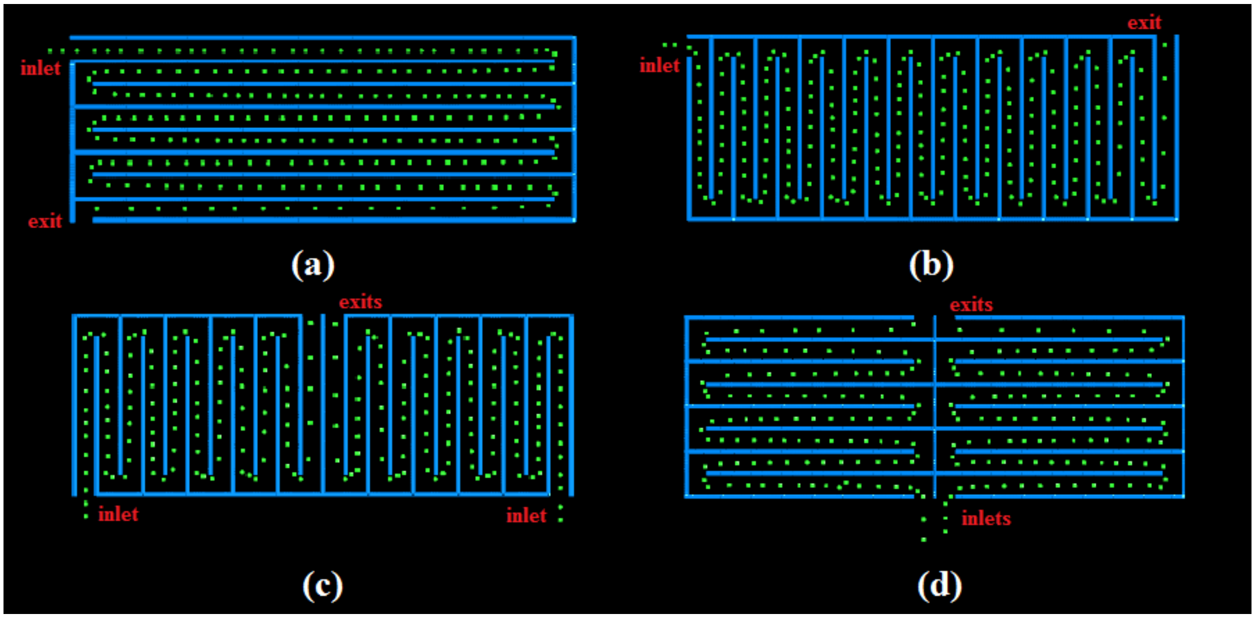
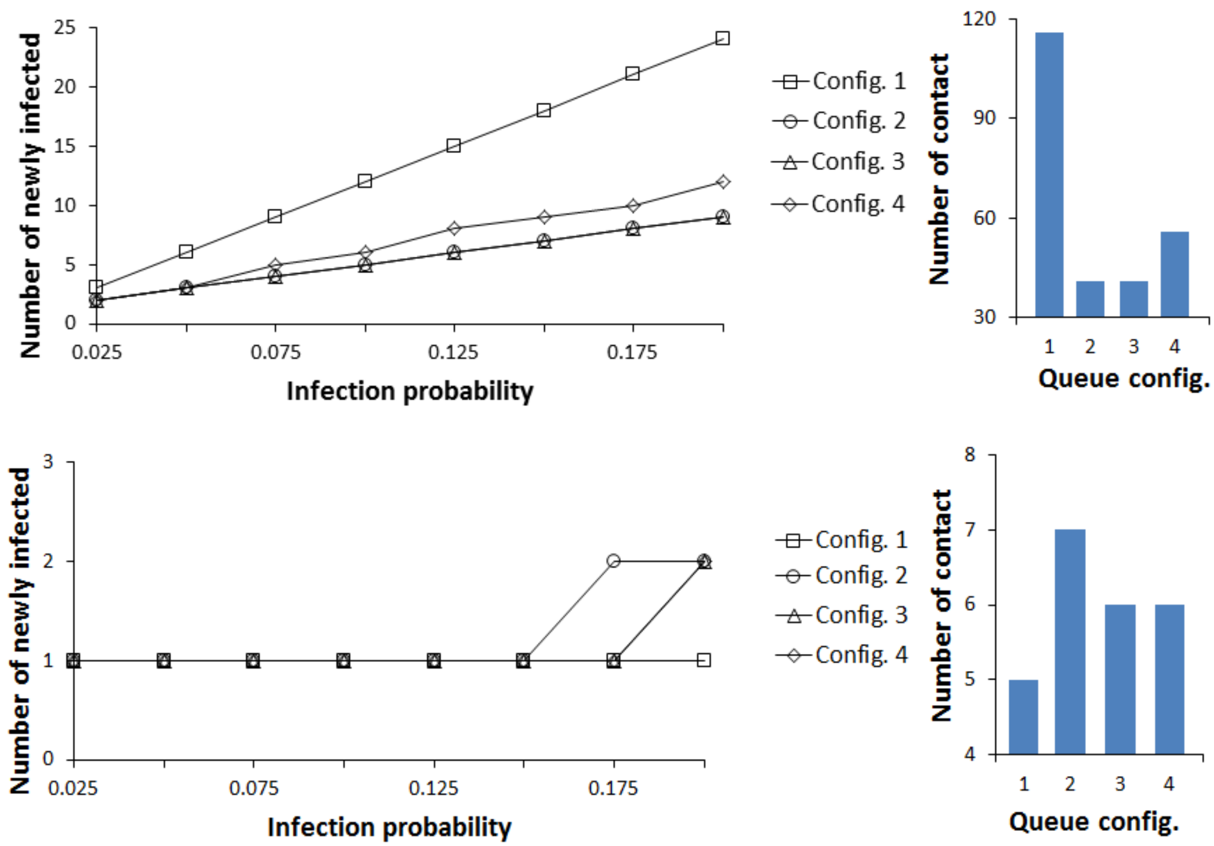


Figure 43. Evolution of pedestrians (t=125s) in single queue layouts of horizontal and vertical patterns for single and double accesses with the same geometric area. (a) Config.1, (b) Config.2, (c) Config.3, (d) Config.4

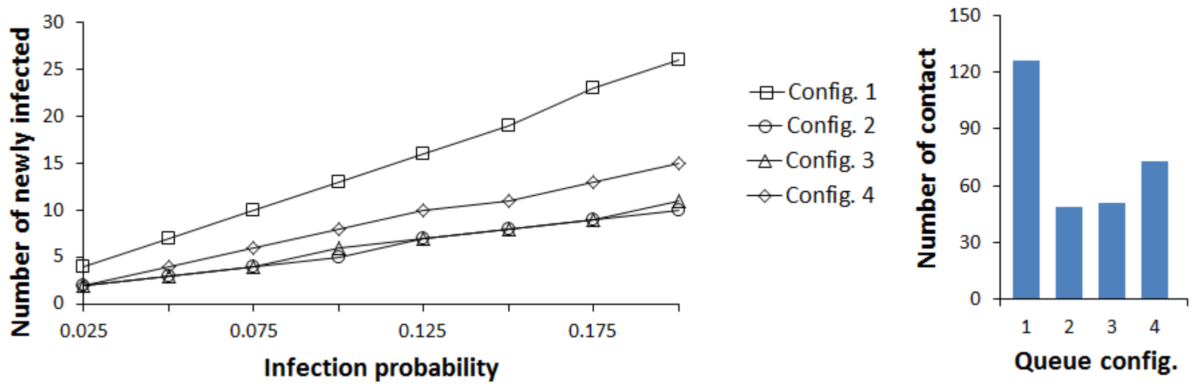
Evaluating the probability range sweep, it is observed that the results of coarse droplets and aerosols transmission mechanism are almost identical for rope separators as in Figure 44a and Figure 45a. The vertical configurations (2 and 3) occupy the lowest mean whereas the horizontal configurations (1 and 4) are of higher values with a maximum reached at configuration 1. This independence of the results from the transmission mechanism, with rope separator, is explained by the lower pedestrian density distribution. Despite the short exit time of configuration 3 over configuration 2, the susceptible population in the next-adjacent aisles does not come into critical contact with the infective causing disease transmission. Only the forward and backward pedestrians in the line, within the same or straight adjacent aisle, are mostly exposed. Also, in all the configurations, the pedestrian-to-pedestrian distance is larger in a single queue, since they are free to move at a higher degree of freedom as of an abreast queue. With the solid walls placed, the density of pedestrians at the corners makes the difference between the configurations for high transmission range, whereas aisles have a greater effect in low infection range. Configuration 1 proves to be the most efficient in reducing contact for a single file formation (Figure 44b and Figure 45b).



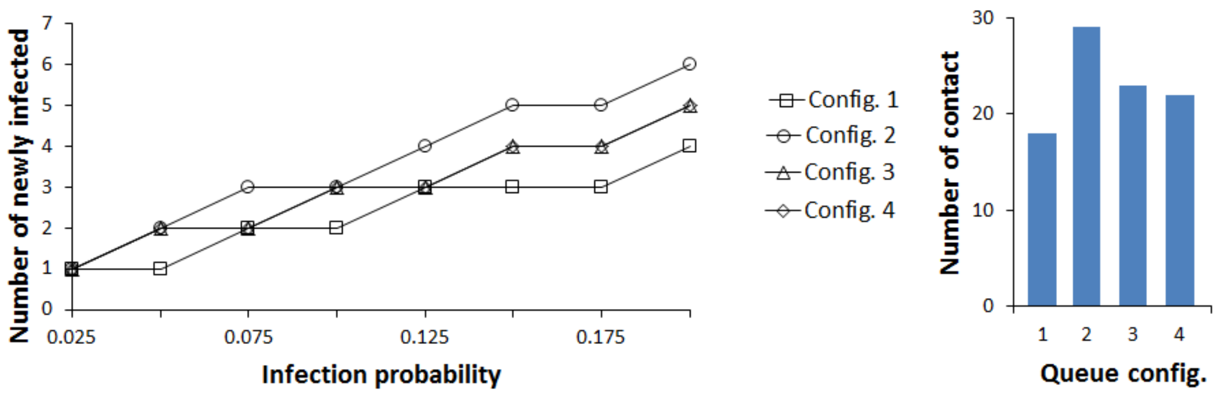
(a)

(b)

Figure 44. Infection distribution profile for different single queue configurations at a contact radius of 1.2m. (a) The rope is used for separation between the rows, (b) The temporary shading walls are used for separation between the rows

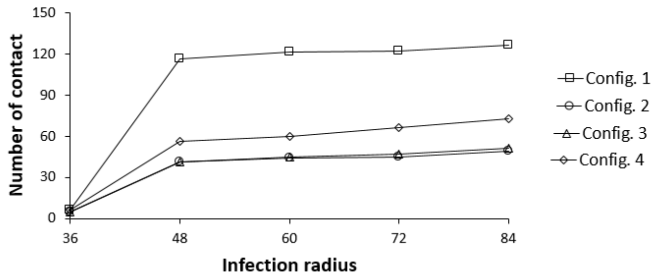


(a)

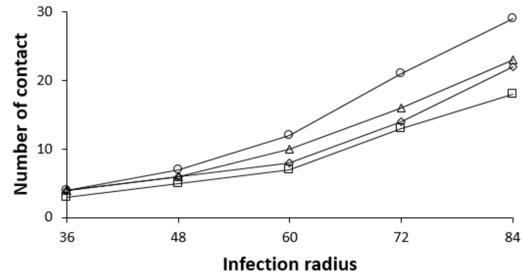


(b)

Figure 45. Infection distribution profile for different single queue configurations at a contact radius of 2.1 m. (a) The rope is used for separation between the rows, (b) The temporary shading walls are used for separation between the rows



(a)



(b)

Figure 46. Contact distribution profile for different single queue configurations. The contact radius is varied. (a) The rope is used for separation between the rows, (b) The temporary shading walls are used for separation between the rows

On the other hand, the variation of the transmission mechanism represented by the radius sweep also impacts the results. With an infection radius smaller than the aisle width, all configurations behave in the same manner (Figure 46a). Here, the contact occurs only within the same aisle; either walls or ropes are used for separation. When the infection radius crosses to the neighboring aisles, the single-zone and double-zone vertical, short aisles allow short mixing (low-time exposure), therefore are favorable to suppression of disease propagation (Figure 46a). The inverse phenomenon is observed when wall separators that isolate each aisle from its surrounding aisles are used. Here, the configurations with higher congestion at the turning corners like configuration 2, result in a higher mean number of infections (Figure 46b).

Discussion

In this study, the researchers analyze the propagation of viral infections in winding queues via a multiscale model combining pedestrian movement and infection models. By tracing the trajectory of each pedestrian in the time frame, the data of contact of each susceptible pedestrian with the infective individual is obtained. Then, applying a susceptible-infected model to the contact data determines the number of the newly infected individual who is in critical contact with the infective member. To account for various transmittance likelihoods, the parameters related to infection transmission are swept over their realistic ranges. The radius of infection is varied to represent disease contraction via inhaled aerosols or coarse droplets. The distance traversed by airborne suspended viral particles before resting on contaminated surfaces is dependent on their microscale size in expulsion events like talking or coughing (Bourouiba et al., 2014). A large droplet is a form of the proximate contact transmission mechanism. The travel distance of these microorganisms is estimated to reach 1m before deposition (Mangili, & Gendreau, 2005). When deposited on the conjunctiva (eyelid mucous membrane) or reaching the gastrointestinal or respiratory tract of a susceptible, infection occurs. Residual droplets or aerosols are also a cause of infection contraction. When droplet nuclei evaporate, microorganisms of the size of 5 microns form (Mangili, & Gendreau, 2005). These microscale particles disperse wider and remain suspended in the air for a long period.

Also, the infection probability of unimmunized individuals is varied to represent the chances of disease contraction depending on its infectiousness. Referring to FIG. 1, the infection probability ranges between 0.025 and 0.2, assuming complete airborne infection among the susceptible population.

Performing various simulations over the parameter sweep ranges, configuration 3 is the best-found layout for the different floor plan geometries, pedestrian alignment patterns, and separators media. Configuration 3 is a combination of the short aisle, low exit time, and separated zones floor plan. Accordingly, in the following, the researchers only compare the behavior of configuration 3 for different infection mechanisms and separators.

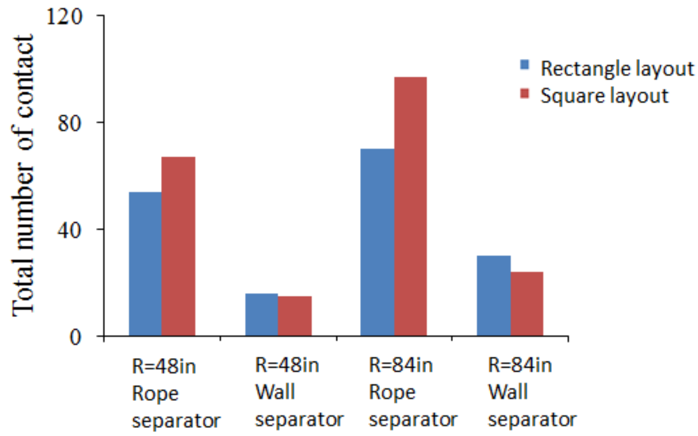


Figure 47. Comparison of the number of contacts between rectangular and square layout for configuration 3

Figure 47 compares the rectangular and square layouts for only configuration 3. It can be observed that there are considerable differences with rectangular layouts being clearly better when using rope separators, while the differences are small for walls. The difference between the two layouts is greater for aerosols transmission with a larger contact radius. This is emphasized by the increase in the length of the aisles in the square layout enabling more frequent interactions. For coarse droplet transmission, the viral particles only cross to one neighboring aisle on each side, resulting in a smaller difference. For wall separators, almost both layouts of different aspects ratios behave the same as contact is restricted within the same aisle.

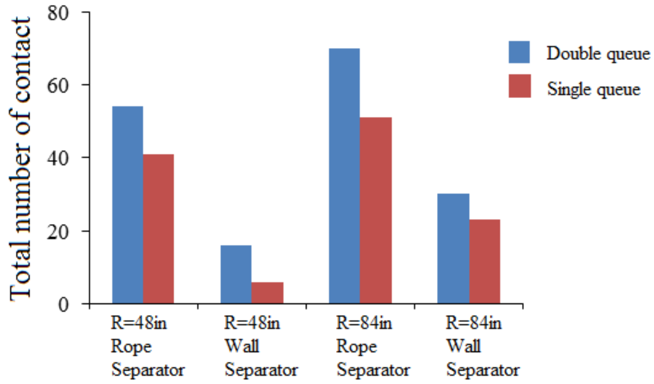


Figure 48. Comparison of the total number of contacts between rectangular double and single queues for configuration 3

The same rectangular configurations are compared between single and double queues. It can be directly inferred from Figure 48 that the infections in double queues are higher than those of a single queue, due to the greater congregation of pedestrian within the same control area. In rope separator scenario, and for wall separator with low transmission radius, there is a great shift in the results that reduce in the case of the greater infection radius with wall separator. This is explained by the jamming at the corner in both double and single queues, especially when the radius (2.1 m) covers the entire turning area.

Conclusion

In conclusion, this study showed that the evacuation time would increase when the number of pedestrians increased, and when fewer exit doors were available. This study has also shown that the shortest queue evacuation policy performed better than the equal distribution policy, and the choice of gates can be a factor that affects the efficiency of evacuation. Additionally, instructions could increase the efficiency of the evacuation process.

The researchers also evaluated the effect of queue configurations on generating contact between neighboring pedestrians. Four distinct queues were evaluated with vertical and horizontal aisle patterns, one or two waiting zones, rectangular and square floor plans, and single-file or abreast pedestrians' distributions within the control area. With rope separators, pedestrians could interact with other pedestrians from neighboring aisles in addition to the forward and backward members in the queue within the same aisle. However, for wall separators, the interaction between pedestrians was restricted to those only within the same aisle.

When single-file pedestrians' motion was assessed in a rectangular floor plan, the spacing between pedestrians was increased compared to a side-by-side walking pattern. For rope separators, the greater distance between pedestrians of neighboring aisles, compared to an abreast motion, creates less contact. The transmission phenomenon was independent of the exiting time and transmission mechanism of the disease. However, the short aisle remains favorable over the longer ones. For wall separators, for low infection radius, the highest contact occurred in the aisle. Since the pedestrians were distributed in the same manner in the case of a one-file queue, all configurations were equivalent. For higher radius, the corner was the platform of higher contact.

On the other hand, there were also limitations to this study. The pedestrians were assumed not to be affected by their situation awareness; which means that they did not dynamically change their evacuation path. Any situational changes in the emergency would affect the results of the study. Another limitation was the software capabilities. The software could not simulate a chaos situation, and only predict a safe condition for the pedestrians to evacuate. In addition, only people who can move at average speeds were considered in this evacuation simulation.

Overall, this study produced a valid baseline to simulate passengers' evacuation paths. For example, Case study 1 had considered various speeds when passengers used the escalators or stairs in normal and emergency conditions. In the experimental design, the study generally predicted an evacuation time by simulating different passenger traffic levels and a different number of airport's exit doors. Most importantly, this study was the development of a valid evacuation simulation model that offers ability to change the variables to test different scenarios that affects the efficiency of evacuation.

Future studies would require a greater amount of data analysis and a real-time pedestrian movement and incorporate more factors that may affect the efficiency of evacuation during emergencies. For example, future studies should consider pedestrians who move at different speeds, such as children, elders, and the disabled. More comprehensive evacuation methods should be tested, including other factors including the waiting time for the exits, weather, terrorism, and hazardous materials.

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Appendices

Appendix A

Observing the arrival rate at the airport

N	Number of passengers	Time (seconds)
1	9	60
2	14	60
3	19	60
4	20	60
5	17	60
6	11	60
7	26	60
8	14	60
9	25	60
10	24	60
11	48	60
12	20	60
13	19	60
14	8	60
15	23	60

16	14	60
17	9	60
18	16	60
19	16	60
20	24	60
21	17	60
22	16	60
23	12	60
24	13	60
25	6	60
26	27	60
27	20	60
28	8	60
29	12	60
30	32	60
31	20	60
32	10	60
33	14	60
34	28	60
35	21	60
36	14	60
37	15	60

38	28	60
39	25	60
40	23	60
41	34	60
42	6	60
43	12	60
44	9	60

Appendix B

Observing the passenger data from the airport

Flights	Number of passengers	Duration of de-boarding and leaving the airport (Seconds)
1	73	478
2	121	815
3	56	323
4	139	739
5	63	413
6	129	561
7	63	303
8	147	673
9	121	623
10	219	744
11	142	816
12	165	826
13	74	463
14	242	1152
15	148	828
16	47	341
17	126	682
18	153	821

19	81	535
20	63	465
21	144	787
22	141	889
23	69	469
24	130	828
25	59	343
26	52	390
27	118	747
28	116	679
29	49	334
30	57	449
31	130	729